Supply Chain Characteristics as Predictors of Cyber Risk: A Machine-Learning Assessment

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This paper provides the first large-scale data-driven analysis to evaluate the predictive power of different attributes for assessing risk of cyberattack data breaches. Furthermore, motivated by rapid increase in third-party enabled cyberattacks, the paper provides the first quantitative empirical evidence that digital supply-chain attributes are significant predictors of enterprise cyber risk. The paper leverages outside-in cyber risk scores that aim to capture the quality of the enterprise internal cybersecurity management, but augment these with supply chain features that are inspired by observed third-party cyberattack scenarios, as well as concepts from network science research. The main quantitative result of the paper is to show that supply chain network features add significant detection power to predicting enterprise cyber risk, relative to merely using enterprise-only attributes. Particularly, compared to a base model that relies only on internal enterprise features, the supply chain network features improve the out-of-sample AUC by 2.3%. Given that each cyber data breach is a low probability high impact risk event, these improvements in the prediction power have significant value. Additionally, the model highlights several cybersecurity risk drivers related to third-party cyberattack and breach mechanisms and provides important insights as to what interventions might be effective to mitigate these risks.

risk management | cyber security | supply chain | network science | machine learning

This paper describes the results of a large-scale data-driven machine learning assessment to identify key predictors of cyber risk in organizations.

Cybersecurity is a high and ever-growing priority for many organizations and country governments around the world. Across multiple industries, companies have been moving increasingly towards digitization of records, processes, and data, which has coincided with a rapid growth in cybersecurity incidents. Many of these incidents result in data breaches, which correspond to any form of unauthorized access to privately held data with potential compromise of its confidentiality (1). The Global Risks Perception Survey conducted by the World Economic Forum in 2019 (2) ranks “massive data fraud and theft” as the fourth important global risk by likelihood over a 10-year horizon. In (3), the IBM and Ponemon 2019 report estimates that the average total economic cost of a single data breach incident for an organization is $3.92M worldwide and $8.19M in the US, with long-term impacts on companies’ reputation, products and clients’ trust. cyberattacks on government organizations can be catastrophic, allowing access to confidential information and potentially affecting important government functions.

Various recent initiatives and directives aim to improve cybersecurity as a risk management discipline, including the 2021 White House Executive Order (4) and 2022 proposed rules from the US Security and Exchange Commission on

Significance Statement

This paper uses large-scale industry data to develop an innovative risk assessment framework to evaluate enterprise’s cyber risk and particularly, the impact of the enterprise’s supply chain structure and attributes on its respective cyber risk. Analysis of massive industry data establishes the significance of supply chain network features as potential cyber risk drivers and identifies specific features as predictive of risk. Moreover, the paper shows that these supply chain features improve the prediction of future cyber data breach incidents, relative to models that merely rely on the enterprise internal factors. The results of this study highlight the relationship between supply chain network structure and the risk of cyber data breach incidents. In particular, it highlights the importance of expanding cyber risk assessment models and methodologies to consider a broader perspective incorporating supply chain characteristics as key risk factors.

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focuses mainly on the robustness of internal security protocols and IT and control infrastructure like Medical Record Systems (21). Other models as in (22) attempt to expand this focus to consider factors related to internal business processes, such as ones ensuring compliance with data security practices (e.g., the Health Insurance Portability and Accountability Act in the healthcare sector), or to other internal organizational factors, such as the number of employees and facilities. However, as the examples discussed above illustrate, relying merely on internal features is not likely to be sufficient to capture the respective complex cyberattack risk drivers.

This study leverages a unique self-constructed comprehensive dataset of more than 30,000 diverse companies, referred to hereafter as entities, with their respective organizational characteristics, their outside-in cybersecurity scores, their digital suppliers and their data-breach history. As part of the analysis, the entity’s digital supply chain network is mapped, and then network science concepts and machine learning methods are used to develop data-driven descriptive and predictive analyses and models to capture hypothesized cyber risk drivers.

This paper is the first to develop a data-driven framework to rigorously assess risks of cyber data breaches. In particular, the paper highlights the fact that the structure and attributes of the enterprise’s digital supply chain play a significant role as predictors and drivers of cyber risk. The analysis results may serve as a foundation for improved methods for assessing cyber risks of organizations as well as for more effective countermeasures for mitigating these cyber risks.

Data

The dataset used in this paper consists of integrated data from BitSight (23), a cybersecurity outside-in score provider, and the Veris Community Database (24). The dataset includes 38345 companies that comprised all enterprises from the Health Care (21093), Oil and Gas (9282), and Retail (7970) sectors within the BitSight database.

Entity data. For each entity company, the dataset contains baseline feature information including employee counts and industry sector. In addition, the dataset includes the respective entity monthly outside-in cybersecurity scores from May 2017 throughout May 2019. These outside-in scores are generated by BitSight based on publicly observable and measurable information, including features such as Patching Cadence (PC), Sender Policy Framework (SPF), Spam propagation, for unsolicited commercial or bulk emails, and others (see SI Appendix for more details of all the observable features utilized by BitSight).

Each of these scores has its own calculation methodology and range in numerical value from 300 to 820, with higher scores meaning to represent better security. These scores attempt to capture important aspects related to the enterprise’s cyber maturity, such as compliance with system, network and application software updates and patching of security vulnerabilities and the existence of an email authentication method as part of mail server authorization.

Supply chain data. Additionally, based on publicly observable and measurable information, the dataset includes a comprehensive description of the digital supply chain relationships for each entity company. Digital supply chain connections were constructed using Domain Name System (DNS) records, website link presence, web records, publicly disclosed information, and additional data analytics. Companies that comprise the digital supply chain of an entity company include hardware and software suppliers that directly provide products or service to the entity company. These digital suppliers are called hereafter third-party suppliers (or third parties). Similarly, suppliers of third-party suppliers are called hereafter fourth-party suppliers (or fourth parties).

Considering the global supply chain graph induced by the dataset, there are overall 38345 entities, 4875 third parties and over 5,000 fourth parties. Each of these companies correspond to a node in the corresponding supply chain graph. The dataset also includes information about the service or product provided through each connection between an entity and its third parties, as well as between a third-party supplier and the respective fourth parties. These connections are captured as product edges on the induced global supply chain graph.

There is a total of over 600,000 distinct product edges between the entities in the dataset and their third parties and over 8,000,000 product edges between third parties and respective fourth parties. The product edges are further classified into product types. There are over 70 different product types and they include, for example, server technologies, DNS services, and payment processing. Finally, for each third-party and fourth-party supplier, the dataset includes information similar to the entity enterprises, including its own respective outside-in scores, employee count and industry sector (see SI Appendix for more details). Additionally, for each entity, there is an induced graph comprised of the entity itself, its third parties, and its fourth parties which is hereafter called the entity’s local supply chain network.

Breach incident data. The dataset also integrates extensive data on documented breaches from May 2017 through May 2020 from data obtained from BitSight (23) and the Veris Community Database (24). The dataset compiles publicly available information on companies that were breached. Overall, the dataset includes 8,344 unique breach incidents. Out of all the entities in the dataset, 3.29% had experienced a breach incident during the three years of the study period. Specifically, 1.00% had a breach incident during May 2017 to May 2018, 1.37% during May 2019 to May 2020, and 1.55% during May 2019 to May 2020. The increasing proportion over each year period highlights two contributing factors. The first is that cyber data breach events are becoming more common for enterprises as time passes, either as a result of improved attack strategies or increase in the number of overall attacks. The second factor is that improvements in data breach incident collection processes have resulted in an increased number of recorded breach incidents with each passing year.

Analysis

The paper first provides a descriptive analysis of the global supply chain network structure described above. This motivates the introduction of the notion of the entity’s local supply chain network, consisting of the entity’s third-party suppliers and their respective fourth-parties. The local supply chain network is then further analyzed to develop features based on the local supply chain structure and attributes, hypothesized to be associated with cyber data breach risk. These features are used to develop and evaluate a machine-learning predictive risk model to assess the role of the local supply chain features.
in predicting risk of future cyber data breaches.

Global supply chain network visualization and description. To gain insights with respect to how supply chain structure and attributes can play a role in driving cyber data breach risk, the sector-specific (e.g., Retail or Oil and Gas) global supply chain networks are created and visualized. For ease of interpretation, only entities and their respective third-party suppliers are included. The analysis is focused on the distribution of the graph degree of the third-party suppliers, which corresponds to the number of customers they serve.

In order to understand how supply chain network structure of the entities and their digital suppliers can be a source of cyberattack risk, the sector-specific (e.g., Retail or Oil and Gas) supply chain networks are created and visualized, consisting of the respective entities and their third-party suppliers. Fourth parties are excluded for ease of interpretation. Additionally, it defines each supplier’s degree as the number of customers they serve, and compares the customers served by large and small degree suppliers. This first step aims to identify structural patterns in the supply chain network and potential sources of differentiated cyber risk.

The global supply chain network of the entities in the retail sector includes 7970 entities and 3156 third-party suppliers. Figure 1 provides a network visualization using a randomly sampled subset of the retail entities within the dataset as well as their most important third-party suppliers (see Appendix for supplier importance details). Specifically, Figure 1 captures a network with a total of 117 nodes including 53 retail entity companies, 64 third parties and 370 edges. It can be observed from Figure 1 that some of the third parties have near universal connectivity to almost all of the entities within the supply chain network. These are typically large service providers with huge customer bases, and they are a source of common risk to many entities. That is, compromising these suppliers could facilitate a cyberattack and potential data breach of many entities simultaneously.

Additionally, Figure 1 also includes third-party suppliers with low-connectivity. These tend to supply mostly highly connected entities (i.e., ones who receive service from relatively many suppliers). Furthermore, these are a source of residual (or differentiated) risk for the specific entities that they serve. That is, compromising these suppliers will only allow potential access to the small number of entities that they serve. The more suppliers with low connectivity an entity has, the higher its individual residual risk might be (see Appendix for additional visualizations).

These insights are further confirmed by degree distribution analysis on the entire retail sector supply chain graph that is presented in Figure 2. Specifically, considering the third-party suppliers with highest and lowest connectivity (top 10% and lowest 10% graph degree among third parties, respectively), the figure contains three plots of the degree distribution (i.e., the number of connections an entity has), including all the entities, the entities served by suppliers with highest connectivity and entities served by suppliers with lowest connectivity. The plots include 10002, 9737, and 310 entities respectively. The degree distributions among all entities and entities served by third-party suppliers with the highest connectivity are nearly identical, with respective median degrees of 13 and 14. In contrast, the degree distribution of entities served by third-party suppliers with the lowest connectivity is significantly higher, having a median of 131. This difference is statistically significant on t-tests, having p-values of essentially 0.

Local supply chain network features. To assess the individual risk level of a specific entity, the analysis attempts to characterize the attributes of the entity’s local supply chain network defined above. This is motivated and informed by the increased prevalence of supply-chain related data breach incidents and also by network risk assessment methodologies (25). The supply chain features consist of connectivity, product/service type, historical cyberattack, and network-wide outside-in features.

Connectivity features describe the number of suppliers within the local supply chain network belonging to each sector. As illustrated in Figure 3, sectorial third-party connectivity indicates the number of third parties for each sector, and
sectorial fourth party connectivity defines the median number of fourth parties of the entity’s third parties. The study then defines a supply chain network exposure feature that corresponds to the total number of fourth parties of an entity. This feature enumerates the number of potential sources of indirect supply chain breach propagation that can occur within the local supply chain network.

Network-wide summary features are developed using the mean outside-in scores of third and fourth parties in the network to approximate the average internal cybersecurity level of the local network. Additional summary features utilizing third and fourth party employee counts are also developed to capture the average size of suppliers within the local network.

Additionally, an aggregated edge-based supply chain network feature is designed utilizing the various types of supplied products being supplied to the entity. Figure 3 demonstrates the product-edge relations that are present between suppliers and customers in the local supply chain. To construct the aggregate feature, each product is ordered according to its relative risk level (see Appendix for risk level computation details). Based on this ordering, the products are sorted into 4 quantiles corresponding then to 4 risk groups. For each entity, the number of edges belonging to each of the four groups are counted and then aggregated via a weighted sum to create the product-edge aggregate feature, where a weight of 4 is given to the highest risk quantile, 3 to the second highest, 2 to the third highest, and 1 to the lowest risk quantile.

Finally, for each entity, the number of breaches that had been reported 2 years prior to May 2019 by the third parties were counted to describe the historical vulnerability of the company’s direct suppliers. A similar feature was constructed using breaches reported by the fourth parties for indirect suppliers. This feature is motivated by the fact that supply chain related cyberattacks typically start with the attacker compromising a supply chain partner of the attack’s target (see Appendix for a table of all of these network features and their descriptions).

All of these features of interest can potentially provide insights about the overall attacker access and security of the supply chain network and are included in the predictive algorithms introduced in the following section.

**Machine learning framework.** To assess the predictive value of the supply chain network features, three machine learning models are trained on the data and evaluated out of sample. Model 1 (baseline) includes only basic features on each entity, specifically, sector and the number of employees. Model 2 adds to that the entity’s outside-in score features. Finally, Model 3 includes in addition the local supply chain network features.

All the models are trained using the binary classification gradient boosting algorithm (26) which integrates interaction between features and delivers the highest out-of-sample predictive power of the models tested. A stratified split of the dataset into a training (70%) and test (30%) set is performed to get a balanced split with respect to sector and data breach status. Then, a 5-fold cross-validation is applied on the training set for hyper parameter tuning to define the best learning rate, number of estimators, maximum depth and L1 regularization parameter (27). This procedure is repeated on 20 random training-test splits to confirm the consistency of the performance assessment.

The output of each of the models is a risk score for each entity.

**Machine learning cyber risk assessment**

Table 1 summarizes the respective out-of-sample performance of Models 1, 2, and 3 using the area under the curve (AUC) metric to evaluate model performance with a 95% confidence interval over 20 trials. In these results, the basic model with employee count and sector achieves an AUC of 76.5%. When the BitSight score features are included in Model 2, the AUC increases to 77.8%. The AUC of Model 3 further increases to 78.7% upon adding the local supply chain features. Both of these AUC increases are significant at the 95% confidence level.

The performance of Model 1 implies that organizational features are predictors of cyber risk, as the model already outperforms a random guess AUC of 50%. This supports the idea that cyberattacks are not uniform among all companies, but instead are more likely to target large organizations and certain sectors, like healthcare, that have more attractive data and could be more vulnerable. The improvement in AUC from Model 1 to Model 2 provides evidence that outside-in scores are effective in providing additional useful information about the internal cyber risk posture for individual entities that cannot be derived from the baseline features.

Model 3, which includes suppliers’ outside-in cyber scores and supply chain structural characteristics underscores the added value of considering an entity’s supply chain cyber history and structure to predict future breaches. The improved performance supports the hypothesis that supply chain attributes provide an important signal regarding the cyber data breach risk level of an entity beyond what internal features are able to capture. This also underscores the observed increased cyber risks arising from the entity’s supply chain and the growing number of cyberattacks that are conducted through third-party suppliers.

Moreover, because the breach incidents used in this classification are not all likely to be third-party breach incidents, this may serve as evidence that supply chain related features could potentially be useful for assessing not only third party breach risk, but also overall breach risk. Specifically, these supply chain features may provide a measurement of the complexity of a company that cannot be inferred from just its internal characteristics. Because general breach incidents can arise from just a single issue within the company’s systems and high complexity companies are more likely to experience such an issue, companies with larger supply chain features may be more at risk for not only breaches involving third or fourth parties but also any cyber breach incidents.

**Detection rate comparison**

Another metric to further compare the relative predictive power of the three models is the detection rate, which is calculated as follows. For each model, the entities in the test data are ranked from highest to lowest model score. The detection rate is calculated based on the proportion of breached entities identified for any specified number of top ranked entities.

Figure 4 plots the out-of-sample detection rate of each of the models. A random guess performance is also included to serve as a benchmark comparison. A perfect predictive
Table 1. Models out-of-sample performance results

| Model Description                                                        | AUC  | 95% confidence interval |
|-------------------------------------------------------------------------|------|-------------------------|
| 1. Basic features                                                       | 76.5%| 76.1%-76.8%             |
| 2. Basic features and entities cyber scores                             | 77.8%| 77.3%-78.2%             |
| 3. Basic features, entities, suppliers cyber scores and supply chain structure | 78.7%| 78.2%-79.1%             |

A model would rank all the entities that were breached at the top of the list. The figure reveals that all three models have a significantly better detection rate than a random guess. Both Model 2 and Model 3 perform noticeably better than Model 1 except for the detection rate among the highest ranked entities. Additionally, Model 3, which uses both supplier scores and supply chain features, has noticeably better detection rate than Model 2 between the 5th and 40th percentiles of the ranked companies.

Analysis of entities with high-inter-model risk ranking differences

To further understand the performance differences between Model 3 and models 1 and 2, respectively, for each pair of models (3-1 and 3-2), the entities are ordered according to the rank difference between the two respective models from highest to lowest. Then the cumulative number of companies that were breached as one moves down the ordered list of entities is counted. This is then compared to the expected number of accumulated breached entities if using a random ordering instead, which is represented as a straight line in Figures 5 and 6.

In Figure 5, the breach accumulation for entities with a positive difference is much higher than the expected breach accumulation. In fact, there is a visible separation when considering entities that have a positive difference in rank. An additional paired t-test between the accumulated breaches for entities with a positive difference and the expected accumulated breaches confirms that this difference is significant with a p-value of essentially 0. Figure 6 demonstrates a similar pattern.

The patterns displayed within these two graphs reveal that the entities that the supply chain model rates as riskier compared to the other two models appear to be significantly more likely to be breached. Thus, this serves as additional evidence that the inclusion of supply chain features allows the model to more effectively identify vulnerable companies.

Feature assessment for identifying cyber risk drivers

To identify potential cyber risk drivers for breached entities, the most important features utilized by model 3 are examined. Figure 7 (A) illustrates the Shapley impact of the top 20 features with highest importance values in model 3 (28, 29).

The most important organizational risk drivers are the Hospital and healthcare identifier and employee count, for which the larger the values are in red, the riskier a company is considered. The Oil and gas identifier on the other hand shows a negative correlation with risk in the model. Additionally, a company’s local supply chain features also appear to be predictive of data breach risk. It is observed that a high exposure generally results in a higher risk score, which suggests that having a great number of fourth parties is correlated to increased cyber risk. The organizational and outside-in score of the suppliers are also features of importance. At the third-party level, the model finds that several third-party outside-in score metrics (e.g., desktop software and open port features), which are represented by the mean of the third parties’ outside-in scores, are correlated with a higher risk of data breach for the entity. Furthermore, connectivity to large third parties with high employee counts appears to be a significant risk driver. At the fourth party level, entities served by large fourth parties in terms of employee count and fourth parties that previously experienced a breach exhibit greater risk scores. In addition, connectivity to Healthcare...
and wellness suppliers is also among the top 20 risk drivers. The product edge feature further differentiates an entity’s risk. Specifically, a higher product-edge feature value appears to indicate an overall higher risk.

The result regarding the healthcare feature is in line with the current literature, as it points out the healthcare sector as one of the most susceptible to publicly disclosed data breaches (30). Reasons for this could be the value of sensitive patients’ information, the nature of the industry that is heavily data driven and progressively digitizing (30), and the reporting requirement of these companies as a result of HIPAA security regulations. Additionally, the importance of employee count could be explained by increased individual vulnerabilities and risky behaviors from a cyber perspective that result in social engineering incidents, employee data theft and data leaks as explained in (31).

The model also reveals system vulnerabilities at different levels of the supply chain that could impact an entity’s cybersecurity. The companies that are connected to many fourth parties have more potential paths which an attacker can leverage in order to then penetrate the entity itself, assuming that attackers have a means to access the organizations that a penetrated company supplies. If an entity’s fourth party is more vulnerable, then there is a higher potential that the entity will be affected downstream. The third-party outside-in measures serve as proxies for third-party supplier security maturity and may capture additional risk information regarding secure connections between entities and their suppliers. In other words, these scores could represent information not only about whether an attacker has greater ease in accessing the third parties, but also if it is easy to gain access to their customers’ systems. Healthcare and wellness third-party connectivity features are critical not only as an indicator of health care parent entities but also as a proxy for their supply chain size, and specifically, the number of their suppliers.

Finally, the high importance of the number of products and services that an entity receives indicates that companies with a greater number of products and services received are at greater risk of being breached, potentially because a high number of products could imply that an attacker has more opportunities to identify weaknesses that will allow an attack on the entity’s IT system.

It is also important to note that these local supply chain features could be further capturing information regarding an entity’s overall complexity. As such, they could provide significant signals about an entity’s vulnerability to non-third party related breach incidents as well.

**Analysis of distinguishing features that explain inter-model rank differences**

To analyze the features that explain the rank differences between Model 3 and Model 1, the 10 entities with the most positive and negative rank differences are analyzed. Specifically, the values of the baseline features as well as important supply chain features (according to the Shapley impact value) are then analyzed. Tables 2 and 3 contain the employee count, second degree breach, product edge, healthcare connectivity, and exposure features for each of these entities, as well as the percentile for these features relative to the rest of the population. Additionally, the mean value across the population for each of these features is included.

In Table 2, which represents the entities with the largest rank difference from Model 3 to Model 1, every entity has an employee count of 100, which is far below the mean. In comparison, nearly all of the supply chain related features for each of these entities are within the top 95th percentile of the population.

This anecdotal evidence suggests that Model 1 relies heavily on employee count information to produce its predictions and thus rates most companies with low employee counts, such as the ones included in Table 2, as safe. Model 3 is instead able to differentiate further utilizing the local supply chain network features. As such, entities that are small according to employee count but have large local supply chain network features such as the ones included in the table are rated as far more relatively risky by Model 3 compared to Model 1.

Conversely, the entities in Table 3, which have the most negative rank difference, have larger employee counts, with all of them having an employee count greater than the mean and all but one being in the 95th percentile. On the other hand, the local supply chain network feature values for these entities are almost all below the overall population mean. Although these large entities are being rated as risky by Model 1 because of their employee count, Model 3 differentiates them from other large entities by using their smaller supply chain network features to rate them as far less relatively risky (See SI appendix for a similar analysis conducted between Models 3 and 2).

While not exhaustive, this analysis provides evidence for the important role that local supply chain network features play in how Model 3 is differentiating its risk assessment from the other two models.

**Discussion and Conclusion**

This paper establishes the significance of data-driven analysis for deriving important and actionable new cyber risk insights. It demonstrates that a company’s supply chain structure and attributes provide an important signal in assessing its cyber risk of future data breaches. Indeed, it provides evidence that relying only on a company’s internal cybersecurity management may not capture important risk predictors. As the
predictive modelling approach and additional models’ ranking analyses have demonstrated, utilizing the digital supply chain information can significantly improve the ability to more successfully evaluate whether a company is likely to be compromised by a cyberattack. The further assessment of the features’ relative importances show the importance of the local supply chain features in assessing and predicting risk, particularly third-party connectivity, supply chain exposure, and the
overall security of the suppliers within a company’s direct or indirect network.

The findings in this paper provide important insights for practice as well as for future research of cybersecurity risk assessment and management.

First, identifying important predictors of cyber risk related to the enterprise and its supply chain is critical to be able to reliably and proactively assess and manage risk, and it informs what risk indicators should be monitored. The paper’s analyses suggest that while it is important to have comprehensive enterprise cybersecurity internal policy controls and procedures, it may not be sufficient without an effective supply chain cybersecurity risk assessment and mitigation system. In particular, current cybersecurity risk assessment methodologies need to be enhanced to include supply chain network-related indicators to more comprehensively characterize and manage related risks. This will consequently drive more effective cybersecurity decisions and countermeasures.

Secondly, the paper also stimulates and highlights important further research directions. The local supply chain network construction and feature design developed in this study can inform future work for assessing cyber risk within supply chains and large network structures in general. The importance of local network connectivity features and network exposure as risk drivers motivate potential research to explore their role in the mechanisms of cyberattack propagation within supply chain networks. Moreover, increasingly comprehensive and complex features could be built from the overall network structure, which may prove to be even more successful in predicting data breach and cyberattack occurrences. This paper focuses on the digital supply chains of the respective entities, but more research is needed to understand to what extent the structure and dynamics of physical supply chains are predictive of cyberattack risk. Additionally, future work can expand upon the data sources used and design complementary supply chain network features. Finally, the results in the paper motivate the need to standardize how data breach and cyberattack incidents are documented and categorized, especially when it comes to differentiating attacks that are related to the supply chain. More generally, it would be important to develop a comprehensive data breach and cyberattack taxonomy that properly distinguishes cyber risks originating from a company’s internal system versus its external supply chain.

Ultimately, such data-driven approaches will contribute to the important challenge of improving the management of current and future cybersecurity risks with more effective visibility, assessments, insights, and countermeasures.

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