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DATA-DRIVEN DYNAMIC NETWORK MODELING FOR ANALYZING THE EVOLUTION OF PRODUCT COMPETITIONS

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ABSTRACT

Understanding the impact of engineering design on product competitions is imperative for product designers to better address customer needs and develop more competitive products. In this paper, we propose a dynamic network based approach to modeling and analyzing the evolution of product competitions using multi-year product survey data. We adopt Separate Temporal Exponential Random Graph Model (STERGM) as the statistical inference framework because it considers the evolution of dynamic networks as two separate processes: formation and dissolution. This treatment allows designers to investigate why two products enter into competition and why a competitive relationship preserves or dissolves over time. In an open market, the available products to customers are continuously changing over the time, posing challenges for conventional modeling methods concerning fixed product input. Consequently, we propose to leverage "structural zeros" in STERGM to tackle the problem of modeling varying product competitors as nodes in dynamic networks. We use China's automotive market as a case study to illustrate the implementation of the proposed approach and its benefits compared to the static network modeling approach based on Exponential Random Graph Model (ERGM). The results show that our approach identifies the driving factors associated with product attributes and current market competition structures for the change of competition in both formation and dissolution processes. The insights gained from this paper can help designers better interpret the temporal changes of product competition relations and make product design decisions with the aid of dynamic network-based models.

Keywords: engineering design, product competition, dynamic network analysis, ERGM, STERGM

1. INTRODUCTION

The **objective of this paper** is to study the impact of engineering design and existing market competitions on the evolution of product competition relations. To achieve this objective, we develop an approach based on dynamic network modeling using multi-year product survey data. Product competition occurs when customers consider multiple products for evaluation before making the final purchase decision [1]. Therefore, product competition can be indicated by customers' consideration sets [2]. It is therefore of great importance for product designers to gain insights into the factors that can impact product competition relations, such as key design attributes, similarities or differences of design attributes among competing products, design improvement as well as existing market competition structures. These insights can help designers develop more competitive products thus better address customer needs. They can also support companies' strategic decision making, such as branding, product positioning, and marketing.

Our recent studies explored the capability of utilizing network analysis to model product competitions [2,3]. Network-based approaches model products as nodes and the co-

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consideration relations (competition) between products as links. By taking the dependencies among links into consideration, network-based approaches are effective in modeling complex and interdependent relations [4,5]. In our previous research, we developed a unidimensional network-based approach based on Exponential Random Graph Model (ERGM) [6] to study product competitions in the form of product co-considerations [3], and used this model to assess the impact of technological changes (e.g., turbo engine) on product competitions and customers' co-consideration behaviors [1]. Later, we extended the unidimensional network-based approach to a multidimensional network structure where customer social relations were included to study their influence on heterogeneous customer preferences [5]. Despite the strength of these earlier developed network models [1–3,5,7,8], they are static in nature that ignore the dynamic change of product competitions over time. The models are limited in explaining why a product may maintain or lose its competitive advantage over time.

In a highly dynamic market environment, product competition changes over time [9], e.g., due to release of new products, withdrawal of outdated products, technological progress, and social changes. For example, the market share of U.S. brands in the Chinese auto market fell from 12.2% in 2017 to 10.7% in 2018, possibly due to a delayed refresh of the U.S. lineups [10], which demonstrates the negative effect of untimely design improvement on product competition. The change of customer preferences is another potential cause for the evolution of product competition. Fuel-efficient cars have been more desirable since the energy crisis in 1970s as customers become more sensitive to rising gas prices [11]. Since early 2000s, higher fuel efficiency has also contributed to the increasing competitiveness of hybrid vehicles [12]. Therefore, a thorough understanding of the dynamic changes in market competition is of great significance in many engineering design scenarios, such as product feature competition (e.g., whether to upgrade design features of an existing car and by how much) and new product positioning (e.g., whether to develop a new car model to fill a specific market niche).

To address this research need, we propose a dynamic network modeling approach to study the evolution of product competition relations. Specifically, we adopt Separable Temporal ERGM (STERGM) [13,14] as the statistical inference framework for dynamic network modeling. The reasons are in three aspects:

- First, existing degree-based generative dynamic network models (e.g., small world network [15], scale-free network [16], and the dynamic stochastic block model [17]) are limited in modeling the influence of nodal and edge characteristics (e.g., customer demographics and relation strength) on the change of network structures [18]. In contrast, STERGM [13] can study both growing and shrinking dynamics, i.e., how the explanatory factors influence the formation of new links and the dissolution of old links, an important feature to study the impact of product design decisions. Compared to Stochastic Actor-Oriented Model (SAOM) [19], another widely used longitudinal network model which treats nodes as actors who make active decisions, STERGM is more advantageous for our purpose because it is a link-oriented model that can include nodes which are not actors, e.g., products in our work that cannot be treated as intelligent decision makers [20].
- Second, in the social network literature, STERGM has been applied in modeling various dynamic social relations, such as the evolution of social networks of politicians [21] and international trade networks [22]. Researchers found that both exogenous factors (e.g., economic characteristics of counties) and preexisting network structures (e.g., reciprocity for bilateral trade relations and triadic closure effects for trilateral trade relations) can influence international trade networks over time [22]. Thus, STERGM allows us to investigate how preexisting competition relations would influence product competitions in addition to the impact of product features.
- Third, STERGM can be viewed as an extension to the static ERGM. Therefore, the results from STERGM and ERGM can be compared and connected to further advance our understanding on product competition relations.

The **main contribution** of this work is the development of a dynamic network-based modeling approach rooted in STERGM for studying the evolution of product competition relations using customer survey data from multiple years. On the other hand, in previous work, STERGM only handles the same set of nodes over time in modeling dynamic networks [21,22]. However, for product competition modeling, the sets of products in different years are inconsistent because new products appear in the market and existing products exit the market from time to time. In this research, we leverage the concept of "structural zeros" [23] to tackle the problem (see Section 2.3 for details). So the secondary contribution is the "structure-zero" technique that successfully tackles the inconsistency of product consideration set from year to year in dynamic network modeling. Results from STERGM can be used to explain why two products enter into competition and why a competitive relationship is preserved or dissolved over time. We demonstrate the proposed approach using multiple-year survey data from China's auto market, and show the benefits of our approach compared to the static ERGM.

The remaining of the paper is organized as follows. Section 2 provides the technical background of network analysis, the static network modeling technique (ERGM), the dynamic network modeling technique (STERGM), and the structural zeros method. In Section 3, a general approach for modeling dynamic product competition relations based on STERGM is introduced and illustrated using the data associated with China's SUV market. The process of preparing the dataset, identifying modeling attributes, and handling inconsistent vehicle nodes in dynamic network modeling are explained. The results of STERGM are presented and compared with the results of the static network modeling approach (ERGM). To verify the results, model fit evaluation is performed at both the link level and the network level. Section 4 concludes with closing thoughts, the implications in engineering design and future research opportunities.

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2. TECHNICAL BACKGROUND OF DYNAMIC NETWORK ANALYSIS AND MODELING

Network analysis has been recognized as an essential method for analyzing and modeling complex systems in a wide variety of fields such as biology, computer science, social science, and engineering [5,24–26]. With network analysis, the structure of a system is visualized and simplified as a graph, where nodes represent entities in the system and edges/links represent relationships between entities. In this section, two statistical network models for network analysis, i.e., Exponential Random Graph Model (ERGM) and Separable Temporal Exponential Random Graph Model (STERGM), and the structural zeros method are introduced.

2.1 Exponential Random Graph Model (ERGM)

ERGM is a flexible statistical inference framework, which assumes an observed network y as an instance of random networks $\boldsymbol{Y}$ given by the distribution in Eqn. (1),

$$Pr(\boldsymbol{Y} = \boldsymbol{y}) = \frac{exp\left(\boldsymbol{\theta}^{\boldsymbol{T}} \cdot \boldsymbol{g}(\boldsymbol{y})\right)}{\kappa(\boldsymbol{\theta}, \boldsymbol{y})} \ , \qquad (1)$$

where $\boldsymbol{\theta}$ is a vector of corresponding model parameters, and $\kappa(\boldsymbol{\theta}, \boldsymbol{y})$ is a normalizing constant to guarantee the equation is a proper probability distribution. In the context of this work, network $\boldsymbol{Y}$ captures product competition relations, which are identified based on product co-considerations from the customer survey (see more details in Section 3.1). $\boldsymbol{g}(\boldsymbol{y})$ is a vector of network statistics of interest including attributes of nodes, attributes of links as well as network structure attributes [5]. For example, the two-star structure in a vehicles competition network shows whether a car is co-considered with other two distant competitors. Fig. 1 provides three exemplary network structures that can be modeled by ERGM. Eqn. (1) suggests that the probability of observing a specific network structure is proportional to the exponent of a weighted combination of network statistics. The estimated ERGM parameters $\boldsymbol{\theta}$ indicate the importance of the network statistics to the formation of links in a network. For example, a positive $\boldsymbol{\theta}$ of the triangle effect in an ERGM for the vehicle competition network implies that those vehicles involved in three-way competitions are more likely to compete with each other.

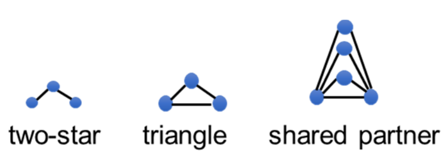

FIGURE 1: Exemplary network structures in a vehicle competition network. The two-star structure indicates whether a car will have two distant competitors. The triangle structure indicates whether three cars compete with each other (three-way competition). The shared partner structure indicates whether two cars sharing the same set of competitors will be considered.

The estimated ERGM parameters $\boldsymbol{\theta}$ can also be used to calculate the log-odds of the formation of certain links, i.e., how likely a link will exist between two nodes given their nodal attributes and the structure of the rest network as shown in Eqn. (2):

$$Logit\ Pr\left(y_{ij} = 1 | \boldsymbol{y}_{-ij}\right) = log \frac{Pr\left(y_{ij}=1|\boldsymbol{y}_{-ij}\right)}{Pr\left(y_{ij}=0|\boldsymbol{y}_{-ij}\right)}$$
$$= \boldsymbol{\theta}^{\boldsymbol{T}} \cdot \left(\boldsymbol{g}\left(\boldsymbol{y}|y_{ij} = 1\right) - \boldsymbol{g}\left(\boldsymbol{y}|y_{ij} = 0\right)\right) = \boldsymbol{\theta}^{\boldsymbol{T}} \cdot \boldsymbol{\delta}_{ij}(\boldsymbol{y}) \ , \qquad (2)$$

where y_{ij} is the link between node i and j, $\boldsymbol{y}_{-ij}$ is the network excluding the link between node i and j, and $\boldsymbol{\delta}_{ij}(\boldsymbol{y})$ is the difference of the network statistics between the network where the link between node i and j exists (i.e., $\boldsymbol{g}\left(\boldsymbol{y}|y_{ij} = 1\right)$) and the network where the link between node i and j does not exist (i.e., $\boldsymbol{g}\left(\boldsymbol{y}|y_{ij} = 0\right)$). If we get positive log-odds for nodes i and j, this indicates that having a link between them is more likely than not having the link and *vice versa*.

2.2 Separable Temporal Exponential Random Graph Model (STERGM)

As an extension of ERGM, STERGM is established to model dynamic networks. As an example shown in Fig. 2, STERGM treats the evolution from the network at time t ($\boldsymbol{Y}^{\boldsymbol{t}}$) to the network at time $t+1$ ($\boldsymbol{Y}^{\boldsymbol{t+1}}$) as two separate processes: 1) **link formation** in which new links are created following $Pr(\boldsymbol{Y}^{+} = \boldsymbol{y}^{+} | \boldsymbol{Y}^{t}; \boldsymbol{\theta}^{+})$, and 2) **link dissolution** in which old links disappear following $Pr(\boldsymbol{Y}^{-} = \boldsymbol{y}^{-} | \boldsymbol{Y}^{t}; \boldsymbol{\theta}^{-})$. The network at time $t+1$ is constructed by applying the changes in $\boldsymbol{Y}^{+}$ and $\boldsymbol{Y}^{-}$ to $\boldsymbol{Y}^{t}$ following $\boldsymbol{Y}^{t+1} = \boldsymbol{Y}^{-} \cup (\boldsymbol{Y}^{+} - \boldsymbol{Y}^{t})$. Here $\boldsymbol{\theta}^{+}$ and $\boldsymbol{\theta}^{-}$ denote the parameters of the formation model ($\boldsymbol{Y}^{+}$) and dissolution model ($\boldsymbol{Y}^{-}$), respectively.

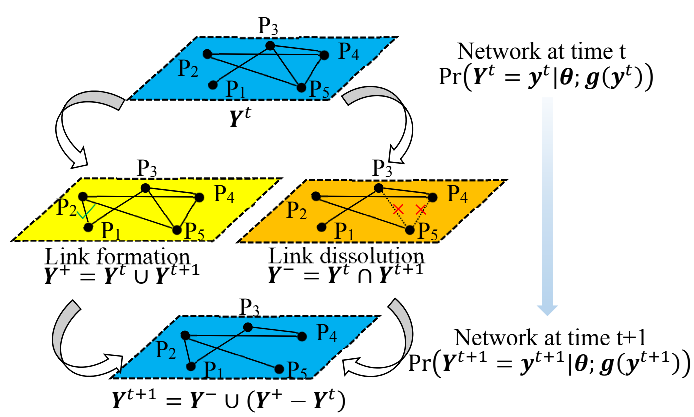

FIGURE 2: Evolution dynamics of product competition network

For each discrete time step, the process of formation and dissolution are independent conditional on the network at time t. This means,

$$Pr(\boldsymbol{Y}^{t+1} = \boldsymbol{y}^{t+1} | \boldsymbol{Y}^{t} = \boldsymbol{y}^{t}; \boldsymbol{\theta}) = Pr(\boldsymbol{Y}^{+} = \boldsymbol{y}^{+} | \boldsymbol{Y}^{t} = \boldsymbol{y}^{t}; \boldsymbol{\theta}^{+}) \cdot Pr(\boldsymbol{Y}^{-} = \boldsymbol{y}^{-} | \boldsymbol{Y}^{t} = \boldsymbol{y}^{t}; \boldsymbol{\theta}^{-}). \qquad (3)$$

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Associating STERGM with ERGM, the probability distribution of formation model and dissolution model are expressed as

$$Pr(\boldsymbol{Y}^{+} = \boldsymbol{y}^{+} | \boldsymbol{Y}^{t} = \boldsymbol{y}^{t}; \boldsymbol{\theta}^{+}) = \frac{exp\left(\boldsymbol{\theta}^{+T} \cdot \boldsymbol{g}(\boldsymbol{y}^{t+1}, \boldsymbol{y}^{t})\right)}{\kappa(\boldsymbol{\theta}^{+}, \boldsymbol{y}^{t})}, \text{ and} \quad (4)$$

$$Pr(\boldsymbol{Y}^{-} = \boldsymbol{y}^{-} | \boldsymbol{Y}^{t} = \boldsymbol{y}^{t}; \boldsymbol{\theta}^{-}) = \frac{exp\left(\boldsymbol{\theta}^{-T} \cdot \boldsymbol{g}(\boldsymbol{y}^{t+1}, \boldsymbol{y}^{t})\right)}{\kappa(\boldsymbol{\theta}^{-}, \boldsymbol{y}^{t})}. \quad (5)$$

The normalizing denominator $\kappa(\boldsymbol{\theta}^{+}, \boldsymbol{y}^{t})$ and $\kappa(\boldsymbol{\theta}^{-}, \boldsymbol{y}^{t})$ are the sum of network statistics of all possible formation and dissolution networks, respectively. Here these formation and dissolution networks only include possible variations to $\boldsymbol{Y}^{t}$ (i.e., the additions and subtractions). In contrast, the normalizing denominator of ERGM includes all networks from an empty network to a complete network (i.e., a network in which all nodes are linked with each other).

Similar to ERGM, STERGM can include both exogenous (e.g., nodal attributes) and endogenous (network structures) variables in network modeling. This enables the prediction of products' future competition relations considering the market's present competition structure and the influence from design changes. In addition, not only can STERGM identify the design features contributing to the formation of competition between two products, it can also identify the features influencing the dissolution of competitions. For example, when assessing the influence of certain SUV attributes on vehicles' competitiveness given the current market structure, if the estimated effect of third-row seat feature is positive and statistically significant in the formation model, it implies that improving the design by including third-row seats would make the SUV more likely to be co-considered against its competitors. In the dissolution model, if the estimated parameter of fuel consumption is negative and statistically significant, it means that better fuel economy in the SUV would make its competing relationships more likely to persist (not dissolve).

2.3 Structural zeros method

To address the challenge of modeling changing network nodes in STERGM, we propose a new method based on *structural zeros*. Given a unidimensional network consisting of N nodes, this network can be presented by a $N \times N$ matrix with entries of binary indicator 0 or 1. *Structural zeros*, which also called fixed zeros or necessarily empty cells, are a set of predefined zero inputs in the matrix to restrict the relations among some nodes in the network (i.e., these nodes have no links) [27]. Therefore, the distribution of dynamic network at time $t+1$ can be written as

$$Pr(\boldsymbol{Y}^{t+1} = \boldsymbol{y}^{t+1} | \boldsymbol{Y}^{t} = \boldsymbol{y}^{t}; R^{t} = r^{t}; \boldsymbol{\theta}), \quad (6)$$

where $R^{t} \in \mathbb{R}^{N \times N}$ is binary matrix corresponding to $\boldsymbol{Y}^{t}$ and r^{t} is a realization of R^{t}, such as

$$r = \begin{bmatrix} \mathbf{0} & 1 & 1 & \mathbf{0} & \mathbf{0} \\ 1 & \mathbf{0} & 1 & \mathbf{0} & 1 \\ 1 & 1 & \mathbf{0} & \mathbf{0} & 1 \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & 1 & 1 & \mathbf{0} & \mathbf{0} \end{bmatrix}, \quad (7)$$

where blocks denoted as $\mathbf{0}$ are structural zero blocks which enforce $\boldsymbol{y}_{15}$, $\boldsymbol{y}_{x4}$, $\boldsymbol{y}_{4x}$ and $\boldsymbol{y}_{xx}$ $(x = 1, 2, \dots, 5)$ to be 0 in $\boldsymbol{Y}^{t+1}$, while the other entries denoted as 1 indicate corresponding relations in $\boldsymbol{Y}^{t+1}$ have no restrictions (i.e., they are free to change to 0 or remain as 1). Fig. 3 shows an exemplary network following this matrix r.

FIGURE 3: A network example based on matrix r

Thus, the dynamic network model based on structural zeros can be represented as

$$Pr(\boldsymbol{Y}^{t+1} = \boldsymbol{y}^{t+1} | \boldsymbol{Y}^{t} = \boldsymbol{y}^{t}; R^{t} = r^{t}; \boldsymbol{\theta}) = \frac{exp\left(\boldsymbol{\theta}^{+T} \cdot \boldsymbol{g}(\boldsymbol{y}^{t+1}, \boldsymbol{y}^{t})\right)}{\kappa(\boldsymbol{\theta}^{+}, \boldsymbol{y}^{t}, r^{t})} \cdot \frac{exp\left(\boldsymbol{\theta}^{-T} \cdot \boldsymbol{g}(\boldsymbol{y}^{t+1}, \boldsymbol{y}^{t})\right)}{\kappa(\boldsymbol{\theta}^{-}, \boldsymbol{y}^{t}, r^{t})}, \quad (8)$$

where possible networks of $\boldsymbol{Y}^{+}$ and $\boldsymbol{Y}^{-}$ in $\kappa(\boldsymbol{\theta}^{+}, \boldsymbol{y}^{t}, r^{t})$ and $\kappa(\boldsymbol{\theta}^{-}, \boldsymbol{y}^{t}, r^{t})$ have been reduced because of r^{t}.

Several applications of structural zeros can be found in different areas, such as parametric models [28], control system [29] and social network [30,31]. It was used commonly in network modeling since Robins et.al. [30] who used structural zeros to represent the relationship in those ordered pair of actors that are not couple. In addition, Fu et al. [8] and Sha et al. [32] used structural zeros to restrain customers to purchase products outside their consideration sets in a bipartite network-based approach for modeling customer preferences over two stages (consideration and purchase). Snijders et al. [19] used structural zeros to deal with the missing data in friendship networks. In this paper, we employ this concept to handle the issue of varying nodes from one time period to another in dynamic network modeling.

3. UTILIZING STERGM TO MODEL EVOLUTION OF PRODUCT COMPETITIONS

3.1 Overview of the dynamic network analysis approach

Fig. 4 illustrates the procedure of utilizing STERGM for understanding the evolution of product competitions in market. The detailed description of each of the three steps is provided as follows.

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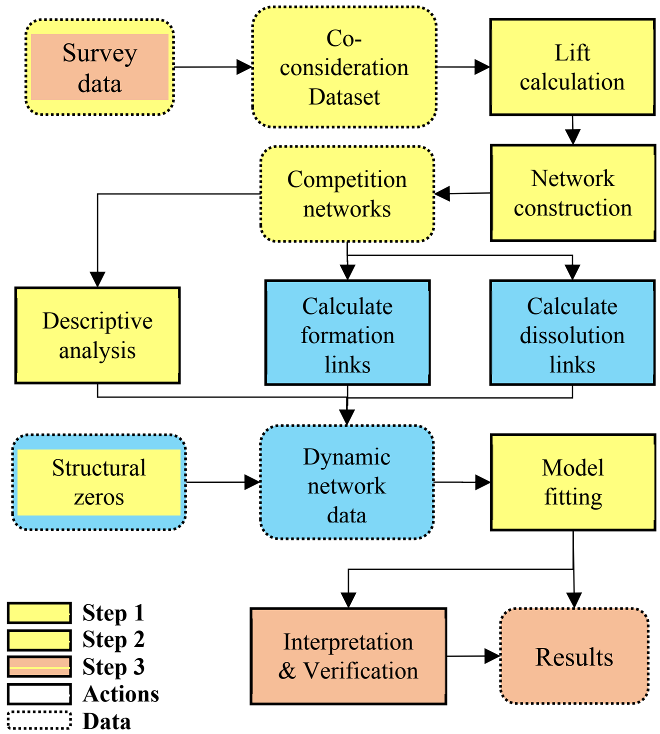

FIGURE 4: Overview of the proposed approach

Step 1-*Network construction and descriptive analysis*. Product competition relationship is identified in this work based on the survey data of considerations, i.e., the products in the same consideration set before a customer makes the final choice. In the formed network, whether the competition relationship exists is determined by the *lift* criterion [7]. The calculation of *lift* and the criterion for link formation are illustrated in Eqn. (9),

$$Lift(i,j) = \frac{Pr(i,j)}{Pr(i)\cdot Pr(j)},\ y_{ij} = \begin{cases} 1, & if\ lift(i,j) > 1 \\ 0, & otherwise \end{cases}, \quad (9)$$

where $Pr(i,j)$ is the probability of products i and j being co-considered by customers, $Pr(i)$ is the probability of individual product i being co-considered with other products, and y_{ij} is the competition link between product i and product j. The *lift* value measures the likelihood of competition between two products given their respective frequencies of considerations and indicates the dependence of the two products being considered. If the *lift* between product i and product j is greater than a threshold, then the competition link between these two product nodes exists. If two products are completely independent, the *lift* value will be 1 [1]. In this paper, we set the threshold equals to 1 to capture two products that are competed more likely than expected in random [3]. After the *lift* calculation, a unidimensional undirected competition network can be constructed. Fig. 5 provides an illustrative vehicle competition network, in which the numbers represent the *lift* values. A larger *lift* value between two vehicles indicates that they are more frequently co-considered by customers, i.e., there is a stronger competition relationship between them. Descriptive analysis and visualization of the obtained network can provide an intuitive understanding of the nodal attributes and network structures.

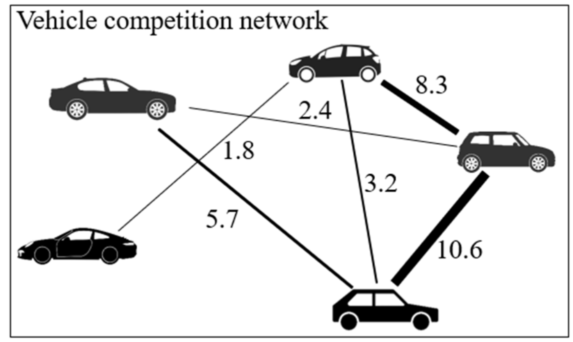

FIGURE 5: An illustrative vehicle competition network

Step 2-*Dynamic network modeling*. After generating the product competition networks in different time periods, we can construct the formation and dissolution networks between each pair of two consecutive networks (see Fig. 2), and use STERGM to investigate the evolution of network structures. The results of descriptive analysis from previous step can help the selection of explanatory factors in network statistics $\boldsymbol{g}(\boldsymbol{y}^{t+1}, \boldsymbol{y}^{t})$. To deal with the varying nodes, structural zeros were utilized in STERGM to generate the dynamic network model (see Eqn. 8). Fig. 6 shows how this method works for link formation process by using three networks, represented by adjacency matrices, in time $t-1$, t and $t+1$ (i.e., $\boldsymbol{Y}_{t-1}, \boldsymbol{Y}_t, \boldsymbol{Y}_{t+1}$) as an example. The formation network between $\boldsymbol{Y}_{t-1}$ and $\boldsymbol{Y}_t$ is noted as $\boldsymbol{Y}_{t-1}^{+}$, and the formation network between $\boldsymbol{Y}_t$ and $\boldsymbol{Y}_{t+1}$ is noted as $\boldsymbol{Y}_t^{+}$. The *structural zeros* method contains the following steps:

a) Combine all possible formation networks ($\boldsymbol{Y}_{t-1}^{+}$, $\boldsymbol{Y}_t^{+}$ in this example) in one matrix. If we need to model four-year networks, there will be three formation networks, i.e., three blue regions in Fig. 6 (a). Since STERGM only supports consistent sets of nodes in principle, here the matrices of $\boldsymbol{Y}_{t-1}^{+}$ and $\boldsymbol{Y}_t^{+}$ include the union set of nodes from $\boldsymbol{Y}_{t-1}, \boldsymbol{Y}_t, \boldsymbol{Y}_{t+1}$, which means the sizes of these two sub-matrices are the same as shown in the blue regions in Fig. 6 (a). Apparently, the whole matrix is symmetric with zero diagonal cells (self-competitions are not considered).

b) Fill zeros to specific blue regions of Fig. 6 (a) to ensure those new nodes appearing in the other years have no links. For example, the red region $\boldsymbol{Y'}_{t-1}^{+}$ in Fig. 6 (b) only includes the vehicles appearing in $\boldsymbol{Y}_{t-1}$, and $\boldsymbol{Y'}_t^{+}$ only includes the vehicles appearing in $\boldsymbol{Y}_t$.

c) To ensure that the model captures the changing effect for both preserved and created nodes, the new nodes in the second year of a two-year formation network which are not considered in the red zone in Fig. 6 (b) will be included in the yellow zone in Fig. 6 (c). For example, the difference between the yellow region $\boldsymbol{Y''}_{t-1}^{+}$ in Fig. 6 (c) and the red region $\boldsymbol{Y'}_{t-1}^{+}$ in Fig. 6 (b) is the new nodes appearing in $\boldsymbol{Y}_t$.

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When finished, the matrix in Fig. 6 (c) will replace the original matrix in Fig. 6 (a) in fitting the formation model of STERGM. Here we focus on the formation process for illustrative purpose, and the dissolution process follows the same procedures except that the dissolution networks are used.

Step 3-*Interpretation and verification*. Since STERGM is an extension of ERGM with separated effects on formed links and dissolved links, STERGM can be estimated by methods commonly used in ERGM such as maximum likelihood and generalized moments [28]. The estimation results should be verified based on both model fitting and model interpretability. Extracted insights from how product competitions change over time can be used to support product upgrade and new product development strategies in engineering design.

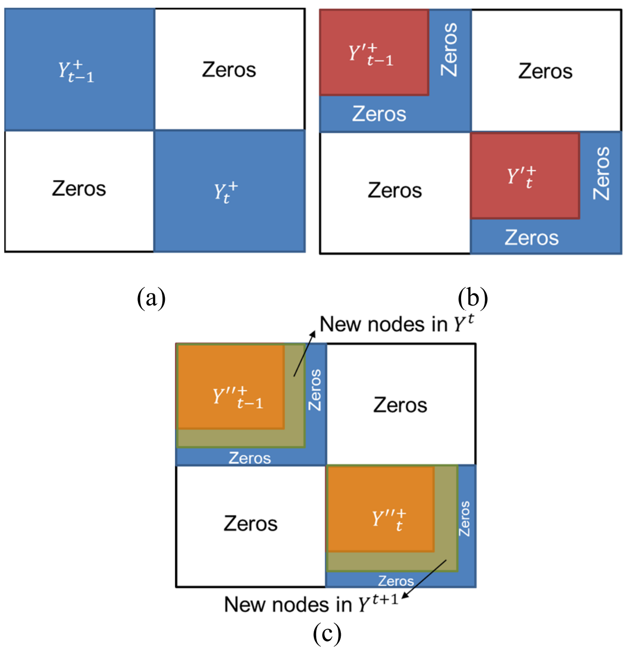

Figure 6: Structural zeros used in STERGM for dynamic network with varying nodes

3.2 Dataset for a Case Study on China's Crossover SUV Market

To demonstrate the proposed approach, we carried out a case study using the data from a recognized new car buyer survey from 2013 to 2015 in China's auto market [8]. The dataset in each year consists of 50, 000-70,000 new car buyers' responses including approximately 400 unique car models. Respondents were asked to list up to three vehicles (including final choice) they considered when purchasing the car. Customer demographics, such as income, city of residence and education, and car attributes, such as price, power, and fuel consumption, are reported in the survey and verified by the data company. In each year, the survey was collected every four months. However, we use yearly data in this paper to avoid the seasonal effects on customers' choice behaviors. In this case study, we focus on market competitions among crossover SUVs. A crossover SUV, such as an Audi Q7, BMW X6, or Ford Edge, is a vehicle with the body and space of an SUV, but the backbone of a sedan. Crossover SUVs inherit the advantages of spacious interiors from vans, the off-road performance of SUVs and the light-weight and fuel economy of sedans. Our interest is in demonstrating why two crossover SUVs enter in a competitive relationship and why the competition ceases.

3.3 Descriptive analysis

Once we obtain the customers' consideration sets from the survey data, the *lift* value for all competitions between car models can be calculated. We constructed three competition networks corresponding to years 2013, 204 and 2015. There are roughly 100 car models from 2013 to 2015 considered in our study (including both crossover SUVs and other conventional or SUV vehicles co-considered with crossover SUVs) and 600 pairs of competitions in each year. Fig. 7 illustratively shows partial competition networks in 2014 and 2015 with 10 vehicle models. The node size is proportional to its degree and the nodes with green color represent selected vehicle models for log-odds calculation in Section 3.5 (this is to verify the STERGM modeling results at link levels). The blue line indicates newly formed competitions in 2015 while the grey lines indicate the dissolved ones. The *lift* value marked on each link shows the strength of competitions. For example, in Fig. 7, Audi FAW Q5 (Q5) competes with three cars - Toyota GAIG Highlander (Highlander), Dongfeng Yulong Luxgen Grand 7 (Luxgen Grand 7), and BMW X6 (X6). For a customer considering the Q5, in 2014 the Highlander is the most likely co-considered car whereas in 2015 the closest competitor changes to X6.

Table 1 provides the mean value and standard deviation (presented in brackets) of vehicle attributes from 2013 to 2015 for all pairs of competing vehicles versus all possible pairs of competing vehicles. The major difference is that the car models in the set of "all possible pairs of competing vehicles" do not necessarily hold a direct competition relation (e.g., car A and car B are not competitors, but they both compete with car C). Based on our previous research in choice modeling and product competitions [2,5,33], three categories of vehicle attributes are considered in this study: 1) regular vehicle attributes such as the price, power and fuel consumption of vehicles; 2) vehicle attribute difference. For example, the price difference between two competed vehicles allows us to investigate whether vehicles with similar or different attributes are more likely to compete with each other; and 3) SUV-relevant attributes, such as seat position. In total, nine vehicle attributes are considered including price, power, fuel consumption (FC), turbo, make origin, all-wheel drive (AWD), seat position, legroom, and third row. Among them, price and power are preprocessed using log2 transformation to handle their non-normal distributions. Turbo, AWD, and third row are binary variables describing whether such a property is available in a car or not. Seat position and legroom are customer satisfaction Likert-scale ratings from 1 (dissatisfy strongly) to 4 (satisfy strongly). It can be seen that the mean values of price, power, fuel consumption, vehicle attributes difference, and third row are lower on average in competing vehicles than that in all possible pairs of competing vehicles.

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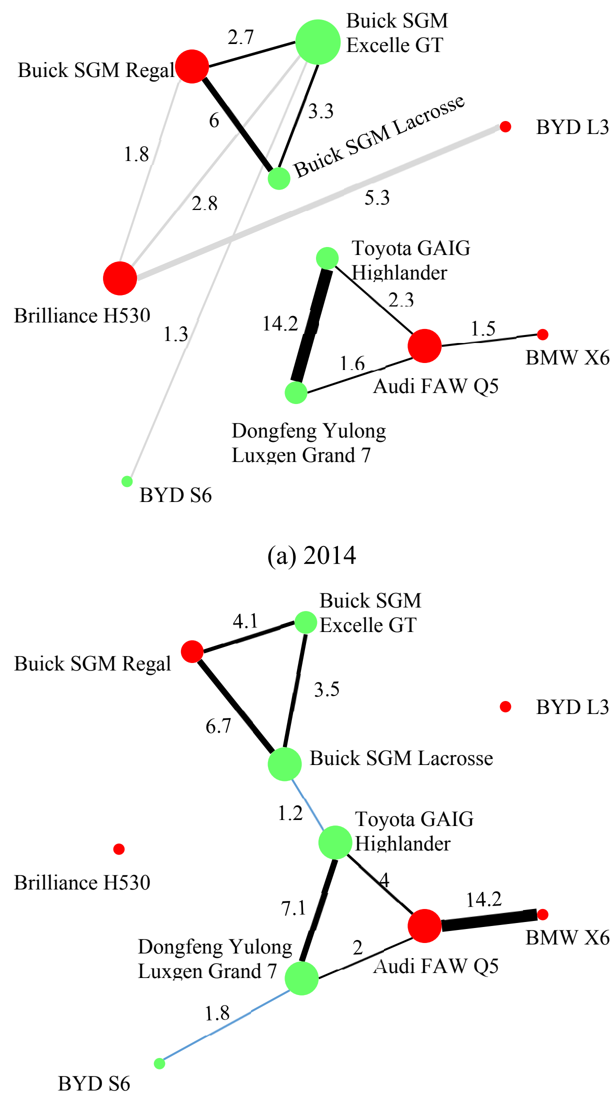
Some vehicle attributes changed from 2013 to 2015; for example, the mean value of power for all possible pairs of competing vehicles increased from 7.25 to 7.35 and fuel consumption decreased from 10.13 to 9.96.

Table 1. Descriptive analysis of competing vehicle pairs versus all possible pairs of competing vehicles

	Pairs of competing vehicles			All possible pairs of competing vehicles		
	2013	2014	2015	2013	2014	2015
Regular vehicle attributes						
Price (log2)	16.95 (0.94)	17.37 (1.22)	17.04 (0.99)	17.43 (1.22)	17.55 (1.37)	17.52 (1.32)
Power (log2)	7.03 (0.42)	7.20 (0.52)	7.18 (0.41)	7.25 (0.56)	7.28 (0.58)	7.35 (0.55)
FC (L per 100 km)	9.24 (1.79)	9.82 (2.07)	9.36 (1.73)	10.13 (2.3)	10.07 (2.17)	9.96 (2.09)
Turbo	0.14 (0.28)	0.28 (0.39)	0.37 (0.37)	0.19 (0.33)	0.28 (0.39)	0.39 (0.40)
Origin (US)	172 (14%)	239 (16%)	138 (15%)	23 (20%)	21 (15%)	18 (15%)
Origin (EU)	188 (15%)	366 (25%)	111 (12%)	20 (17%)	36 (26%)	27 (23%)
Origin (JP)	183 (15%)	167 (11%)	107 (12%)	19 (17%)	17 (12%)	18 (15%)
Origin (KR)	275 (22%)	128 (9%)	59 (7%)	17 (15%)	14 (10%)	10 (8%)
Origin (CN)	438 (35%)	566 (39%)	485 (54%)	36 (31%)	51 (37%)	46 (39%)
Vehicle attribute difference						
Price difference	0.47 (0.39)	0.49 (0.43)	0.44 (0.36)	1.40 (1.01)	1.57 (1.13)	1.52 (1.09)
Power difference	0.25 (0.21)	0.25 (0.22)	0.27 (0.21)	0.64 (0.47)	0.67 (0.49)	0.63 (0.46)
FC differences	1.08 (0.94)	1.08 (0.94)	1.04 (0.86)	2.61 (1.95)	2.48 (1.80)	2.42 (1.71)
SUV-relevant attributes						
AWD	0.14 (0.29)	0.26 (0.36)	0.22 (0.30)	0.23 (0.36)	0.26 (0.37)	0.24 (0.36)
Seat position	3.08 (0.11)	3.08 (0.11)	3.08 (0.14)	3.09 (0.13)	3.07 (0.13)	3.09 (0.19)
Legroom	3.20 (0.09)	3.17 (0.10)	3.14 (0.10)	3.21 (0.14)	3.16 (0.13)	3.13 (0.16)
Third row	0.10 (0.29)	0.14 (0.35)	0.12 (0.33)	0.16 (0.36)	0.16 (0.37)	0.20 (0.40)

3.4 Results of Dynamic Network Modeling

The R package “tergm” is used to fit the STERGM models [34]. As shown in Table 2, the explanatory variables in our dynamic network models correspond to two types of variables: endogenous variables (i.e., network structures) and exogenous variables consisting of the main effects and homophily effects of vehicle attributes. The main effect measures the impact of the existence or value of a vehicle attribute on the competition link probability, whereas the homophily effect measures the impact of the similarity or difference of the attributes of two vehicles on their competition link probability [2]. In this study, we consider two network structure effects: Geometrically Weighted Edgewise Shared Partner (GWESP), which is referred to as the shared partner structure in Fig. 1; and Geometrically Weighted Degree (GWD), which measures the centralization effect of the network (i.e., the evenness of degree distribution). In a vehicle competition network, a positive coefficient of GWESP means it is very likely for two cars to compete with each other if they share the same set of competitors. A positive coefficient of GWD means most cars have similar numbers of competitors.



(b) 2015

Figure 7: An example of partial vehicle competition networks evolving from 2014 (a) to 2015 (b). Black lines indicate preserved competitions, grey lines indicate dissolved competitions, and blue lines represents new competitions.

Three STERGM models (A, B, C) are created with different model specifications. In Model A, we only consider main effect of regular vehicle attributes and homophily effects, and results are used as the baseline for comparison. Model B includes main effect of regular vehicle attributes, homophily effects, and network effects. In Model C, we consider all endogenous and

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exogenous variables including main effect of SUV-relevant attributes. The 17% decrease of AIC value from Model A to Model B in Table 2 indicates model improvement due to the introduction of network structure effects. On the other hand, introducing SUV-relevant attributes in Model C leads to slightly worse model fit compared to Model B, and SUV-relevant attributes are not significant in both formation and dissolution models.

When examining the results from the STERGM formation model, the coefficients of all three network structure effects are significant. The positive sign of "closure effect" indicates that a new competition is more likely to form between two vehicles if they shared the same set of competitors previously. The negative sign of "centralization effect" denotes that new competitions are more likely to form between vehicles that have been in competition with many other car models already. Among the regular vehicle attributes, we observe the estimated coefficients of -0.34 and -0.35 for vehicle brands from Japan and Korea, respectively. The negative signs indicate that, compared to domestic vehicles, vehicles from Japan and Korea are less likely to form new competitions from 2013 to 2015. Although the main effects of price, power, FC, and turbo show no significance in the formation model, the homophily effects are significant. The negative coefficient of price difference indicates that vehicles tend to form new competitions with those having similar prices. In contrast, two vehicles with a higher difference in power and FC are more likely to create a new competition between them as time goes by.

When examining the results from the link dissolution model, it is important to note that the estimations measure the persistence of competition, *not* disappearance. As shown in Table 2, the estimates of closure effect, centralization effect and vehicles from Japanese and Korean brands significantly influence the preservation of existing competitions. The interpretation of dissolution model is somewhat similar to the formation model except that one is for the formation of new competitions while the other is for the preservation of old/existing competitions. For example, the estimate of closure effect being 0.41 indicates that existing competitions are more likely to persist over time if two vehicles share the same set of competitors.

To better understand the differences between STERGM and ERGM, we compare the results of the two models in Table 3. It is noted that the statistical significance of the attributes in ERGM is different from one year to another. In many cases, it is also different from the significance obtained from STERGM. These differences can be explained by the fact that ERGM is a static network modeling approach based on single-year data, assuming there are no pre-existing network relations (i.e., no competition at all), whereas STERGM is a dynamic network modeling approach focused on detecting the **changing pattern** that best describes the formation and dissolution of competitions conditional on the pre-existing competitions.

Table 2. Results of the STERGM fitting for dynamic competition networks from 2013 to 2015

	Formation			Dissolution		
Model	A[1]	B[2]	C[3]	A	B	C
Network effects						
Closure		1.15***	1.15***		0.41**	0.41**
Centralization		-2.79***	-2.79***		-1.03***	-1.06***
Edges	3.80*	-3.59**	-3.55*	-2.91	-4.55	-3.18
Main attributes effects						
Price	0.03	0.01	0	-0.24	0.07	0
Power	-0.79***	-0.15	-0.17	0.86	0.17	0.3
FC	0.15***	0.03	0.05*	-0.19	-0.09	-0.13
Turbo	-0.08	0.06	0.07	-0.22	-0.16	-0.19
Origin (US)	0.29***	0	-0.01	0.18	0.05	0.12
Origin (EU)	0.42***	0.07	0.07	0.59*	0.19	0.29
Origin (JP)	-0.39***	-0.34***	-0.34***	-0.53	-0.48*	-0.37
Origin (KR)	-0.26**	-0.35***	-0.33***	-0.39	-0.43**	-0.35*
AWD			-0.04			0.12
Seat position			0.01			0.69
Legroom			0.02			-0.75
Third row			-0.10			0.04
Homophily effects						
Price diff.	-0.33***	-0.22***	-0.22***	-0.14	-0.06	-0.11
Power diff.	0.54***	0.41**	0.42**	0.37	0.41	0.43
FC diff.	0.09**	0.07*	0.06*	0.03	0.05	0.07
AIC	9340	7740	7747	841	787	792

***$p<0.001$, **$p<0.01$, *$p<0.05$.

[1] Model A-only consider regular attributes and homophily effects

[2] Model B-consider regular attributes, homophily effects and network effects

[3] Model C-consider all attributes

The differences in the model coefficients of ERGM over time (2013-2015 as shown in Table 3) imply the change of customer preferences from one year to another. For instance, the coefficient for fuel consumption is insignificant in 2013 but becomes significant in both 2014 and 2015 with a value of 0.07 and 0.10, respectively. On the other hand, a significant coefficient (0.5) for fuel consumption in the STERGM formation model indicates that based on the three-year data, fuel consumption has a positive influence on forming new competitions. It is also found that SUV specific attributes such as AWD are shown to be significant in each year's statistic ERGM modeling but are insignificant in influencing the forming of new competitions over time compared to other main attributes.

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Table 3. Comparing results of ERGM versus STERGM for competition networks from 2013 to 2015

Coefficients	ERGM			STERGM	
	2013	2014	2015	Formation	Dissolution
Network effects					
Closure	0.77***	0.99***	0.87***	1.15***	0.41**
Centralization	-0.51	0.24	-0.86*	-2.79***	-1.06***
Edges	7.11*	-2.42	2.6	-3.55*	-3.18
Main attributes effects					
Price	-0.30*	-0.15	-0.22	0	0
Power	-0.09	-0.17	-0.06	-0.17	0.3
FC	0.03	0.07*	0.10*	0.05*	-0.13
Turbo	-0.17	0.08	0.07	0.07	-0.19
Origin (US)	0.12	0.13	-0.14	-0.01	0.12
Origin (EU)	0.54***	0.31**	0.13	0.07	0.29
Origin (JP)	0.54***	0.21	-0.08	-0.34***	-0.37
Origin (KR)	0.49***	-0.1	-0.19	-0.33***	-0.35*
AWD	0.56***	0.35***	0.38***	-0.04	0.12
Seat position	-0.02	0.58*	-0.09	0.01	0.69
Legroom	0.22	0.35	0.33	0.02	-0.75
Third row	-0.24*	-0.16*	-0.35***	-0.10	0.04
Homophily effects					
Price diff.	-1.41***	-1.16***	-1.59***	-0.22***	-0.11
Power diff.	-0.56*	-0.42	0.32	0.42**	0.43
FC diff.	-0.10	-0.21***	-0.22***	0.06*	0.07
AIC	2993	3776	2317	7747	792

3.5 Results verification

To further verify the results in Section 3.4, the link-level verification and the goodness-of-fit analysis at the network level are performed.

3.5.1 Link-level verification

Link-level verification compares the log-odds of those hypothetical links (i.e., those links do not exist in observed networks and are solely for testing purposes) to the log-odds of the real links in observed networks. In general, newly formed competitions in observed networks (i.e., real links) are supposed to have higher log-odds than those hypothetical links. The vehicles represented by green nodes in Fig. 7 are selected for the link-level verification. Table 4 provides the value of significant variables in Model C for these vehicles.

Table 4. The value of vehicle attributes for selected vehicles

Model name	Price	Power	FC	Make origin
Buick SGM Excelle GT	16.78	6.85	8.67	American
Buick SGM Lacrosse	17.89	7.60	11.07	American
BYD S6	16.71	7.16	10.09	Chinese
Dongfeng Yulong luxury grand 7	17.84	7.46	12.56	Chinese
Toyota GAIG Highlander	18.08	7.56	12.31	Japanese

By inserting the estimated coefficients obtained from Table 2 into Eqn. (2), the log-odds of a link forming conditional on the rest of network can be calculated:

$$Logit\ Pr\left(Y_{ij}^{+}=1\right)=\boldsymbol{\theta}^{\boldsymbol{T}}\cdot\boldsymbol{\delta}_{ij}^{+}(y)=-3.55\times\delta_{Edges}+0.05\times\delta_{Fuelconsump}-0.34\times\delta_{Origin(JP)}-0.33\times\delta_{Origin(KR)}-0.22\times\delta_{Price\ diff.}+0.42\times\delta_{Power\ diff.}+0.06\times\delta_{FC\ diff.}+1.15\times\delta_{GWESP}-2.79\times\delta_{GWD}\ , \quad (10)$$

Plugging the attribute values from Table 4 into Eqn. (10), we calculate the log-odds of real links compared with a hypothetical link to verify the accuracy of our model; results are illustrated in Fig. 8, using the same set of vehicles shown in Fig. 7. It is observed that the real links (e.g., the competition link between Highlander and Buick SGM Lacrosse) reach higher log-odds than the hypothetical links (e.g., the dash link between Highlander and Buick SGM Excelle GT) in 2015. This indicates that the STERGM results can successfully capture the influence of exogenous variables (e.g., fuel consumption, price difference, power difference, fuel consumption difference, and make origin), and endogenous variables (e.g., centralization and closure effect) on the formation of vehicle competitions shown in Fig. 7.

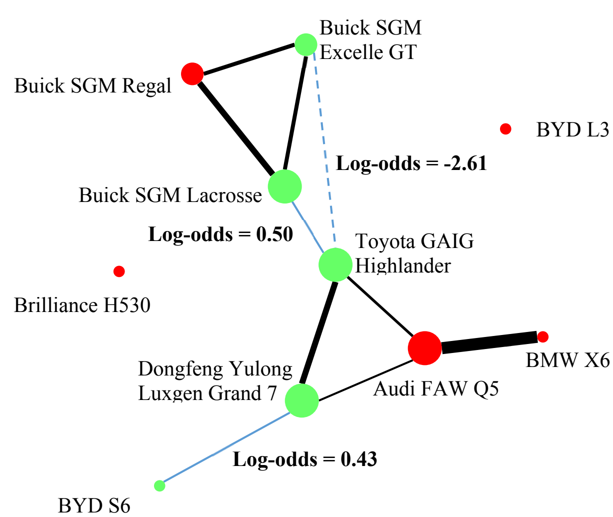

Figure 8: The log-odds results of two newly formed links (solid blue lines) and a hypothetical link (dash blue line) in the competition network from 2014 to 2015

3.5.2 Network level verification

The goodness-of-fit analysis at the network level verifies the model through comparing the simulated networks from the

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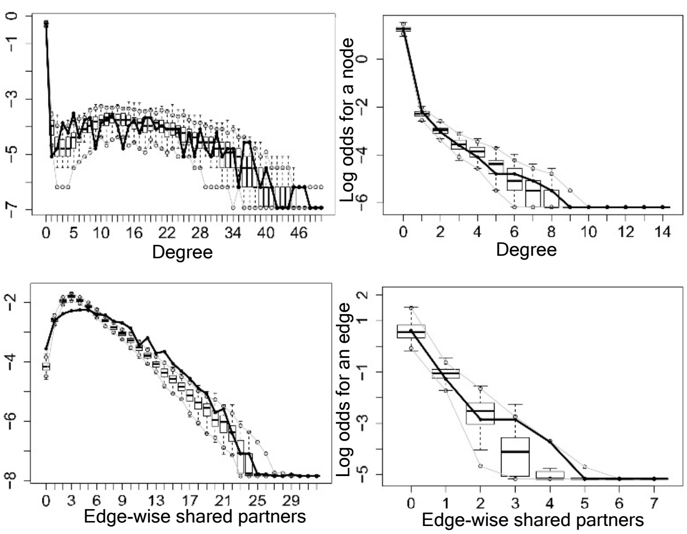
estimated models with observed networks in terms of the distributions of certain endogenous variables such as the degree of nodes and GWESP as well as exogenous statistics. We use competition network in 2014 as the target data for STERGM simulations. Fig. 9 provides the results of 100 simulated competition network of 2014 with STERGM (using competition network in 2013 as the starting network) for examining the explanatory variables. The vertical axis in each plot represents the logit (log-odds) of the relative frequency, the solid line represents the statistics for the observed network, the boxplots indicate the median and interquartile range of the simulated networks, and the light-grey lines represent the range in which 95% of simulated observations fall. We can see most observed value lies in the 95% range of simulated observations which indicates that STERGM performs relatively well in both the formation model and the dissolution model.



(a) (b)

Figure 9: Goodness-of-fit plots of STERGM using competition network in 2014 as the target data. (a) Formation model. (b) Dissolution model.

4. CONCLUSION

The major contribution of this study is the development of a dynamic network analysis approach to modeling the evolution of product competition relations. Even though a network-based approach was previously adopted in modeling vehicle competitions to overcome the limitations of DCA [35,36], this is the first attempt to systematically analyze and model product competitions based on longitudinal market data and dynamic network analysis. Different from our previous study on multi-year analysis using cross-sectional network data, this research provides insights into the factors (such as product attributes, homophily effects, and network structure effects) that drive changes of product competitions.

Our proposed STERGM approach models the impact of endogenous variables as well as exogenous variables on the formation and dissolution of product competitions separately. A three-year customer survey from China's auto market was utilized and three crossover SUV-oriented competition networks were constructed to illustrate the implementation of dynamic network modeling. By utilizing the structural zeros method, we addressed the challenge of longitudinal network modeling with varying sets of nodes from year to year. We observe an obvious improvement of model fit after the network structural effects are introduced into the dynamic model. The results from STERGM formation model indicate that two unrelated vehicles tend to form a competition relation if they are not Japanese or Korean brands, have lower price difference, higher fuel consumption, higher power difference, higher fuel consumption difference, compete with more other cars, or have more shared competitors. The dissolution model results indicate that competing vehicles may lose their competition in the future if they are Korean vehicles, compete with fewer other cars, or have fewer shared competitors. Our verification at both the link level and the network level further demonstrates the model fit.

Our work also illustrates the difference between the static ERGM and the dynamic STERGM. In summary, ERGM is a static network modeling approach assuming there are no pre-existing network relations (i.e., no pre-existing competition at all), whereas STERGM is a dynamic network modeling approach focused on detecting the changing pattern that best describes the formation and dissolution of competitions conditional on the pre-existing competitions.

Our future work will focus on examining the use of STERGM for prediction, given the current competition structure and product design change. For example, we may use the STERGM results obtained in this work to predict the competition network in 2016 based on the competition network in 2015. By studying the impact of improving existing products and releasing new products on future product competitions, this dynamic network modeling approach can support engineering design decisions and companies' strategic decision making.

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