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A Statistical Modeling Approach to Estimate Plant Closure Durations in Department of Defense (DOD) Supply Chains

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Abstract

Plant closures have always concerned supply chain purchasers. A supplier plant could close anytime due to natural disasters, strikes, pandemics, or financial distress. Supply chain purchasers must assess potential suppliers' risk when identifying annual contracts and evaluating capacity planning. Previous models in literature determine the likelihood of a supplier's plant closure within a year. In this paper, we expand beyond likelihood to determine the predicted length of plant closure using linear regression, cox proportional hazards, and accelerated failure time models. We apply our models to a case study within the Department of Defense (DoD). Our results demonstrate that these predictive models have the potential to aid in the mitigation of supply chain risk, improving capacity allocation, and saving taxpayer dollars.

Keywords
Supplier Risk, Plant Closure, Cox-Proportional Hazards Model, Accelerated Failure Time Model

1. Introduction
The Department of Defense (DoD) spends over $600 billion annually, accounting for 3.5% of the United States' Gross Domestic Product (GDP). Supply chains within the DoD play a crucial role in national and global economics. The

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manufacturing industry comprises a large portion of the DoD supply chain, which consists of thousands of suppliers. These suppliers range from large multi-plant firms to small single-source manufacturing plants (Melnyk et al., 2021). At any given time, these suppliers' plants face the risk of closure. Closures can be temporary or permanent. Each plant has a unique risk profile based on factors like Turbulence, Deliberate Threat, External Pressures, and Resource Limits (Pettit et al., 2010).

Plant closures within the manufacturing industry are well-studied (Beer et al., 2019). Plant closures can be classified as either planned or unplanned. Planned closures are usually permanent, scheduled well in advance, and often part of a parent firm decision. Child plants are subject to these decisions within larger manufacturing firms and plant networks. Planned closures are usually linked to insufficient funds and/or industry transition (Richbell & Watts, 2000). Less studied in literature are unplanned closures, which are generally temporary. Such closures can be attributed to natural disasters, strikes, pandemics, financial distress, etc. (Pettit et al. 2010). In this paper, we seek to expand the literature on unplanned closures by proposing models that predict plant closure duration.

The COVID-19 pandemic was an unprecedented worldwide challenge experienced throughout supply chains (Monczka et al., 2020). Its effects are still felt today and have caused disruption in supply chain operations across the manufacturing industry and DoD suppliers. During this time, the disruption of smaller suppliers in the DoD was especially dangerous as they could be sole providers of niche equipment (Interagency Taskforce, 2018). Notably, firms were concerned with the availability of a qualified workforce and the ability to keep facilities safe for workers (Melnyk et al., 2020). Sanders (2023) built a novel data-driven supplier risk identification and assessment framework that examines the riskiness of DoD supplier plants for potential unplanned closure. This framework has been proven effective in both disruption and non-crisis situations.

1.1 Objectives

In this paper, we build off the work of Sanders (2023) by predicting the closure duration for expected at-risk plants. We built three models: a Linear Regression Model, a Cox Proportional Hazards Model, and an Accelerated Failure Time Model. We then applied them to a case study within the DoD to assess their performance. This paper uses the proposed models for two critical insights: the time at which the closure of the at-risk plant will occur and the duration of the closure.

2. Literature Review

Supplier risk assessment models in literature are either conceptual (Pettit et al., 2010) or proposed applied models with narrow implementation (Pettit, 2013). Pettit (2010) built a conceptual framework for supply chain resilience that identifies several sources of supply chain vulnerability, such as deliberate threats, sensitivity, and resource limits. There is a call for the practical implementation of supplier risk models. Sanders (2023) presents a novel risk assessment framework, a hybrid procedure, that combines a linear discriminant analysis (LDA) bankruptcy model (Dickerson et al., 2022) with a multi-criterion scoring procedure built using the DELPHI method. The methodology calculates individual plant-level supplier risk indices using public information, which can be used to aid defense purchasers and contract negotiators in choosing more reliable suppliers. While Sanders was able to predict whether a plant could face closure, the expected time and duration of closure were not identified.

Detecting plant closures or disruptions before they occur is critical in maintaining resilience within any supply chain. Similarly to Sanders (2023), several studies have focused on creating predictive models to detect these occurrences within their operations. For example, Kanna (2022) tested several machine-learning methods to develop predictive models that would improve the efficiency of a quarry company's production lines by reducing production delays. Similar studies sought to predict closures or disruptions in a system and identify the factors that influence them within other areas of industry. A multinomial logistics model was constructed to identify closures or necessary consolidations of schools in the Chicago public school system (Weber et al., 2018). The purpose of the model was to enable more efficient school facilities planning and provide insights on factors to evaluate when deciding to close or consolidate a school.

With research primarily focused on estimating the time a closure will occur, limited research has been done to assess the closure length. However, some studies sought to increase the impact of their predictive modeling for resilience by extending these models to evaluate the duration of the closures. A.C. Caputo and Paolacci (2017) conducted a study that focuses on estimating the seismic resilience in processing plants and led to the creation of a method that provides rapid calculations of key resilient metrics such as capacity loss, reconstruction, business interruption costs and the timeline for recovery (Caputo & Paolacci, 2017). The closure duration plays an integral role in creating these key metrics. Using the time needed to repair equipment and restore production capacity, the closure duration is calculated to determine estimated downtime and economic loss (Caputo & Paolacci, 2017). To increase accuracy, future research suggests incorporating "walk-downs or a walk-by" that assess specific equipment for vulnerabilities. However, a key limitation of this model is its reliance on a plant's specific architectural structure to calculate the variables of interest. This information is typically not publicly available. Different plant layouts could require adjusted modeling that could disrupt the model function when expanded to a vast list of closures.

To effectively estimate plant closure durations in Department of Defense (DoD) supply chains, this study explores three distinct statistical modeling approaches: Linear Regression, Cox Proportional Hazards (CPH), and Accelerated Failure Time (AFT) models. Each model offers unique advantages in predicting time-dependent events, providing a comprehensive framework to analyze unplanned plant closures. By leveraging these three models, the study aims to identify the most effective approach for predicting closure durations, thus enhancing supply chain resilience.

Linear Regression is a well-established statistical method that predicts the dependent variable based on the linear relationship with one or more independent variables (Montgomery et al., 2012). Its simplicity and ease of interpretation make it a valuable starting point for understanding the impact of various risk factors on closure durations. In supply chain disruptions, linear regression has been successfully applied to forecast delays and downtimes, providing actionable insights for operational planning (Kannan, 2022). Additionally, linear regression models have been utilized in manufacturing to predict equipment failures and optimize maintenance schedules, helping organizations mitigate disruptions (Nateghi et al., 2014). While it may not capture complex, non-linear relationships as effectively as other models, its straightforward nature allows for quick implementation and preliminary risk assessment. Moreover, linear regression serves as a benchmark model against which the performance of more sophisticated survival analysis techniques, such as CPH and AFT, can be compared.

As we look further to enhance the predictive modeling of plant closures and recovery, integrating survival analysis offers an additional statistical approach for estimating the closure time and, more accurately, the duration of plant downtime. Initially developed in medical and biological research to study survival times, such as the time until death (Bustan et al., 2018) or the recurrence of disease (Tibshirani, 2022), survival analysis is a set of statistical methods used to examine and predict the time until a specific event occurs (Denfeld, 2023). There is ample literature that uses predictive survival analysis – but none that applies the methodology to plant closure.

For example, Bustan (2018) uses a Cox Proportional Hazards (CPH) model to determine the survival rate of patients with breast cancer. This model also quantifies the influence each specified factor has on the survival rate (Bustan et al., 2018). Orbe (2002) and others conducted similar research using CPH to assess breast cancer in women while also expanding their analysis to assess estimated survival time for gastric cancer patients based on treatment types. In their study of breast cancer patients, they were provided the predicted survival times for patients based on their HPA staining results, positive or negative. The desired assessment was to determine a significant difference in survival times based on these two groups of women (Orbe et al., 2002). With the unknown survival time distribution, CPH was identified as a possible model for assessment due to its assumed proportionality. Orbe et al. (2002) conducted similar modeling to assess the significant difference between two treatment types of chemotherapy, alone and a combination of chemotherapy and radiology, on the survival time of gastric cancer patients (Orbe et al., 2002). Other literature utilizes CPH to estimate downtimes and their durations. Specifically, Thijssens and Verhagen (2020) implemented CPH to assess the longevity of specific aircraft components based on operational factors. Focusing on time-to-event analysis, survival analysis can be directly relevant to the study of closures and disruptions to estimate the time from closure to reopening. Paired with Sanders' (2023) risk assessment framework, implementing a similar statistical model could identify the expected time and duration of closure for a supplier classified as at-risk. Table 1 below identifies similar literature that uses a variety of applications to evaluate risk assessments and survival analyses.

An alternative to survival analysis for duration prediction is the mean time to repair. Commonly assessed in manufacturing and production, mean time to repair (MTTR) is the expected time to recover a system from failure (Torell and Avelar, 2004). MTTR can be estimated using a parametric model, the Accelerated Failure Time model (AFT). The Accelerated Failure Time model is primarily used in industrial fields. For example, Liu et al. (2007) used the AFT to statistically forecast the electrical power restoration times in hurricanes and ice storms in North Carolina, South Carolina, and Virginia plants. The models were built using historical outage data from the three major east coast power companies. When tested against a hurricane and ice storm, this model's accuracy was shown to be promising for companies' management of storms in the future. AFT was also utilized to predict the duration of traffic incidents in China (Wang et al., 2013). This model was tested using incident duration data derived from the Freeway Monitoring Center in Zhejiang Province, China, and the distribution assignment allowed for several distributions to be tested to determine the best fit for the predictions (Wang et al., 2013).

However, similar to Cox's Proportional Hazards Model, this model can be utilized to assess survival time (Saikia and Barman, 2017). Liu et al. (2007) demonstrated this model's capabilities through their implementation to estimate the restoration times for electric power following hurricanes and ice storms. In this case, the AFT model was effectively applied to forecast the duration of the storm-caused power outages before they occurred, and its results are being used to aid people and companies in mitigating the disruption caused. The insights derived from these papers provide a solid foundation for implementing the AFT model in our case, as both scenarios center on analyzing the duration of downtime. Lastly, output is the key factor differentiating the AFT and CPH models. While the CPH model provides a hazard ratio understood as a probability of a hazard happening, the AFT model can provide a duration derived from the covariates acting multiplicatively on time directly (Saika and Barman, 2017).

Table 1. Model Definitions and Applications

Model	**Definition**	**Application Types**
Linear Regression	A basic statistical method that models the relationship between a dependent variable and one or more independent variables by fitting a linear equation to observed data.	Forecasting Production Delays in Quarry Operations (Kannan, 2022), Predicting School Closures (Weber et al., 2018), Estimating Equipment Downtime in Manufacturing (Nateghi et al., 2014)
Cox Proportional Hazards	A regression method for survival analysis that assumes proportional hazard rates and evaluates the impact of predictors through hazard ratios without requiring a specified baseline hazard function. (Cox, 1972)	Length of Survival of Breast Cancer patients (Bustan, 2018), Length of Survival of Gastric Cancer patients (Orbe et al. 2002), Mean Time Between Repair of Aircraft Components (Thijssens and Verhagen, 2020)
Accelerated Failure Time	A model is a regression approach for survival analysis that models the logarithm of survival time as a linear function of covariates, providing intuitive insights into how predictors affect survival time. Serves as a valuable alternative to CPH. (Wei, 1992)	Estimation of Electrical Restoration Times (Liu, 2007), Length of Survival of Gastric Cancer & Breast Cancer (Orbe et al. 2002), Length of Stay for Discharged Patients (2017)

3. Methods

This study employed a multi-model approach to predict best the duration of plant closures within Department of Defense (DoD) supply chains. By leveraging Linear Regression, Cox Proportional Hazards (CPH), and Accelerated Failure Time (AFT) models, we aimed to capture different techniques that could yield accurate predictions. Data was collected from supplier plant closures, incorporating various disruption causes such as natural disasters, pandemics, and company decisions. For each model, specific variables were selected based on their relevance to closure risk factors. The models were then trained and evaluated using statistical performance metrics, including the concordance index and Akaike Information Criterion (AIC), to determine their accuracy and applicability in predicting closure durations.

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3.1 Linear Regression Model

Linear regression is a statistical technique used to model the relationship between a dependent variable and one or more independent variables by fitting a linear equation to the observed data. The general form of a linear regression model is given by:

$$\textbf{(1)}\quad Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \ldots + \beta_e X_e + \varepsilon$$

Y represents the dependent variable (closure duration), $\boldsymbol{X_1}$ to $\boldsymbol{X_e}$ are the independent variables (risk factors), $\boldsymbol{\beta_0}$ is the intercept, $\boldsymbol{\beta_1}$ to $\boldsymbol{\beta_e}$ are the coefficients representing the impact of each independent variable, and ε is the error term.

3.2 Variable Selection for Linear Regression Model

Stepwise Regression was employed to identify the most influential factors in our linear regression models. Within R, we implemented an iterative script using forward selection to evaluate each variable comprehensively. Starting with an empty model, variables were incrementally added based on their statistical significance, as determined by p-values, with respect to plant closure duration. This process is checked by the Akaike Information Criterion (AIC), which balances the model fit and complexity.

3.3 Cox Proportional Hazards Model

Cox's Proportional Hazards Model is a semiparametric regression model that does not follow a specified distribution and is centered around a quantity known as the hazard function (Tibshirani 2022). The function is below:

$$\textbf{(2)}\qquad h(t) = h_0(t) \cdot exp(\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i)$$

The formulation identifies t as time, h_0 as the baseline hazard ratio when our predictors, X_i, equals zero, and β_i is the regression coefficient associated with the covariates. Concerning our problem, $h(t)$ can be described as the probability that a plant w/ predictors x will open at time t, given that the plant was closed before t. This model was built through an R script to read the dataset, run the regression based on the determined covariates, and return the regression coefficients, associated p-values, and concordance score. In addition, the values for the likelihood test, Wald test, and score test are output to provide the significance of the model in its entirety.

A unique aspect of our CPH is that it works inversely compared to similar applications used in survival analysis. For example, CPH models commonly look at time to death. Therefore, it displays an onset time of diagnosis with the survival rate decreasing as it approaches the time of death. For our CPH model, our onset or initiation of the survival analysis will be the plant's closure, and our survival rate will decrease as we approach the time of reopening. This is a key concept to understand while interpreting the CPH model results.

3.4 Variable Selection for Cox Proportional Hazards Model

Univariate analysis determines the influential factors in our Cox Proportional Hazards Regression model. Using R, we implement an iterative script that evaluates the significance of variables concerning plant closure durations. This is conducted with the coxph function, which is used to create the final regression model. Without specifying independent variables, the function assesses the significance of all variables regarding the dependent variable. Like stepwise regression in linear models, the coxph function returns a p-value for each variable. Significant variables are then incorporated and specified in the function to build and evaluate the final model, where all selected variables are considered simultaneously.

3.5 Accelerated Failure Time Model

The Accelerated Failure Time model is a parametric regression model that requires a distribution to be assumed (Weibull, log-normal, etc.) and is focused on a survival function like Cox's. The survival function is below:

$$\textbf{(3)}\qquad \ln(T_i) = X_i^{\top}\beta + \varepsilon_i$$

This formulation mirrors Cox's, with T representing survival time, X_i being predictors and β standing for the regression coefficients. However, the AFT Survival Function also includes an error term, ε_i. This term follows a specific distribution (Saika and Barman 2017). For our model, we will assume that this error term follows a log-normal distribution. This assumption is based on a best-fit distribution test conducted on our preliminary datasets separated by the root cause of plant closures. The iteration of this model in R follows a process similar to that of the CPH model. The regression coefficients are returned along with the p-value assessments of these covariates. However, the significance of the model is determined using Chi-Squared.

3.6 Variable Selection for Accelerated Failure Time Model

The variable selection for our Accelerated Failure Time (AFT) model followed a similar selection process used for the CPH Model with the respective functions used for AFT in R.

4. Data Collection

Sanders' (2023) multi-criteria risk model evaluates potential plant closures based on several risk factors. These factors are sourced from several public data sources, including companies, and are provided in the table below.
We will use the risk factors and corresponding scores from Sanders' methodology as the independent variables affecting the plant closure durations, along with the reason for closure provided by the company. Specifically, our models will assess the key factors of financial risk, natural disasters, geopolitical disruptions, terrorism, a right-to-work state, work stoppages, human rights, and conflict minerals. All scores are based on geographic location except for bankruptcy risk. Therefore, each county's zip code list is connected to the dictionary records we have created to enable easy assignment of these factor scores to each company based on location. We will also consider the root cause of closure as provided by the plant suppliers. The root causes identified and evaluated within our model are COVID-19, Company Decisions, Local Government Direction, Financial Distress, Labor Shortages, and Supply Chain Disruption. These risk records will serve as our final dataset in conjunction with closure duration data and root cause information.

Table 2. Risk Components and Source (Sanders, 2023)

Risk Criterion	Component	Country	Scale	Data Title	Data Source
Turbulence	Natural Disasters	USA	County	US Natural Hazards Index	National Center for Disaster Preparedness at Columbia University
Turbulence	Natural Disasters	Foreign	Country	Global Climate Risk Index	Germanwatch
Turbulence	Geopolitical Disruptions	All	Country	Political Risk Map	Marsh
Deliberate Threat	Terrorism	ALL	Country	Global Terrorism Index	Institute for Economics & Peace and National Consortium for the Study of Terrorism & Responses to Terrorism at US Department of Homeland Security
Deliberate Threat	Labor Disputes	USA	State	US Work Stoppages	US Bureau of Labor Statistics
Deliberate Threat	Labor Disputes	Europe	Country	ETUI Strikes Map	The European Trade Union Institute financially Supported by the European Union
Deliberate Threat	Labor Disputes	Canada	Country	Canada Work Stoppages	Employment and Social Development Canada, the Government of Canada
Deliberate Threat	Labor Disputes	Australia	Country	Australia Industrial Disputes	Australian Bureau of Statistics, the Australia Institute Centre for Future Work
Deliberate Threat	Labor Disputes	USA	State	Right to Work Laws	National Right to Work Committee
Financial Risk	Dickerson et al. Model	USA	Firm	Financial Data	Wharton Research Data Services (COMPUSTAT), Yahoo Finance, S&P Global Capital IQ
Foreign Influence	Human Rights Laws	ALL	Country	Human Rights Laws	Fund for Peace
Foreign Influence	Conflict Minerals	ALL	Country	Conflict Minerals	SEC
Foreign Influence	Foreign Entity	ALL	Country	N/A	N/A

Closure duration and root cause data used to construct this predictive modeling originate from a government agency and comprise 200 observations representing unique supplier plant closures in 2020. Our initial cleaning process involved removing any observations with incomplete records and international locations. The cleaned dataset contained 139 observations and maintained the integrity of key variables such as closure duration, the plant's geographic location, and the root cause of plant closure. Further data analysis was conducted to identify and exclude outliers and implausible close durations. Specifically, all closures that exceeded 35 days were removed, and to account for COVID-mandated two-week closures, all 14-day closures with a root cause, COVID-19, were removed from the dataset. After this data was cleansed, our final 105 observations remained.

5. Results and Discussion

We randomly separated our data for modeling iterations to create a training and test set. Our training set contained 85 closures, and our test set contained 20. These models incorporate independent variables, including those introduced by Sanders (2023) and the root cause of closures with duration as the dependent variable.

5.1 Models

5.1.1. Linear Regression Model

Our final linear regression model can be seen below:

$$\textbf{(4)}\quad y = 17.611 - 9.806X_1 - 7.711X_2$$

Stepwise regression determined that the statistically significant variable for this linear regression was root cause. X_1 is the root cause of COVID-19, and X_2 is the root cause of Local Government Direction. This model was found to be significant, with a p-value of 0.001576.

5.1.2 Cox Proportional Hazards Model

Our final CPH model can be seen below:

$$\textbf{(5)}\quad h(t) = h_0(t) \cdot exp(1.06527X_1 + 0.92858X_2)$$

The univariate analysis determined that the statistically significant variables for this model were root cause and natural disasters (DisastersUSA). In this case, X_1 represents the root cause of COVID-19 Cases and X_2 represents natural disasters (DisasterUSA). This model was found to be significant based on the initial test run simultaneously with the creation of the model. The initial significance tests conducted in correspondence with the *cph* function were the likelihood, Wald, and Score tests. All three tests return significant p-values of 0.03, 0.05, and 0.04, respectively. Our further assessment of this model in relationship to our test set can be found in section 5.3.

5.1.3 Accelerated Failure Time Model

Our final AFT model can be seen below:

$$\textbf{(6)}\quad ln(T) = 2.7918 - 1.1211X_1 - 0.8636X_2$$

As previously stated, the variables found statistically significant for CPH, root cause, and natural disasters were used in the initial creation of the AFT model. After reevaluation, the model performed best with the root causes as the independent variables. Specifically, the root causes of COVID-19, X_1, and Local Government Direction, X_2 were found to be the most significant. This model is significant, with an overall p-value of 0.00059.

5.3 Model Assessments

For each model, we established a function that would use the created model to predict the duration of closures for each test set. Below are the results for four random predictions for each dataset with respect to their test set.

Table 3: Predictions

Company	Actual	Linear Prediction	CPH Prediction	AFT Prediction
Company E	17	18	1	16
Company F	17	18	1	16
Company G	15	18	1	16
Company H	16	18	1	16

An important aspect of predictive modeling is assessing the final model's accuracy and significance. The created linear and AFT models seem to produce the most accurate predictions. However, we evaluated and compared the concordance scores and AIC for each model to assess the accuracy further. The concordance index (C-index) is a key metric for assessing predictive models in survival analysis, measuring how well the model ranks survival times relative to observed outcomes. A C-index of 0.5 suggests no better predictive ability than random chance, while values approaching 1.0 indicate more substantial predictive power. In predictive modeling literature, a C-index above 0.7 is often regarded as acceptable for distinguishing between different risk profiles (Caputo & Paolacci, 2023; Hartman, 2023). However, its effectiveness can vary depending on data quality, censoring levels, and underlying model assumptions. Given these considerations, our analysis assesses model accuracy through the C-index and additional measures to ensure robust performance in estimating plant closure durations. Moreover, including the last three columns provides an understanding of the number of predictions within a specified percent range of the actual value for each model. The results are below in Table 4.

Table 4: Accuracy Assessment

Model	**C Index**	**AIC**	**Within 20%**	**21%-50%**	**+50%**
Linear Model	0.7247	578.696	7	5	8
CPH Model	0.3089	590.294	0	1	19
AFT Model	0.7360	564.952	10	5	5

Based on our assessments, the CPH model performed no better than random guessing, as the C-Index was less than 0.5. However, the Linear and AFT models perform well with C-Indexes of 0.7247 and 0.7360, respectively. In addition, the AFT model has a better lower AIC, which is preferred when assessing AIC. Therefore, we can assume that our AFT model is our best model. This is reflected in the predictions and the actual predicted percentages.

6. Conclusion

6.1 Discussions

Accurately predicting plant closure durations is essential for enhancing supply chain resilience, particularly within the Department of Defense (DoD) and other critical sectors. Our analysis compared three modeling approaches: Linear Regression, the Cox Proportional Hazards (CPH) model, and the Accelerated Failure Time (AFT) model to determine their effectiveness in estimating closure durations. The results indicate that while the CPH model helps understand the timing of reopening, the AFT model offers superior predictive accuracy for closure durations, making it a stronger candidate for practical implementation.

The AFT model consistently outperformed the other approaches, demonstrating the lowest Akaike Information Criterion (AIC) score and the highest concordance index (C-index), incorporating a broader set of closure causes. A higher C-index suggests that the model has a strong capability to predict closure durations accurately. Additionally, the AFT model's parametric nature allows for direct interpretation of time-to-recovery, providing a more actionable tool for decision-makers in supply chain management. The model’s ability to incorporate covariates such as work stoppages and right-to-work laws further displays its adaptability in capturing systemic risks.

In contrast, the CPH model, while useful for survival analysis applications, showed limited predictive accuracy in this context. The assumption of proportional hazards may not hold across different closure scenarios, particularly when considering disruptions caused by varying root causes such as COVID-19, local government mandates, and company decisions. The CPH model's weaker performance suggests that while it can estimate hazard ratios effectively, its ability to translate these insights into actionable closure duration predictions is constrained.
The Linear Regression model performed inconsistently, with lower predictive accuracy than the AFT model. This outcome reinforces the importance of using survival analysis techniques when modeling time-dependent outcomes such as plant closures. While Linear Regression can identify key contributing factors, its reliance on mean closure times does not fully capture the variability in closure durations, making it less suitable for supply chain resilience planning.

A key insight from our findings is that the root cause of closure plays a significant role in predictive performance. This suggests that models trained on a more diverse dataset, accounting for multiple sources of disruption, may translate better to real-world scenarios. The variability in closures highlights the need for adaptable modeling approaches that dynamically adjust to different risk environments.

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Given the strong performance of the AFT model, we recommend its use for predictive risk assessment in DoD supply chains. This model can be integrated into existing supplier risk evaluation frameworks, such as Sanders' (2023), to improve contingency planning and supply chain resilience.

6.2 Implications for Supply Chain Resilience

The results of this study have direct implications for improving supply chain resilience within defense and manufacturing industries. Procurement and supply chain managers can make data-driven decisions regarding supplier selection, inventory buffering, and contingency planning by accurately predicting closure durations. The AFT model's ability to estimate downtime with high accuracy can help optimize resource allocation, ensuring that supply chain disruptions are mitigated more effectively. Furthermore, integrating survival analysis into supplier risk assessments can significantly advance traditional binary risk classification models. Instead of merely identifying whether a supplier is at risk, organizations can now estimate how long a disruption will persist, allowing for more strategic mitigation efforts. This approach aligns with broader efforts to enhance supply chain visibility and predictive analytics in government contracting and defense logistics.

6.3 Limitations and Future Research

Despite the promising results, this study has several limitations. The dataset used was limited to U.S.-based suppliers, restricting the generalizability of the findings to international supply chains. Additionally, the data was collected during the COVID-19 pandemic, which introduced unique volatility and unpredictability that may not represent expected supply chain disruptions. Expanding the dataset to include more diverse closure events across multiple industries would strengthen the model's applicability.

Future research should explore approaches combining AFT modeling with machine learning techniques, such as random forests or neural networks, to capture complex, non-linear interactions among risk factors. Additionally, incorporating dynamic risk factors, such as real-time geopolitical data, economic indicators, and supplier financial health, could further enhance model robustness. Expanding this research beyond the aerospace and defense sectors would provide insights into supply chain resilience across broader industrial applications.

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