Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AP06.20250076
Published: August 5, 2025

Visualizing Resilience to Egg Supply Risk Based on Consumer Purchasing Data

Yuta Nasu
Master's Degree Program in Business Architect
Kanazawa Institute of Technology, Ishikawa, Japan
c6502003@st.kanazawa-it.ac.jp

Yukito Yamaguchi, Takayuki Sato
Bachelor's Degree Program in Mathematical Sciences
Shibaura Institute of Technology, Saitama, Japan
bv22032@shibaura-it.ac.jp, bv22051@shibaura-it.ac.jp

Yu Kawamukai
Bachelor's Degree Program in Faculty of Business Administration,
Daito Bunka University, Tokyo, Japan
s22161274@st.daito.ac.jp

Masahiko Ishihara
Graduate School of Engineering, Kanazawa Institute of Technology, Ishikawa, Japan
masa_ishihara@neptune.kanazawa-it.ac.jp

Yasuyuki Shirai
Faculty of Business Administration, Daito Bunka University, Tokyo, Japan
yshirai@ic.daito.ac.jp

Yusuke Goto
College of Systems Engineering and Science, Shibaura Institute of Technology, Saitama, Japan
y-goto@shibaura-it.ac.jp

Abstract

This study proposes a method to visualize the relationship between supermarket chains and suppliers at the time of egg supply risk at the avian influenza pandemic in Japan in 2022, using GTIN-coded purchasing data, and to observe differences in purchasing tendencies and trends in market structure before and after the occurrence of risk. In particular, using bipartite graphs and features based on normalized entropy, the dependence and dispersion trends of the business relationship are captured in a time-series manner, making it possible to visualize in real time the scale-specific strategies of supermarket chains and changes in the supply structure on the supplier side. This is expected to contribute to the understanding of risk response trends and network reconstruction in the market as a whole, as well as to the establishment of a basis for decision-making among the business relationships involved.

Keywords
Customer Purchasing Data, Supply Chain Risk, GTIN Codes, Entropy, Avian Influenza

1. Introduction

Modern supply chains are becoming increasingly complex due to globalization and leaner operations, which in turn increases their vulnerability to external risks. Since sudden events such as natural disasters, infectious diseases, and geopolitical risks can disrupt supply chains and their effects can ripple throughout companies and markets, the ability to respond to risk and the structure of supply chains can significantly affect a company's competitiveness and market performance (Christopher & Peck, 2004; Manuj & Mentzer, 2008). Against this backdrop, there is an urgent need to establish a comprehensive supply chain risk management (SCRM) framework that includes risk identification, assessment, response, and monitoring, and related research is rapidly developing (Fan & Stevenson, 2020). Today, supply chains are no longer simply means to reduce costs, but rather a strategic asset that determines a company's competitive advantage, and methods to enhance their flexibility and resilience are becoming even more important.

An example of such supply chain risk is the avian influenza pandemic in Japan in 2022, when mass control of poultry farms through quarantine measures temporarily reduced domestic egg supply by 10-15% (MAFF, 2023), resulting in shortages in some regions and a sharp rise in retail prices (JA Zen-Noh Egg Co, n.d.). According to the International Egg Commission (IEC) in 2023, Japan ranked fourth in terms of annual per capita egg consumption, and the stable supply of eggs is part of the social infrastructure. The egg distribution structure is a multi-stage pipeline that extends from chicken farms to grading and packaging centers (intermediate centers that grade and package eggs collected from chicken farms and send them downstream) to supermarket chains, forming a complex system in which bottlenecks at each stage affect the stability of the entire system (Guidelines for the Introduction of Traceability for Poultry and Eggs, 2025). However, in response to a decrease in supply due to the killing of eggs at poultry farms, which is an upstream process, downstream supermarket chains took time to secure alternative suppliers, resulting in a “shortage” situation in which eggs disappeared from the sales floor at many stores. As a result, the supply could not keep up with the demand, and the price of eggs skyrocketed, causing confusion in consumer purchasing behavior and exposing the vulnerability of the supply chain as a whole to resilience to supply shortages. This case is a classic example of how quickly external shocks can disrupt supply chains and have a significant impact on the construction of downstream procurement networks.

1.1 Objectives

Using the above avian influenza case as a case study, this study aims to visualize the trading relationship between poultry farms, GP centers (facilities for grading and packing eggs), and supermarket chains in a network structure, observe the strength of the relationship and the increase or decrease in the number of transactions, and contribute to the construction of a network against supply chain risk from measures and tolerance to supply risk in the market as a whole. The objective is to contribute to the construction of a network against supply chain risk from countermeasures and tolerance to supply risk in the market as a whole. The insights gained will help individual supermarket chains sort out bottlenecks and relationships in their own procurement networks and contribute to optimal supply chain restructuring. This methodology is not limited to the egg market, but is intended to have broad utility as a generic approach to supply chain risk management in the fresh food and general retail industries.

2. Literature Review

With the increasing globalization and complexity of supply chains, ensuring sustainability in a highly uncertain environment is considered an extremely important management issue (Amofa et al., 2023; Han et al., 2024). Ming et al. (2019) categorized risks in the supply chain into “operational risk,” “social risk,” and “environmental risk,” and pointed out that supply risk, which is included in operational risk, has a particularly large impact on the continuity of the entire chain.

Different frameworks have been proposed for the analysis and management of supply risks, depending on the industry sector. Mogale et al. (2023) and Jayaratne et al. (2024) presented risk management frameworks for online retail and the automotive industry, respectively. Ganguly (2013) examined the risk of supplier bankruptcy due to natural disasters and how to respond to it, using the case of Toyota Motor Corporation.

In general, diverse supply risks exist in the poultry industry. Purwaningsih et al. (2021) identified 26 risk factors based on the SCOR model, especially the impact of disease, transportation, and price fluctuation risks at the "procurement" stage. Xu et al. (2025) analyzed supply risk in Chinese livestock farms and found that epidemic risk has a significant impact on supply structure. Mitchell et al. (2024) analyzed the mechanism of price spikes and prolonged supply constraints in the egg market caused by highly pathogenic avian influenza (HPAI) from the perspective of biological delay.

Studies on epidemic risk include retail price impact analysis (Mitchell et al., 2024; Zamani et al., 2024) and machine learning approaches for early detection (Morales et al., 2016; Soltani et al., 2025). Weiser et al. (2016) and Ganas et al. (2021) visualized the variation in the supply structure after an outbreak, and Ganas et al. constructed a network model showing the production, distribution, and consumption of chicken eggs at each distribution center. However, the model relies on data from a single year and is limited in its ability to capture dynamic changes in the structure.

In this study, we attempt to visualize the supply structure using actual purchase data and product identification codes, targeting the risk of epidemic disease in the egg market. While previous studies using actual purchase data and product identification codes focused on demand forecasting (Abolghasemi et al., 2022), this study aims to quantitatively understand the response and resilience of the supply structure by utilizing the network relationship between poultry farms, GP centers, and retailers and its changes.

3. Experimental Data

The analysis will be conducted using "KAI LOG®," a database provided by Research & Innovation, Inc. that accumulates receipt OCR data registered by users of the "CODE" application. Columns such as product name, JAN code, age, and gender are present. JAN code refers to a 13-digit code internationally known as "GTIN-13," one of the global standard product identification codes defined by GS1. Supplier refers to the manufacturer of the product; WB (weight-back) value refers to the size of the market when the population is assumed to be 1 million.

Table 1. Data Sample

Date	Gender	Age	JAN code	Product Name	Supplier	Mode Unit Price	Quantity(WB)	Purchase Amount(WB)
2022-12-11	Man	31	1234567891011	Bean Sprouts	Supplier1	30.0	2.32	75.23
2022-02-03	Woman	54	1234567891012	Banana	Supplier2	140.0	1.37	175.34
2021-05-22	Man	41	1234567891013	Mentaiko	Supplier3	250.0	1.23	276.76

Regarding data cleansing and scope, the data used in this study were purchase histories related to "eggs" in Tokyo from January 2021 to the end of June 2024, as provided by "Buy Log View" shown in Table 1. The data covered approximately 134,000 items and was developed using product identification based on JAN codes.

JAN codes were used because each product is assigned a unique code, which is highly traceable; the 13-digit code is fixed, which reduces errors in product identification due to distortion during data cleansing, and improves accuracy; and the JAN code is a unique code for each product, which is highly traceable. As an overview of the data used, there are 214 products, 27 supermarket chains (these chains will be represented in this paper as supermarket chain (1) – chain (27), and are abbreviated as "SC(n)" (n=1,2,, ⋯, 27) hereinafter.). There are 66 suppliers (referred to as Supplier (n) (n=1,2,, ⋯, 66)in this paper). The cleansing methods used included unifying distortions, filtering by the 13-digit JAN code standard, excluding outlier values, and excluding duplicate manufacturer products.

4. Methods

In this study, the above avian influenza case is analyzed as a case study. By visualizing the business relationships between SC and suppliers in the event of risk occurrence, we can identify bottlenecks in the procurement network and analyze the strength of relationships and changes in business relationships over time. We aim to gain insights into countermeasures and resistance to supply risk (resilience). To this end, we propose the following methodology.

4.1 Visualization of Purchasing Information

First, we will visualize four years of "sales period," "sales ratio," and "price trends" for egg products (SKU: Stock

Keeping Unit) at each supermarket chain in a single time series chart and systematically organize the procurement information. The definitions of each indicator are as follows.
Sales period: This indicates the period between the month when a specific egg product first appeared in purchase data and the month when it was last confirmed. This allows us to grasp the stable supply period for each product and instantly detect sudden discontinuation of sales immediately after a risk occurs.

Sales ratio: This is the ratio of the sales amount of the target product for one month divided by the total egg sales amount for the chain for that month ([sales amount of target product] / [total sales amount for the chain]). By tracking the monthly changes in this ratio, it is possible to evaluate the relative importance of each product within each chain.

Price trends: The monthly average price of the same product is calculated, and the frequency distribution of price trends is represented by a gradient of blue, green, and red, ranging from "low" to "high." The color changes allow for an intuitive understanding of sudden price increases or discount periods before and after the occurrence of a risk.

By calculating these indicators monthly and integrating and visualizing four years of data, you can understand the sales situation of each supermarket chain based on the product lifecycle of egg products (from the introduction phase to the maturity phase and decline phase). This provides insights into each chain's procurement strategies in response to sudden price fluctuations or stockouts during risk events.

4.2 Network Visualization with Bipartite Graphs

In this method, suppliers and supermarket chains are placed as left and right nodes (Figure 1), respectively, and the size and color of the nodes are represented by gradations according to market size. The edges between the nodes are adjusted in thickness to reflect the width of the transaction sales ratio for the relevant period, and a bipartite graph is created for each half-year to visualize the structural changes in the relationship. For example, if a chain X receives 30% and 10% of its supply from suppliers Y and Z, respectively, the edge to Y is drawn thicker than the edge to Z. This visualization allows us to intuitively understand the following time-series changes:

1. which supermarket chains maintained or expanded business with how many suppliers before and after the risk occurred
2. trends in the turnover of major suppliers and the entry/exit of new nodes

By reducing high-dimensional transaction data to "nodes and edges," the degree of concentration of business relationships and major communities (major supplier networks) can be clearly identified, and changes in the number of suppliers and supplier composition at the time of risk can be grasped at a glance.

Figure 1. Example of bipartite graph, Gradient based on total sales

4.3 Dependency Quantification

Visualizing the transaction structure between supermarket chains and suppliers by means of a bipartite graph provides a bird's-eye view of the number of suppliers and their dependence on major suppliers in each period. However, it is difficult to directly compare the number of nodes and edge widths across multiple chains and periods. Therefore, in this study, we replaced this business relationship with a single numerical indicator called "degree of dependence" to enable objective comparison of the strength of dependence for each chain.

The specific equations are shown in (1) ~ (3). First, for equation (1), N is the total number of suppliers with which the supermarket chain in question does business, p_i is a probability value indicating the sales ratio (transaction ratio) to supplier i among them, and H is the entropy (degree of variance) of the distribution of those sales ratios. Based on the edge widths of the bipartite graph, the sales ratio p_i to each supplier in the chain is considered as a probability distribution and its dispersion (entropy) is calculated.

$$H = -\sum_{i=1}^{N} p_i \log_2 p_i \quad (1) \qquad H_{\text{normalized}} = \frac{H}{\log_2 N} \quad (2) \qquad D = 1 - H_{\text{normalized}} \quad (3)$$

Next, normalization is performed to eliminate the influence of transaction size, and the degree of dependence is defined on a scale of $0<H_{\text{normalized}}<1$ (2). Finally, normalized entropy is a measure that is "larger the more diverse the number of trading partners and smaller the more concentrated." Since it only indicates diversity as it stands, it is necessary to reverse the positive and negative values so that the interpretation becomes "larger for more concentrated transactions and smaller for more dispersed transactions." Therefore, we define the final metrics shown as (3).

This indicates that the degree of dependence is greater for larger values, indicating greater dependence on a specific supplier (concentrated transactions), and smaller values, indicating equal transactions with a wide range of supermarket chains (dispersed transactions). By calculating this degree of dependence semiannually, it is possible to quantitatively compare changes in the number of transactions and relationships in each supermarket chain before and after the occurrence of risk. As a result, it will be possible to objectively evaluate which chains have increased their resilience by diversifying their suppliers in the wake of supply shocks, and to compare and analyze the traces and effects of the chains' diversification strategies at the time of risk across the market.

4.4 Creating a Scatter Plot

The number of customers and dependency trends for each supermarket chain are summarized in a single scatter plot. Specifically, for each half-year period, the number of suppliers (nodes) is plotted on the horizontal axis, and the normalized dependency ratio is plotted on the vertical axis. Sales growth rates from the base period of the first half of 2021 are represented by the size of the circles. This visualization method allows multiple indicators to be grasped simultaneously on the same coordinate system, enabling an intuitive understanding of each chain's procurement strategy patterns. Furthermore, by tracking the movement trajectories of points over each period, resilience restructuring patterns such as "diversification orientation (movement toward the upper right)" or "concentration orientation (movement toward the lower left)" before and after risk occurrence can be confirmed at a glance.

This scatter plot is a tool that enables "simultaneous comparison of multiple indicators" and "understanding of strategic change trends," which are difficult to achieve with bipartite graphs or dependency indicators alone. As a result, it is possible to clearly distinguish between chains that actively diversified their suppliers to strengthen resilience during supply risks and chains that maintained their robustness while maintaining dependence on specific suppliers. This enables the quantitative identification of the most resilient supermarket chains and those that will require diversification in the future.

4.5 Resilience Visualization Methodology Based on Clustering of Suppliers

In order to gain a more multifaceted view of each supermarket's ability to respond to risk, we conducted a clustering analysis focusing on sales trends on the supplier side. The period covered was from January 2021 to June 2024, and the "monthly sales amount" and "monthly number of supermarkets" of each supplier were standardized by Z-score, and then clustered using the *k*-means method. The number of clusters *k* was set to 3, which was set in terms of prior distribution trends and interpretability. The purpose of the analysis was to understand the characteristics of resilience based on changes in sales trends by supplier, and to visualize how this is reflected in the supermarket's procurement strategy.

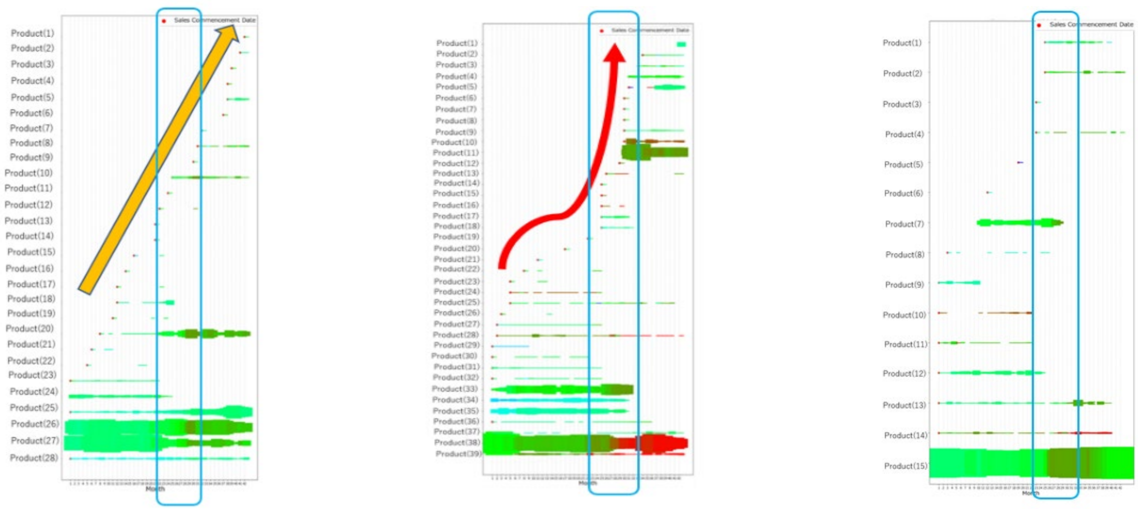
The clustering results are shown on a monthly basis, and the visualization uses color gradations (high sales = red, low sales = blue) to indicate the size of the sales amount, and the number of supermarket chains is indicated by the thickness of the line, so that suppliers can intuitively grasp market trends.

5. Results and Discussion

The avian influenza pandemic of 2022 caused a serious supply shock in the domestic egg market, and mass pest control at poultry farms temporarily led to a significant decrease in supply and a sharp rise in wholesale prices. In this study, we visualize and quantitatively evaluate the business relationships between supermarket chains and suppliers using four visualization methods, using the purchasing data in Tokyo from 2021 to the end of June 2024, including before and after such risks. The purpose is to visualize the business relationships between supermarket chains before and after the occurrence of risk in terms of network structure, observe the supply strategy and time-series transition of each chain before and after the occurrence of risk, and obtain suggestions for the construction of supply chain networks that contribute to measures and resistance (resilience) to supply risk in the market as a whole.

5.1 Results of visualization of purchasing information

The replacement and dependence of egg products in each supermarket chain are summarized on the same chart to visualize the sales life, sales ratio, and price transition. Each SKU (Stock Keeping Unit)is represented by a horizontal straight line, with the length of the line representing the sales life (first month to last month of confirmation), the thickness of the line representing the sales ratio, and the color representing the price transition, blue to green to red where blue means ‘low price’ and red means ‘high price’, with the avian influenza risk period highlighted by a blue frame as in Figure 2. As a result, the sales situation of supermarket chains in the egg market can be classified into three main cases, Pattern A to Pattern C.



Pattern A: e.g., SC(2) Pattern B: e.g., SC(21) Pattern C: e.g., SC(24)

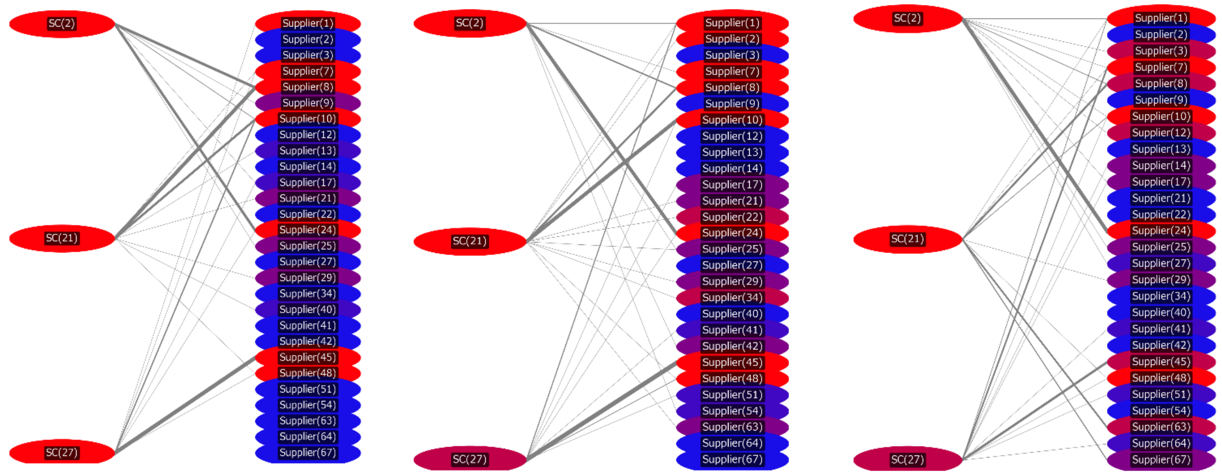
Figure 2. Sales of three main types of products

Pattern A: e.g., SC(2)
SKUs are replaced at a constant pace throughout the period, and a stable rotation is maintained in terms of sales life, sales composition, and price trends. This is a case where the normal supply network is functioning.
Pattern B: e.g., SC(21)
Handling of existing SKUs was temporarily suspended during the risk period, followed by a rapid increase in the pace of introduction of new SKUs. This is considered to be a quick risk hedging measure to avoid supply disruptions of mainstay products due to avian influenza.
Pattern C: e.g., SC(24)
Sales are concentrated in a small number of mainstay SKUs, and price fluctuations and replacement frequency are extremely small even in times of risk. By adhering to a concentrated sales strategy, the supermarket chains in this class are able to maintain a high price level and achieve short-term stability.

These three patterns clearly show the diversity of supermarket chains' procurement responses to the avian influenza disaster, and Pattern B in particular illustrates the significant impact that supply risk had on the chain's operations. However, the data obtained this time does not provide direct evidence of each supermarket's strategic intentions or decision-making processes. Therefore, expressions such as “rapid risk hedging” and “intensive sales strategy” are merely speculations based on sales data. Nevertheless, the fact that different responses were taken by each chain when a similar external shock (bird flu) occurred suggests that there was a business strategy focused on resilience behind the scenes. Specifically, this suggests that policies and systems that took into account business scale and the robustness of commercial networks with suppliers may have influenced the responses.

5.2 Network Visualization Results Using Bipartite Graphs

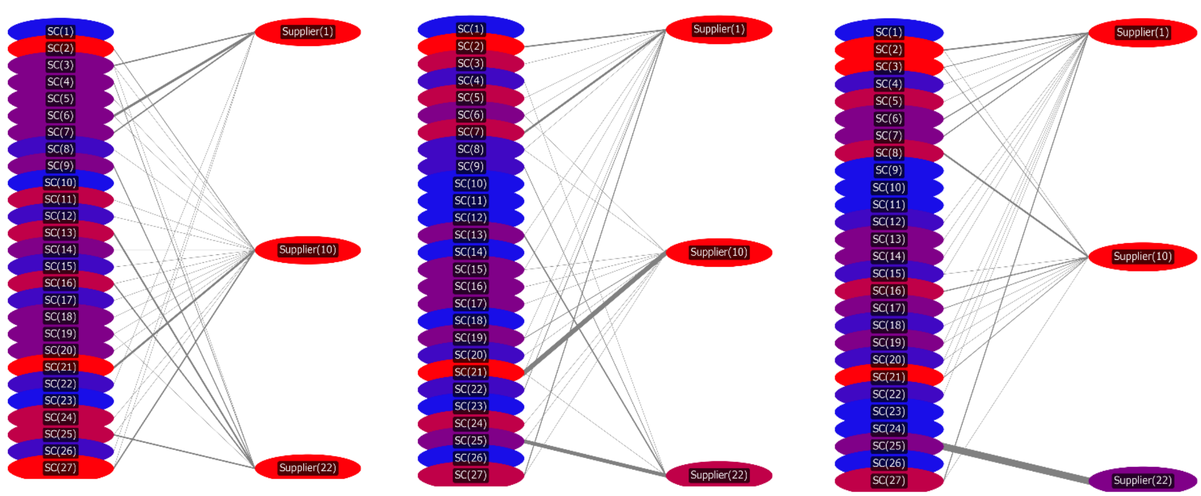
In this section, we explain the results of changes in transaction structure on the supermarket chain side and the supplier side separately, using a bipartite graph constructed for each half-year period. In each bipartite graph, the left node represents the supermarket chain and the right node represents the supplier, and the size and color of the node indicates total sales and the thickness of the edge indicates the percentage of transactional sales, indicating the existence of a business relationship.



(1) Period Before Risk Occurrence (2021) (2) Period of Risk Occurrence (2023) (3) Period After Risk Occurrence (2024)

Figure 3. Time-Series Transaction Trends for Three Supermarket Chains

First, looking at the relationships between supermarket chains shown in Figure 3, where we show the three major chains, "SC(27)", "SC(2)", and "SC(21)" as examples, all increased the number of suppliers during the risk period. Compared to the first half of 2021 before the risk, the network has diversified since the risk period. This reflects the emergency response of rapidly expanding the network and securing new suppliers for SKUs due to the disruption of existing SKU supplies during the risk period. The impact of avian influenza has continued even after the risk occurred, and it appears that the market as a whole is anticipating similar risks and has adopted a new trend of securing suppliers in preparation for recovery in times of turmoil.



(1) Period Before Risk Occurrence (2021) (2) Period of Risk Occurrence (2023) (3) Period After Risk Occurrence (2024)

Figure 4. Time-Series Transaction Trends for Suppliers

Next, Figure 4 shows the supplier side and compares the three companies (Supplier (1), Supplier (10), and Supplier (22)) that were positioned as major suppliers in the first half of 2021. These suppliers achieved “diverse transactions” in the first half of 2021 and conducted transactions evenly with many supermarket chains. However, the situation changed after the risk occurred. During the risk period, two suppliers maintained stable relationships, while Supplier (22) saw a decrease in the number of transaction supermarket chains from 6 to 1 after the influenza risk occurred, resulting in an approximately 84% decrease in sales compared to before the risk and a shift in market size to a medium market. As a result, the transaction structure shifted to one dependent on a specific supermarket chain. By using the Bipartite Graphs shown here, it is possible to overview the changes in network structure and the strength of transaction relationships before and after the risk occurred. However, some suppliers are small-scale suppliers at the end of the chain, and it is difficult to fully grasp their trends using the data used in this study, so it is not possible to go beyond what can be observed from the data.

5.3 Dependency Calculation and Overhead Analysis with Scatter Plots

In order to compare the visualization results of the bipartite Graphs on the same scale, we first calculated the “degree of dependence” for each supermarket chain. The degree of dependence is an entropy index of the sales ratio that each chain depends on its suppliers, normalized by the number of suppliers. With this normalized degree of dependence on the vertical axis and the number of suppliers (number of nodes) on the horizontal axis, a transition diagram was created for each period, expressing the sales growth rate compared to the first half of 2021 as the size of a dot.

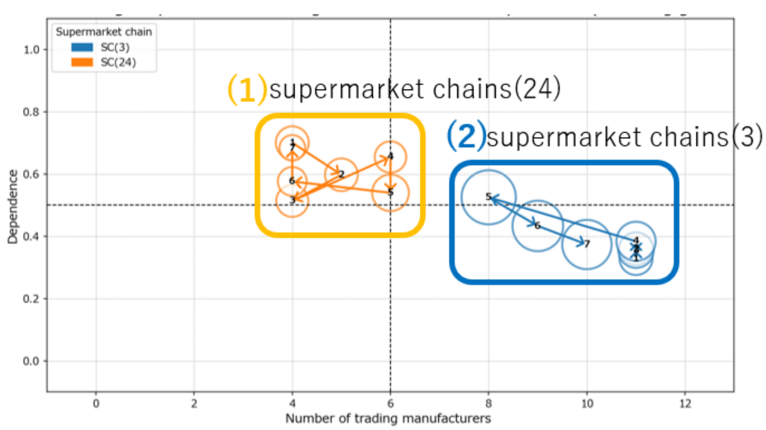


Figure 5. Transition of two types of supermarket chains

Figure 5 shows that the number of suppliers in SC(24) has fluctuated little and is located in the range of 0.6 to 0.8 with a high degree of dependence. This clearly indicates that the company has consistently maintained a concentration strategy of narrowing its focus to a limited number of key suppliers. On the other hand, SC(3) has a large number of suppliers and the dependency ratio is plotted in the relatively low range of 0.4 to 0.6, confirming that the company is building a diversification-oriented procurement network even during the risk period. These patterns clearly indicate contrasting strategies of promoting diversification (number of suppliers increase, and degree of dependency decrease) and maintaining concentration (number of suppliers remains the same, and degree of dependence decrease).

Using the three indices of “degree of dependence,” “number of suppliers,” and “sales growth rate” calculated earlier, we will create scatter plots of the trends of supermarket chains for seven semi-annual periods. However, since it would be complicated to compare 27 supermarket chains at once, scatter plots are created by sales scale (Figure 6 for large scale and Figure 7 for medium scale), and comparisons are made for supermarket chains that are medium-sized or larger.

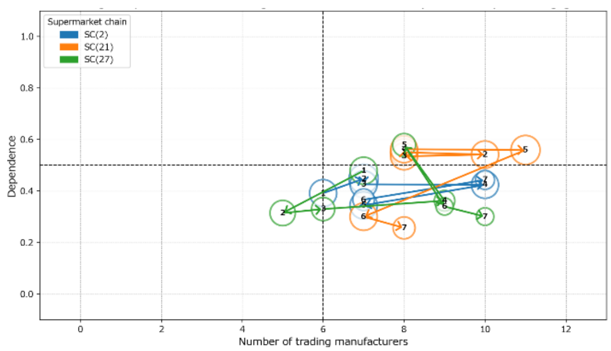


Figure 6. Large-scale supermarket chains.

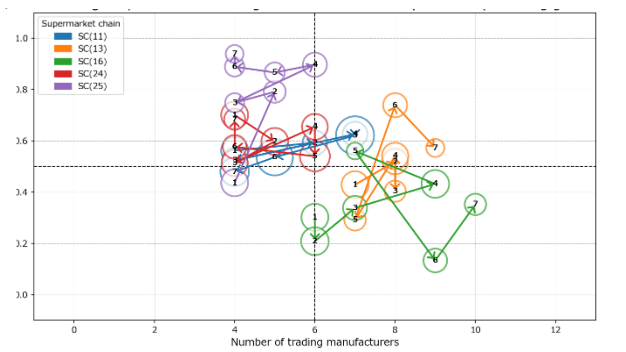


Figure 7. Medium-scale supermarket chains

The major supermarket chain shown in Figure 6 is characterized as "decentralized" because it deals with many suppliers and tends to have low dependency. Looking at the changes after the risk, a decrease in dependency can be seen overall. For example, taking SC(21) and SC(27) as examples, both show a significant decrease in both dependency and number of business partners after the risk, suggesting that they have established a unified transaction structure with specific business partners. On the other hand, in the medium-sized chain group shown in Figure 7, the number of business partners and dependency levels varied between companies, with diverse characteristics even within groups of the same size. Among these, "SC(11), SC(24), and SC(25)" had few transactions, high dependency levels, and stable "transaction patterns" within a limited number of suppliers. These companies showed little change in supply patterns even during risk events. On the other hand, SC(13) and SC(16), which have a high number of transactions but unstable dependency and are considered to be "exploring procurement patterns," typically exhibit fluctuating dependency and may not have established transactions with specific suppliers. As a result, they show broad fluctuations and unstable trends even when risks occur.

5.4 Dependency Calculation and Overhead Analysis with Scatter Plots

Figure 8 shows changes over time in the sales of egg wholesalers and the number of supermarket chains, using some suppliers as examples. It also shows the clustering results for each supplier, with sales represented by color and the number of supermarket chains represented by the thickness of the lines in the time series.

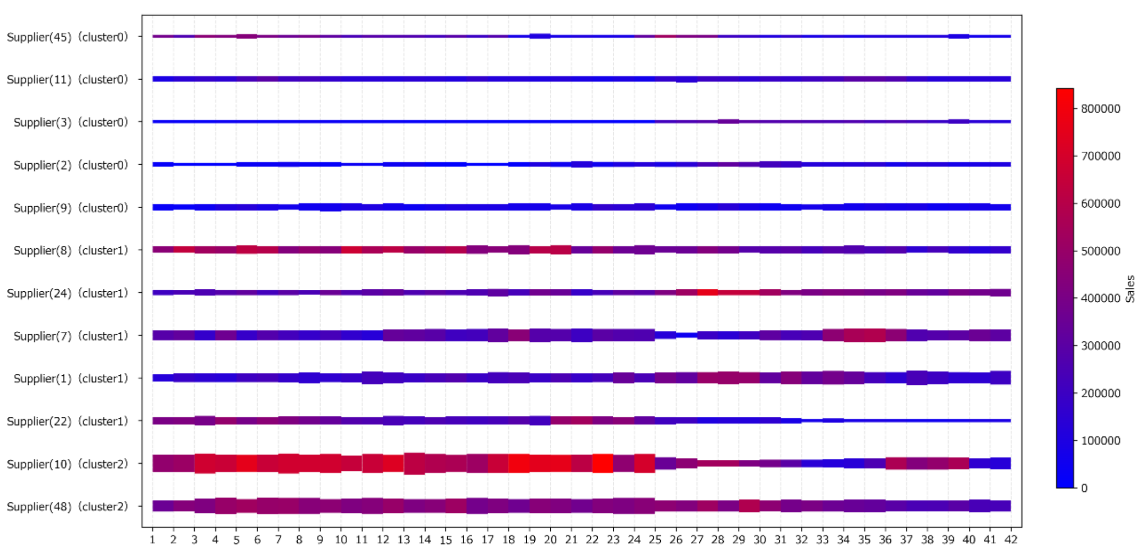


Figure 8. Clustering by supplier sales trends

Figure 8 shows that Cluster 0 is a group that is biased toward continuous transactions with specific supermarket chains, but some of the supplier recovered or expanded their sales and the number of transactions after the occurrence of risk, and are considered to be stable. On the other hand, Cluster 1 is interpreted as a highly resilient group of suppliers that can respond quickly to changes in the external environment, with a strong tendency to flexibly expand the scope of procurement before and after the occurrence of risk, with large fluctuations in sales and the number of supermarket chains with which they do business. In contrast, Cluster 2 has the largest sales and transaction size in the entire market, but both indicators showed a declining trend after the risk occurrence, suggesting that it may have had structural vulnerabilities.

Based on the obtained clustering results of suppliers, we compiled a time series of which cluster each supermarket chain traded with and visualized the sales composition ratio by cluster (Figure 9). By comparing the composition ratios of the source suppliers at each supermarket chain and their changes over time, certain trends regarding resilience strategies for each supermarket chain can be identified. By comparing the percentage of source suppliers in each supermarket chain and their changes over time, certain trends regarding the resilience strategy of each supermarket chain were found. In particular, it was possible to categorize supermarket chains' responses into four major types shown in Figure 9 based on the changes in the cluster of source suppliers.

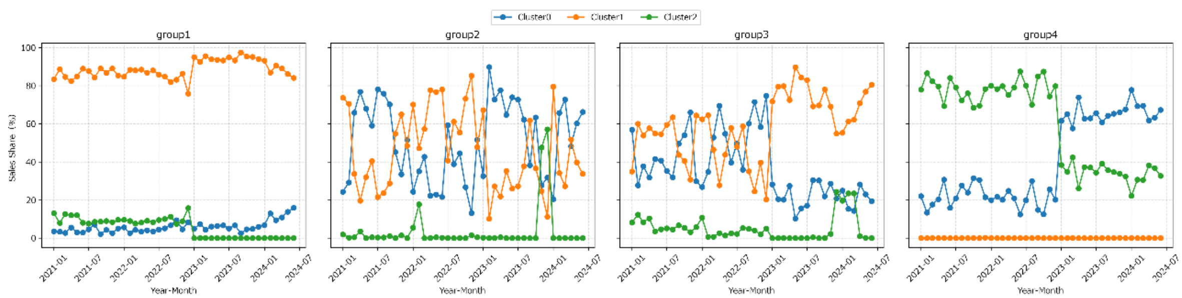


Figure 9. Classification of Supermarket Chains based on the Supplier Selection

Group1 is the supermarket chains that continued their businesses with a specific cluster of suppliers throughout the entire period; Group2 is the chains that did their businesses with multiple clusters of suppliers in parallel before and after the risk occurrence; and Group3 is the chains whose ratio of business with a specific cluster of suppliers which increased rapidly after the risk occurrence, confirming a change in the dependency structure. Group4 is a group of chains that started new transactions with suppliers in clusters that they had not dealt with before after the risk occurrence, indicating that they moved to establish new supply channels. Thus, it is clear that supermarket chains' procurement behavior is not uniform, and that there are various patterns depending on their attitude toward risk response and policies for network restructuring.

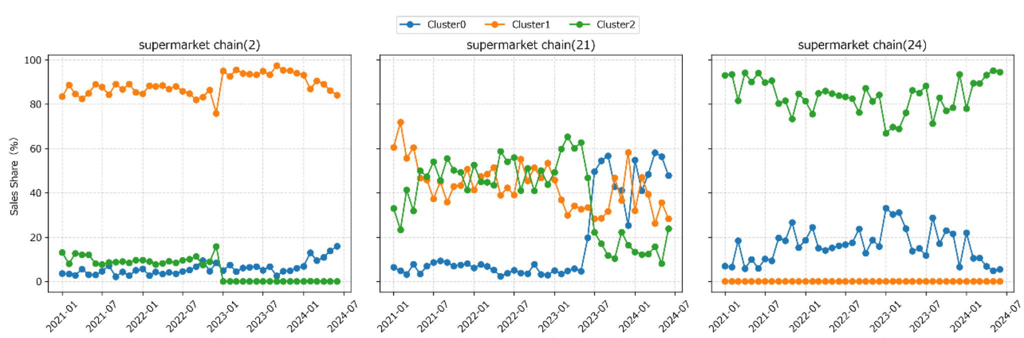


Figure 10. Time series of suppliers transacting business at some supermarket chains

In this section, we will examine more detailed trends in "SC (2)," "SC(21)," and "SC(24)," which were the subject of the previous analysis, by focusing on changes in the cluster composition ratio for each (Figure 10).

First, the “SC(2),” which had a stable SKU replacement throughout the entire period, always had a high percentage of transactions with highly resilient suppliers in Cluster 1, which is consistent with the chain's strategy of maintaining a flexible product mix. On the other hand, in “SC(21),” where rapid SKU replacement was observed during the risk period, transactions with suppliers in Clusters 1 and 2 were the mainstream before the risk period, but during the risk period, the ratio of transactions in Cluster 2 decreased and the ratio of transactions in Cluster 0 tended to increase. However, during the risk period, the ratio of transactions with Cluster 2 declined and the ratio of transactions with Cluster 0 increased. This change indicates that the SC(21) rapidly restructured its procurement sources and may have switched networks flexibly as a risk response. In contrast, the “SC(24)” had been dealing mostly with suppliers in Cluster 2 throughout the entire period, and no major compositional change was observed at the time of the risk occurrence. This suggests that the “SC(24)” emphasized relationships with certain major suppliers and adopted a strategy of prioritizing procurement stability through limited product development.

These analysis results confirm that even in the same market environment, there are clear differences in each supermarket chain’s procurement source selection and response policies, and that tracking changes in supplier profiles and their sales composition ratios through clustering is an effective method for quantitatively understanding supermarket chains’ resilience strategies.

6. Conclusion

This study proposes a method to visualize the relationship between supermarket chains and suppliers at the time of egg supply risk using JAN-coded purchasing data, and to observe differences in purchasing tendencies and trends in market structure before and after the occurrence of risk. In particular, using bipartite graphs and features based on normalized entropy, the dependence and dispersion trends of the business relationship are captured in a time-series manner, making it possible to visualize in real time the scale-specific strategies of supermarket chains and changes in the supply structure on the supplier side. This is expected to contribute to the understanding of risk response trends and network reconstruction in the market as a whole, as well as to the establishment of a basis for decision-making among the parties involved.

Acknowledgments

We used data provided by Research and Innovation Co.Ltd. in the 2024 Data Analysis Competition sponsored by the Joint Association Study Group of Management Science.

References

Abolghasemi, M., Rostami-Tabar, B. & Syntetos, A, The value of point of sales information in upstream supply chain forecasting: an empirical investigation, arXiv preprint, arXiv:2201.10555v1, 2022.

Amofa, B., Oke, A. & Morrison, Z., Mapping the trends of sustainable supply chain management research: a bibliometric analysis of peer-reviewed articles, *Frontiers in Sustainability*, 4, 1129046, 2023.

Christopher, M. & Peck, H., Building the resilient supply chain, *International Journal of Logistics Management*, 15(2), 1–13, 2004

Fan, Y. & Stevenson, M., A review of supply chain risk management: definition, review and future research directions, *International Journal of Production Research*, 58(12), 3602–3628, 2020.

Food Supply Research Center. (n.d.), Guideline for Introducing Poultry Egg Traceability, Retrieved May 14, 2025, from https://www.fmric.or.jp/trace/eggtrace_guideline.pdf

Ganas, P., Fuhrmann, M. & Filter, M., A network model of the egg supply chain in Germany implemented as a FSKX compliant object, *Food and Ecological Systems Modelling Journal*, 2, e74171, 2021.

Ganguly, K., A case study approach for understanding inbound supply risk assessment, *Decision*, 40(1-2), 85–97, 2013.

Han, N. & Um, J., Risk management strategy for supply chain sustainability and resilience capability, *Risk Management*, 26(6), 2024.

Jayaratne, D. N. D., Kamtam, S. H., Shaikh, S. A., Ramli, M. A., Lu, Q., Mepparambath, R. M., Nguyen, H. N. & Rakib, A., A simulation framework for automotive cybersecurity risk assessment, *Simulation Modelling Practice and Theory*, 136, 103005, 2024.

Japan Agricultural Cooperatives Egg Division, 2023 Country Data from IEC Report – Japan Decreases by 19 to 320, Drops Two Places to 4th, *JA Zen-Noh Egg Industry News*, Retrieved May 17, 2025, from https://www.jz-tamago.co.jp/business/news/k00024657/

Japan Agricultural Cooperatives Egg Division. (n.d.), Market information in graphs, Retrieved May 14, 2025, from https://www.jz-tamago.co.jp/business/souba/graph/

Manuj, I. & Mentzer, J. T., Global supply chain risk management strategies, *International Journal of Physical Distribution & Logistics Management*, 38(3), 192–223, 2008.

Ming, X., Cui, Y., Hu, M., Xu, X., Zhang, Z., Liang, S. & Qu, S., Supply chain sustainability risk and assessment, *Journal of Cleaner Production*, 225, 857–867, 2019.

Mitchell, J. L., Thompson, J. M. & Malone, T., Biological lags and market dynamics in vertically coordinated food supply chains: HPAI impacts on U.S. egg prices, *Food Policy*, 126, 102655, 2024.

Mogale, D. G., Wang, X., Demir, E. & Sanchez Rodrigues, V., Modelling and analysing supply chain disruption: a case of online grocery retailer, *Operations Management Research*, 16, 1901–1924, 2023.

Morales, I. R., Cebrián, D. R., Blanco, E. F. & Sierra, A. P., Early warning in egg production curves from commercial hens: A SVM approach, *Computers and Electronics in Agriculture*, 121, 169–179, 2016.

Purwaningsih, R., Ramadani, P. I., Hartini, S. & Putri, A. A. A., Supply Chain Risk Assessment at Poultry Slaughterhouses using House of Risk Method to Define Mitigation Action, *Proceedings of the Second Asia Pacific International Conference on Industrial Engineering and Operations Management* (pp. 2973–2980). Surakarta, Indonesia, 2021.

Soltani, M., Dara, R., Poljak, Z., Dubé, C., Bruce, N. & Sharif, S., Leveraging Social Media and Google Trends to Identify Waves of Avian Influenza Outbreaks in USA and Canada, *arXiv preprint*, arXiv:2503.09725v1, 2025.

Weiser, A. A., Thöns, C., Filter, M., Falenski, A., Appel, B. & Käsbohrer, A., FoodChain-Lab: A Trace-Back and Trace-Forward Tool Developed and Applied during Food-Borne Disease Outbreak Investigations in Germany and Europe, *PLOS ONE*, 11(3), e0151977, 2016.

Xu, M., Yang, X. & Sun, Z., Risk Identification and Prevention of Supply Chain Operation in Small and Medium-Sized Livestock Farms, *Systems*, 13(5), 308, 2025.

Zamani, O., Bittmann, T. & Ortega, D. L., The effect of avian influenza outbreaks on retail price premiums in the United States poultry market, *Poultry Science*, 103(4), 104102, 2024.

Biographies

Yuta Nasu is a first-year master's student in the Department of Business Architect at Kanazawa Institute of Technology. His studying interests include data science, big data analysis, and visualization modeling.

Yukito Yamaguchi is an undergraduate student in the College of Systems Engineering and Science at Shibaura Institute of Technology, Japan. His studying interests include social simulation and data science.

Takayuki Sato is an undergraduate student in the College of Systems Engineering and Science at Shibaura Institute of Technology, Japan. His studying interests include social simulation.

Yu Kawamukai is an undergraduate student in the Faculty of Business Administration at Daito Bunka University, Japan. His studying interests include data science.

Masahiko Ishihara is a Professor in the Graduate School of Engineering at Kanazawa Institute of Technology, Japan. His research interests include management of technology and social data science. He received a Ph.D. in Medical Science from Osaka University in 1997 and a Master of Technology Management from Science University of Tokyo in 2007.

Yasuyuki Shirai is a professor in the Faculty of Business Administration at Daito Bunka University, Japan. His research interests include machine learning and data mining. He received a Doctor's degree in computer science from Kyushu University in 2003.

Yusuke Goto is a Professor in the College of Systems Engineering and Science at Shibaura Institute of Technology, Japan. His research interests include systems engineering, risk analysis, social simulation, and social data science. He received a Ph.D. in Engineering from Waseda University in 2010.