A Bayesian networks approach to infer social changes in burials in northeastern Taiwan during the European colonization period

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Burials provide valuable information to study social structures based on the assumption that burials and associated grave goods can represent social roles and relations in a society. To study social relationships, network analysis has been increasingly applied to archaeological data to infer interactions and relationships between entities. Statistical approaches to network analysis, such as exponential random graph models (ERGMs), provide a way to test hypotheses about dynamic processes of network formation. However, computational difficulties and sensitivity to uncertainties limit the application of ERGMs. In this paper, we introduce a Bayesian framework on ERGMs that enables an efficient computational process, effective quantification of uncertainty, and robust model evaluation of network properties. We tested a hypothesis of social change relative to the arrival of Europeans by studying burial data from Kiwulan, an Iron Age site in northeastern Taiwan. The results indicate a transition among the burials from network ties based on ritual objects to wealth objects, and a more centralized structure with increased social differentiation after the European presence was established in the 17th century. Our case study demonstrates the effectiveness of Bayesian network analysis for archaeological data, and expands the use of burials in understanding the impacts of colonial presence on Indigenous groups in a pericolonial context.

# Introduction

Network analysis has been increasingly used by archaeologists to understand past relationships, interactions, and structures of observed phenomena by visualizing and analyzing relational data (Brandes et al., 2013; Mills, 2017; Peeples, 2019). Recent developments in modeling approaches enable hypothesis testing for the intercorrelations between individual elements and overall structures in networks (Brughmans, 2013; Brughmans and Peeples, 2018; Freeman, 2004; Salvini, 2010). By comparing hypothesized networks with the observed network, statistical network modeling can answer anthropological questions related to exchange (Crabtree, 2015; Gjesfjeld and Phillips, 2013), diffusion (Östborn and Gerding, 2015), or social transformation (Mills et al., 2013) in a statistical way. Among network modeling methods, exponential random graph models (ERGMs) are stochastic models for investigating the process of network formation through dependence assumptions for relationships and simulations for network patterns (Ghafouri and Khasteh, 2020; Handcock et al., 2008; Harris, 2013). ERGMs are promising for evaluating the dynamic social processes behind observed archaeological networks (Brughmans et al., 2014). However, computational difficulties, sensitivities to uncertainties, and ambiguities in interpretation limit the practical applications of ERGMs (Caimo and Friel, 2014).

In this paper, we go beyond ERGMs with a novel Bayesian approach that alleviates the computational issues and other limitations of ERGMs to enable clearer and more robust interpretations of the processes of network formation. Using burial data from an Iron Age site in northeastern Taiwan as a case study, we explore social changes by investigating the formation of material connections between burials. Social changes in Indigenous societies, when faced with colonial powers, are commonly observed in many parts of the world, especially European colonies where Indigenous economic, cultural, or socio-political aspects were substantially impacted (Dietler, 2005; Silliman, 2005; Voss, 2005). Recent studies demonstrate that the indirect effects of colonialism, or involvement in long-distance trade, may also have impacted Indigenous societies, this is known as a pericolonial context (Acabado, 2017; Trabert, 2017; Wang and Marwick, 2020). Burials are important for understanding past societies because material culture and biological records of burial behaviors can represent the social ranking of the deceased, and social relations between them (Binford, 1971; Drennan et al., 2010; Saxe, 1970). Burial treatments can further indicate social complexity or inequality where foreign goods from long-distance trade were used by Indigenous people to express status (Carter, 2015; Dolfini, 2019).

Burial studies are usually based on characterizing each physical trace or burial variable, such as biological records, grave forms and goods, or ritual behaviors, and finally combining and comparing those individual observations to infer the organization of past societies (Byrd and Monahan, 1995; Seikel, 2011). Here we treat burials as a complex network based on the assumption that a network is a patterned aggregation that includes individual elements (i.e. individual burials), pair-wise relationships (the dyads, for example burials with similar types and amounts of grave goods), and an overall structure showing social patterns represented in the data (Brandes et al., 2013). Our case study illustrates how a Bayesian approach to network modeling provides new insights into the formation of archaeological networks and allows testing of anthropological models to better understand dynamic social processes.

# Exponential random graph models in a Bayesian framework

Exponential random graph models (ERGMs) first appeared in archaeology with Brughmans et al. (2014), who studied Iron age settlement patterns in Southern Spain by modeling inter-settlement visibility networks and visual control at 159 sites. By fitting models with the observed network of archaeological data, they proposed that ERGMs are a promising approach for exploration and hypothesis testing of social processes. Similarly, Amati et al. (2019) modeled three networks consisting of 15 sites (AD 100 to 400) in the Caribbean to explore interaction mechanisms, including proximity, inter-cultural items, and pottery types. By comparing hypothesized networks with the observed sites, they found that the presence of hub sites can be efficiently explained by multiple interdependent mechanisms instead of only one variable exclusively.

However, those studies also illustrate some limitations of ERGMs, such as sensitivity to missing data and limited ability to incorporate and represent uncertainty. Also, it is difficult in ERGMs to estimate model parameters and interpret the results due to intractable likelihood normalizing constants and model degeneracy (Caimo and Friel, 2014; Jin et al., 2013). A normalizing constant is a function of the model parameter for making probability distributions integrate to one, which becomes harder to compute with a larger set of networks (Caimo and Gollini, 2017). This is also termed “doubly intractable” since both the likelihood normalizing constant and the marginal likelihood (the evidence of the posterior) are hard to derive (Caimo and Friel, 2013; Lyne et al., 2015). Model degeneracy is another issue where probability models tend to overestimate a small number of extreme graphs by assigning too much weight, e.g., in extreme cases such as empty (all nodes unconnected) or complete graphs (all nodes connected) (Caimo and Friel, 2014; Schweinberger, 2011). One solution to these limitations is to implement ERGMs in a Bayesian framework.

Bayesian approaches to ERGMs are effective tools for network modeling by incorporating prior information about the network configurations (details in Supplementary Online Materials) to better understand dependencies of network variables and overcome computational issues of ERGMs (Caimo et al., 2017; Lehmann et al., 2020). Prior information is derived from previous data or assumptions derived from the context of our data. An important advantage that Bayesian modeling has over traditional ERGMs is the application of Markov chain Monte Carlo (MCMC) simulation using the approximate exchange algorithm (Caimo and Friel, 2011). With the exchange algorithm, Bayesian ERGMs avoid doubly-intractable computations by directly sampling from the not normalized part of the posterior, which alleviates the computational problems and gives better convergence results. This enables us to deal with complicated dependence patterns with ease, providing better estimations for complex social network models with heterogeneous data (Caimo et al., 2017; Snijders et al., 2006). By fitting an ERMG with the approximate exchange algorithm, a Bayesian approach generates posterior probabilities that incorporate our sample data and prior information to estimate the effect of each ERGM parameter in our models (Caimo and Lomi, 2015; Nemmers et al., 2019). This allows robust and interpretable uncertainty quantification by examining the posterior mean and 95% credible intervals (Caimo and Gollini, 2017). In addition, Bayesian approaches are useful to deal with missing data, which is often a problem leading to misinterpretation of networks, especially for archaeological studies. Koskinen et al. (2010) shows that the effect of missing data can be reduced with Bayesian modeling that can accurately predict, on average, 80% of the ties when a third of data is missing.

# Background

## A Case Study from Northeastern Taiwan

We use a Bayesian ERGM to study social changes in a pericolonial context at Kiwulan, an Iron Age site in northeastern Taiwan (Figure 1), which was occupied from the 14th to 19th centuries. This occupation period includes the time before the European arrival, the presence of the Spanish and the Dutch in the 17th century, and finally a large wave of Han Chinese in the 19th century (Chen, 2007). Our anthropological model proposes that the influence of a colonial power, combined with high local values attached to imported goods, led to increased social inequality due to competition among individuals (Brumfiel, 1994; Clark and Blake, 1994). Increased social inequality associated with the use of foreign prestige goods is recognized as a ‘network’ strategy for gaining power (Blanton et al., 1996; Feinman, 2000). Network-based societies are identified in some places in Asia with involvement in long-distance trade (Carter, 2015; Liu and Chen, 2006; Ueda et al., 2016). The observed uneven distribution of burial goods at Kiwulan may be explained as a result of unequal access to trade goods when Indigenous societies became more involved in the complex trade network stimulated by Europeans.

The features of network-based societies include the accumulation of prestige goods, wealth differentiation, and trade monopolization through individual networks (Blanton et al., 1996; Feinman, 2000). These may be contrasted with corporate-based societies that stress communal ritual elements, shared power, and where wealth differentiation, if any, would be associated with corporate groups, such as age groups, rather than individuals (Siegel, 1999). Using the theoretical framework of corporate-network strategies, we test a hypothesis that changes from a corporate mode (a structure showing more subgroups with less wealth differentiation) to a network mode (a centralized structure with more wealth differentiation) can be observed in the Kiwulan burial network after European arrival. We ask: (1) did European colonial activities result in increased social inequality in Indigenous society in ways that can be detected by analysis of burial networks? and if so, (2) what are the major variables affecting or forming unequal social positions that might hint at social heterogeneity? By answering these questions, this case study helps to expand our understanding of European colonial effects on Indigenous groups in a pericolonial context.



Figure 1: The location of Kiwulan and the European forts at Heping dao and Tamsui in northern Taiwan (modified from Wang and Marwick, 2020). Map data from naturalearthdata.com.

## Materials

We analyzed burial data collected from the excavation reports, and the original fieldwork notes for the upper component of Kiwulan (1350-1850 AD) (Chen, 2007). A total of 90 burials were unearthed from adjacent excavation squares that provide continuous stratigraphic sections suitable for temporal comparison (Figure 2). The preservation of human remains at Kiwulan was generally poor, so we have incomplete age and sex data (details in Supplementary Online Materials) and lack health status data. Burials are oriented in an east-west direction on the north side of the residential area, which is indicated by post-holes and *in-situ* wooden posts, suggesting a well-organized spatial arrangement of houses. Previous studies report an uneven distribution of prestige goods across burials without agreement about whether this uneven distribution hints at vertical social differences. For example, Cheng (2008) interpreted the unequal distribution of glass beads, especially the gold-foil beads between burials, as evidence for hierarchy, indicating a stratified society. However, Hsieh (2012) suggested a relatively egalitarian structure based on a comparative analysis of the frequencies of all burial goods. She found that the burials with rare prestige goods were usually associated with elders, which might indicate achieved, rather than inherited, status. One important limitation of these previous studies is that they did not use analytical units suitable for comparing behaviors before and after European arrival. Here, we adopt a new chronological framework for the burials to test if network configurations differ from the pre-European period (before European colonization) to the post-European period (during and after European colonization until arrival of Han Chinese immigrants).



Figure 2: Map illustrating the location of burials by periods at the central excavation area of Kiwulan (each square is 4 X 4 meters). The gray dots are post holes.

To compare burial networks, we assigned burials to the pre-European period (n = 29), European and post-European period (n = 49). Our assignments are based on an established fine-grained chronology that was reexamined and cross-validated by diagnostic materials, stratigraphic data, depth, and radiocarbon ages (for more details see Wang and Marwick, 2020). We excluded burials from the Chinese phase (n = 4) due to the smaller sample size. We also excluded 8 burials that were heavily disturbed by modern construction which prevented accurate determination of their chronology.

Based on the assumption that social status and associated relations can be represented by sharing similar prestige goods (cf. Coward, 2013, p. 252), we built networks where burials (nodes in the network) that are linked when they have the same prestige goods in common. The prestige goods we identified include gold-foil beads, carnelian beads, glass beads, Chinese porcelains, stonewares, gold foils, and fish-shaped ornaments. These items are considered as high-value across different archaeological contexts throughout Taiwan based on their rarity and descriptions in historical records (Cheng, 2008; Hsieh, 2012, 2009; Wang, 2011). European historical accounts mentioned that those items were treated as prestige goods in Indigenous culture (Borao, 2009; Li and Wu, 2006). For example, a Spanish priest described a Spanish soldier exchanging carnelian beads for natural resources with local Indigenous people, because of the beads’ high value in Indigenous culture (Li and Wu, 2006). In addition, Spanish visitors observed that Indigenous people possessing more imported goods were recognized as having higher status in their community (Li and Wu, 2006).

# Methods

## Hypothesis and construction of networks

Our social change hypothesis is that differential access to foreign prestige goods after the European presence led to increased social inequality at Kiwulan, where the social structure changed from a more corporate strategy to a more network strategy (Blanton et al., 1996; Drennan et al., 2010; Feinman, 2000). This would be reflected by the pattern of intercorrelations of foreign prestige goods in burial networks. If social inequality gradually increased as we hypothesize, then we expect to observe a network structure with higher centralization (or popularity) and less transitivity (or clustering), along with network ties determined by wealth, indicative of a network-based society. In contrast, we predict the network before European arrival will show low centralization and high transitivity, and network ties associated with ritual elements, indicative of a corporate-based society. To test this hypothesis, we use Bayesian ERGMs to model the formation of network ties and the underlying mechanisms that shaped relationships between people at Kiwulan. By comparing networks from the pre-European period and the post-European period we can examine the effects of foreign contact on community relationships at Kiwulan.

Trade beads are commonly found across burials with substantial differences in quantities, so we described each burial as having one of four levels, high, upper-middle, lower-middle, and low, according to their distributions across all burials (details in Supplementary Online Materials). For less frequent prestige goods, including imported ceramics, gold foils, and fish-shaped ornaments, we linked two burials when they both possess each type of goods (i.e. presence or absence). Node attributes here include osteological data, such as age and sex, and cultural data, such as ritual pottery, and a burial value index. Ritual pottery was identified as locally-made ceramics placed above an individual. These pots mostly have sooty vessel exteriors and charred residues on interiors that are interpreted as vessels used for funeral feasting (Hsieh, 2009). We calculated our burial value by summing values of all types of prestige goods in each burial context. For example, for gold-foil beads, we take the total number of burials (90) and divide by number of burials with gold-foil beads (46), to give a value of 90/46 = 1.96. We repeat this for each type of prestige item. For each burial we sum these values of each type of prestige item to get a burial value (Jorgensen, 1991).

We then assigned the burials into three ranks according to breaks in the distribution of burial values, high (>24.7, top 10 percent), above average (16-24.7), and below average (<16), as an index of wealth (details in Supplementary Online Materials). Since burials tend to have multiple prestige goods in common, the network ties are weighted instead of binary (the value 1 represents a tie and the value 0 otherwise) (Snijders, 2011). For example, if two burials have both low quantity of glass beads and porcelain in common, the tie is given a value of 2. Our networks are non-directed, which means a mutual relationship where the tie between any two actors is bidirectional. The networks constructed based on these principles show that the network after the European presence has more node connectivity in general with some nodes having a larger number of connections (Figure 3).



Figure 3: A: Burial network before the European arrival, B: Burial network after the European arrival. The size of each node is proportional to node degrees or the number of connections to a node. The thickness of ties represents the number of goods in common between two nodes.

## Model specification in a Bayesian framework

We quantify the relations among burials and test our hypothesis of social change using the R programming language (R Core Team, 2019) with the bergm package (Caimo and Friel, 2014). Table 1 lists the network parameters we used for dependence assumptions that define our models (Morris et al., 2008). Every parameter in an ERGM has an associated algorithm for computing the probability of observing relations between two burials. Based on our hypothesis, we model a network with increased social inequality to be represented by endogenous network effects: low transitivity and high centralization. We include burial-specific attributes as covariate effects for homophily, such as age, sex, ritual activity, and the degree of wealth, to explore the importance of these variables in tie forming. For example, if age-homophily is important here, then people of the same age should have the same burial goods. We also include the physical distance between burials as an indicator of a kinship-based relations since the deceased from the same family were buried nearby (Li and Wu, 2006). Our model may reveal the emergence of social inequality via the presence of a few individuals as network centers, having more relations with others, with more wealth differentiation after the European arrival.

Table 1: Network parameters in ERGMs used for model specifications with associated archaeological interpretation for burial relations. ERGM terminology is from the R package statnet (Handcock, 2008; Morris, 2008)

|  |  |  |
| --- | --- | --- |
| Network variable | Configuration (ERGM term) | Archaeological Interpretation |
| Density/inter-relation | Edges (edges) | constituent element of the network |
| Age-homophily | Uniform homophily (nodematch) | burials in the same age tend to have similar goods |
| Sex-homophily | Uniform homophily (nodematch) | burials in the same sex tend to have similar goods |
| Ritual-homophily | Uniform homophily (nodematch) | burials having ritual practice tend to have similar goods |
| Wealth-homophily | Uniform homophily (nodematch) | burials in the same wealth rank tend to have similar goods |
| Transitivity/clustering | Geometrically weighted edgewise shared partner (gwesp) | burials being connected with a third burial |
| Centralization/popularity | Geometrically weighted degree distribution (gwdegree) | burials being connected with multiple partners |
| Physical distance | Dyadic covariate (dyadcov) | burials close to each other tend to have similar goods |

## Choice of prior values to evaluate our anthropological model

Normal distributions for the priors are typical in network analysis studies that assume networks to have low density and high transitivity, as are commonly found in the real world (Caimo et al., 2017). Thus, we specified the prior of the edge density parameter to low for both network models, following a normal distribution with mean at -3, and standard deviations at 3 (i.e (N(-3, 3))). For covariates about biological features, such as age, sex, we specified a vague prior (N(0, 5)) for both models to explore their effects. For physical distance between burials, we also set a vague prior (N(0, 1)) to explore whether there is kinship-based proximity, e.g. stronger correlations for shorter distances. To evaluate our anthropological model of increased social inequality over time based on assumptions of corporate-network strategies (Drennan et al., 2010; Feinman, 2000), we incorporated different prior information for the network variables that are meaningful for social inequality, especially for transitivity and centralization. We set the priors to higher transitivity (N(2, 2)), lower centralization (N(-2, 3)), and higher covariate effect of ritual activity (N(1, 5)) for the network before European contact to indicate less social differentiation and emphasize the ritual element shared in corporate groups. Conversely, we set the priors for the network after European arrival to lower transitivity (N(1, 3)), higher centralization (N(2, 3)), and a higher covariate effect for burial values (N(2, 3)) to model an increased social differentiation after European contact.

# Reproducibility and open source materials

The entire R code (R Core Team, 2019) used for all the analysis and visualizations contained in this paper is included in the Supplementary Online Materials at <https://doi.org/xxx/xxx> to enable re-use of materials and improve reproducibility and transparency (Marwick, 2017). Also in this version-controlled compendium (Marwick et al., 2018) are the raw data for all the visualizations and tests reported here and additional details of definition of our approach to tie formation, model fitting, assessment of MCMC output and goodness-of-fit diagnostics for our models. All of the figures, tables, and statistical test results presented here can be independently reproduced with the code and data in this repository. The code is released under the MIT license, the data as CC-0, and figures as CC-BY, to enable maximum re-use.

# Results

We examine the estimates from the posterior distributions to compare their differences in structure of the simulated networks (Table 2; Figure 4). For nodal covariates in the pre-European model, the ritual element represented by pots (ritual-homophily) has a significant effect on the formation of relations between burials, while the wealth rank represented by burial values (wealth-homophily) has a negative effect but not significant since its confidence intervals include zero. This demonstrates that burials with ritual pottery tend to form relations, but burials in the same wealth level tend not to. Despite positive mean for some covariates, such as age (age-homophily) and sex (sex-homophily), they do not show a significant tendency. Similarly, the dyadic covariate, physical distance, shows no significant effect, indicating that physical proximity between burials does not reflect similarity in burial treatment. For the endogenous network effects, transitivity presents a significant positive effect, while centralization demonstrates a negative effect. The high positive value for transitivity suggests a tendency of burials with similar burial goods to be clustered as connected communities, indicative of the presence of multiple corporate groups sharing burial goods in common. In contrast, the strong negative centralization shows there is a tendency toward decentralization that reflects most burials having a similar number of ties without any prominent burials. This might imply that individuals have equal access to trade goods in terms of the flow of goods.

Table 2: Estimated posterior means, medians, and 95% confidence intervals for each network parameter of two models. Confidence intervals that do not include zero indicate significant effects of parameters (Caimo, 2017). Posterior means are generally close to posterior medians.

| parameter | pre-European | | | | post-European | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | mean | median | 2.5% | 97.5% | mean | median | 2.5% | 97.5% |
| density | -24.63 | -24.65 | -25.64 | -23.35 | -14.60 | -14.59 | -15.06 | -14.16 |
| age-homophily | 0.34 | 0.36 | -0.23 | 0.89 | 0.14 | 0.15 | -0.22 | 0.48 |
| sex-homophily | 0.27 | 0.30 | -0.41 | 0.81 | -0.12 | -0.12 | -0.45 | 0.19 |
| ritual-homophily | 1.87 | 1.90 | 0.63 | 2.68 | -0.01 | -0.01 | -0.41 | 0.35 |
| wealth-homophily | -0.06 | -0.06 | -0.57 | 0.44 | 0.54 | 0.55 | 0.06 | 0.93 |
| transitivity | 13.81 | 13.87 | 12.94 | 14.47 | 3.63 | 3.63 | 3.45 | 3.81 |
| centralization | -17.75 | -17.89 | -18.69 | -16.15 | 4.95 | 4.94 | 4.43 | 5.48 |
| physical distance | 0.03 | 0.03 | -0.01 | 0.07 | 0.01 | 0.01 | -0.01 | 0.02 |

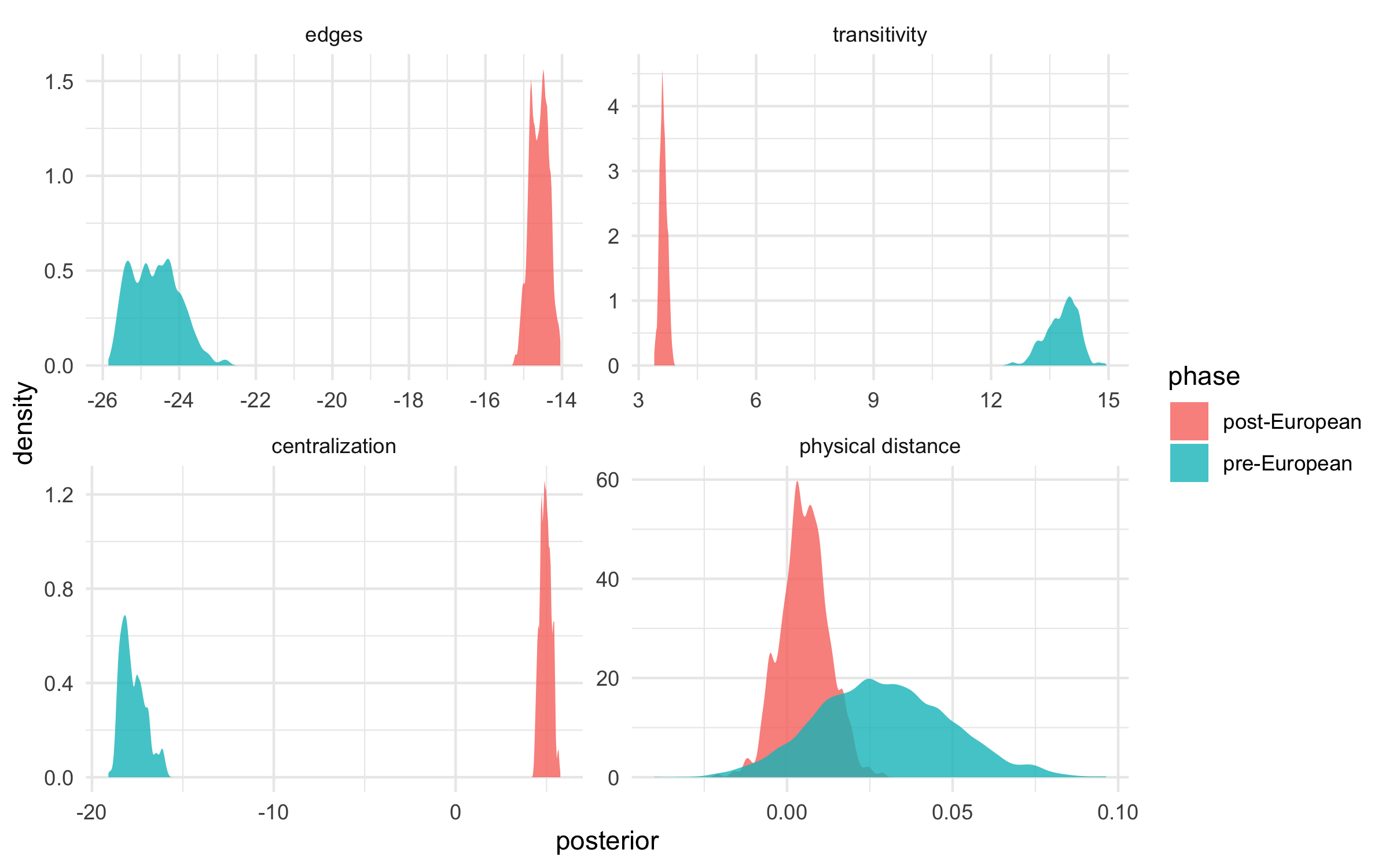


Figure 4: Posterior density estimates for the parameters associated with edges, transitivity, centralization, and physical distance by phases. The pre-European group presents remarkably larger values for the transitivity, but lower values for the edges and centralization parameters compared to the post-European group. The distance parameters overlap between two groups. Both posterior estimates present generally symmetric distributions.

For the post-European network model, the nodal covariate of wealth rank shows significant positive effects. This indicates the burials in the same wealth level tend to have relations. Despite negative effects for the ritual and sex variables, they are not significant. Also, there are no significant effects for the variables of age and physical distance. Similar to the pre-European network, transitivity demonstrates a significant positive effect, but much weaker than the effect of the pre-European network. In contrast, centralization has a significantly higher positive effect than the effect of the pre-European network. This means there is a tendency toward centralization, reflecting a limited number of burials having many more ties than others. This implies that the presence of better access to trade goods and the behavior of wealth accumulation and display in burial events. In general, the post-European network model has a smaller transitivity effect and a positive centralization effect than the pre-European network model. This may suggest a reduced tendency toward clustering but high tendency toward centralization after the European presence.

One key difference between the pre-European and post-European networks is their size, with 29 burials compared to 49 burials. To understand the robustness of comparison between two networks, we used a vertex bootstrap technique to cross-validate the results of our Bayesian ERGMs. The vertex bootstrap is a non-parametric method that conducts resampling for all vertices (i.e. node) to quantify standard errors and estimate sampling variability in the network statistics of interest (Chen et al., 2019; Roberts et al., 2021; Snijders and Borgatti, 1999). This enables the evaluation of uncertainty for networks and tests the difference between multiple networks of different sizes by examining their confidence intervals for the network population. We used the vertex bootstrap to compute endogenous network statistics, including density, centralization, and transitivity for our two networks. We explored the sample size effect by removing nodes at certain percentages (5-40%) for both networks and comparing their confidence intervals. The results demonstrate a consistent difference between the two networks up to 30% node removals (Figure 5). This indicates that the network variables under investigation are robust to the different network size of our sample. Figure 5 also shows consistency with our earlier finding of negative centralization in the pre-European period and positive centralization in the post-European period, over several conditions of node removal. Similarly consistent with our earlier result, the vertex bootstrap shows no significant difference on density and transitivity.

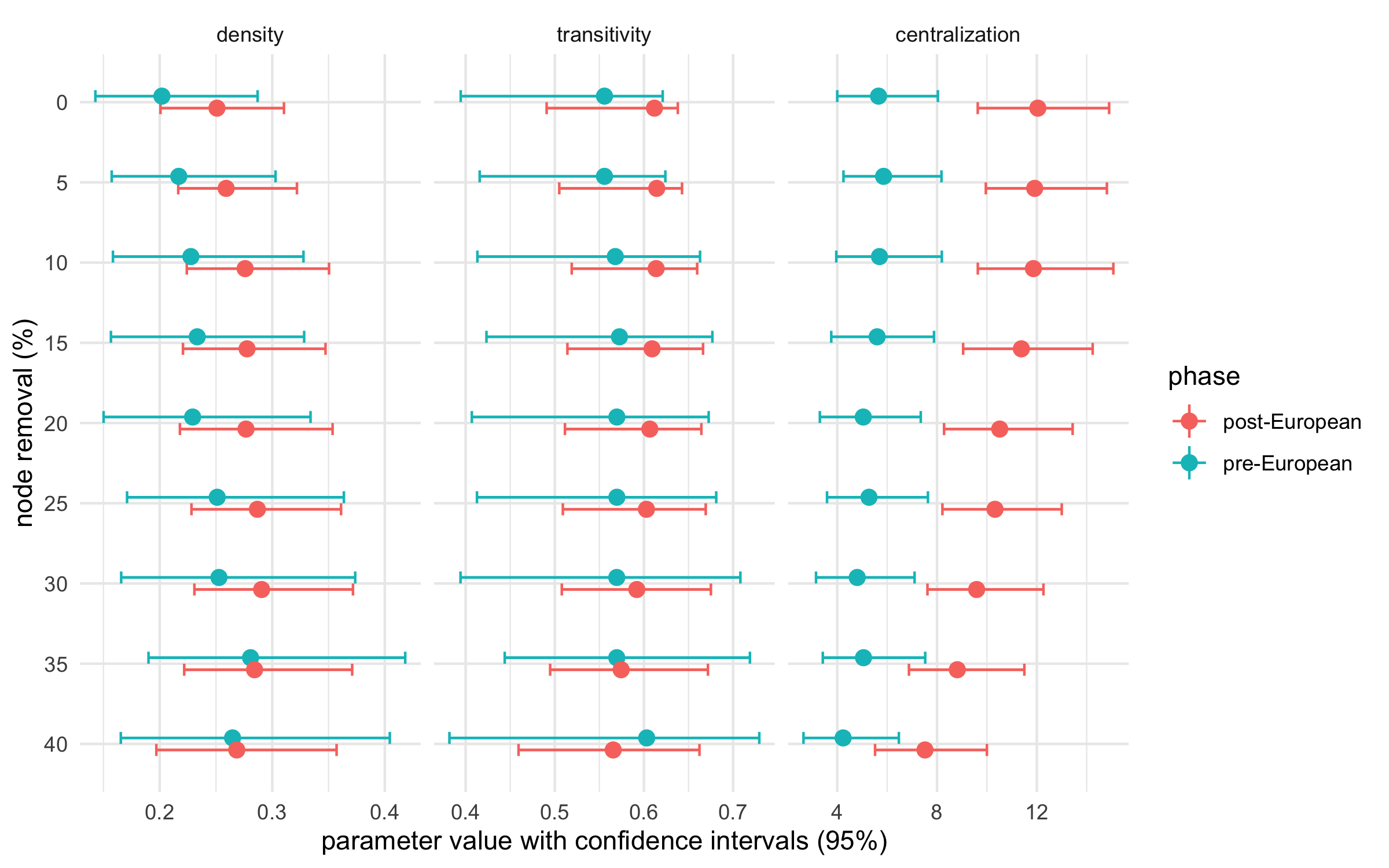


Figure 5: Results of the vertex bootstrap analysis by three network variables, showing the 95% bootstrap confidence intervals for the bootstrapped (n = 1000) networks, for each category of node removal. The 0% node removal category is the original data for the two phases. Networks with nonoverlapping confidence intervals indicate a significant difference between the two phases for that network variable.

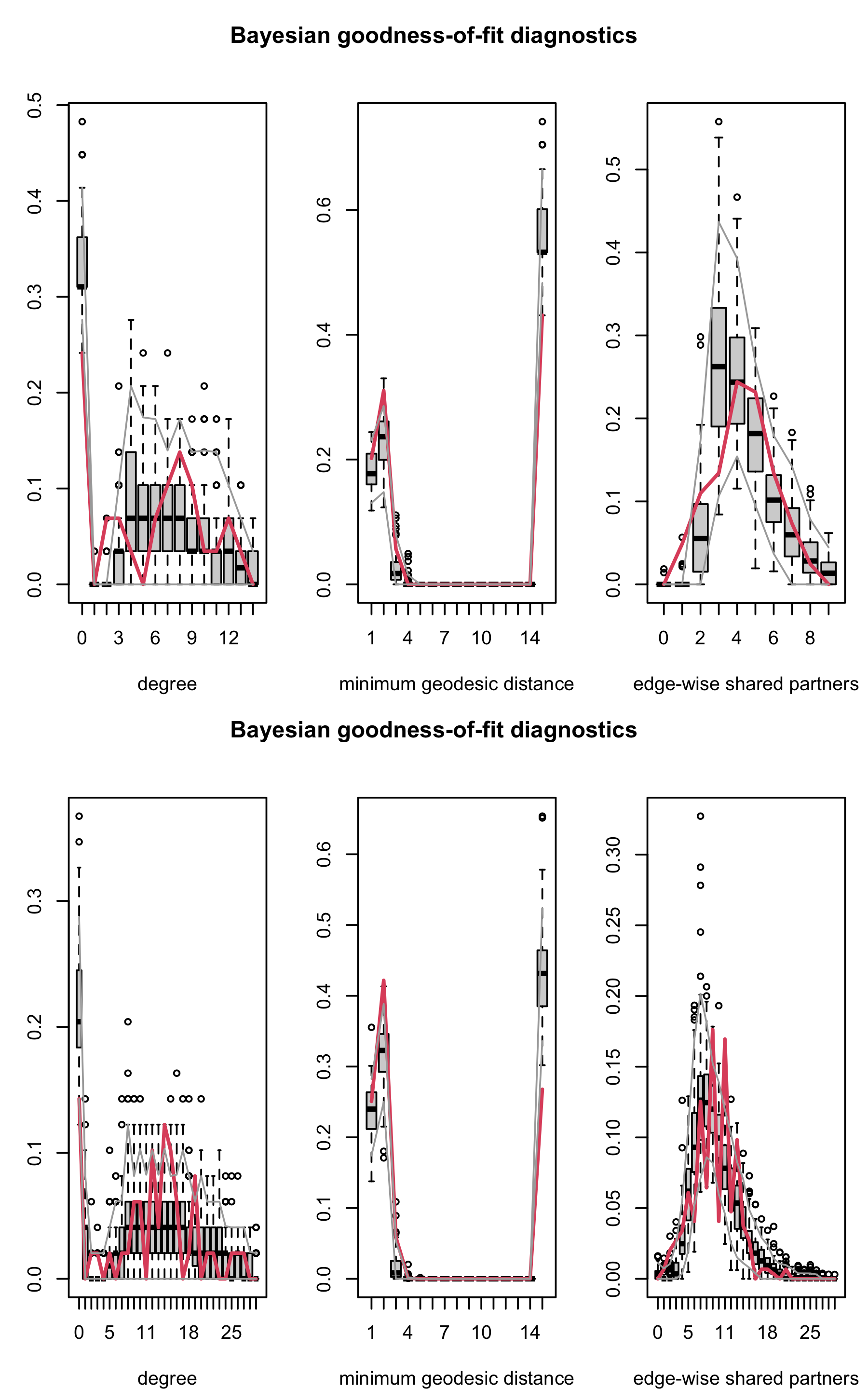


Figure 6: Goodness-of-fit diagnostics for the pre-European model (top) and the post-European model (below). Boxplots represent distributions calculated on 100 network graphs simulated from the estimated posterior distribution. Red lines represent distributions of observed networks, and gray lines show the 95% intervals.

Our computational models reproduce networks that resemble the structural features of our observed networks. Bayesian goodness of fit diagnostics plots (Figure 6; details in Supplementary Online Materials) demonstrate that both models fit the observed networks very well for the minimum geodesic distance distribution (i.e. the number of edges between node pairs in a shortest path, Hunter et al. (2008)) and the degree distribution. For edgewise shared partner distribution, despite some observations falling outside the 95% interval, the fit is generally good with most observations within it. We also compared the first three distribution moments of each observed distribution and their corresponding simulated distributions, represented by means. Figure 7 shows that modeled values from the pre-European network are slightly closer to the observed values for the mean and the variance of distributions, compared to the values from the post-European network. In general, this demonstrates a slightly better fit between model and data for the pre-European network.

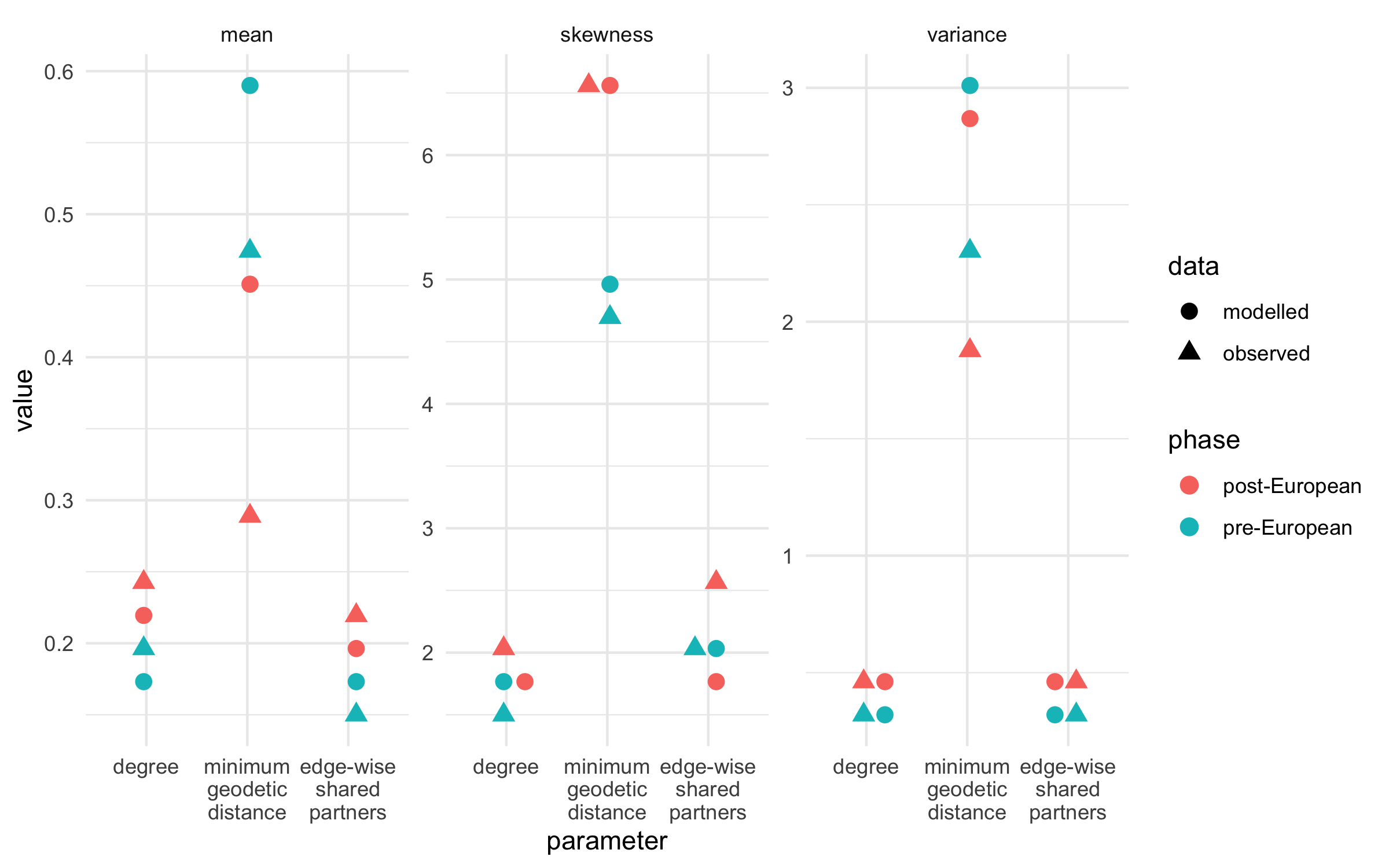


Figure 7: Distribution moments (mean, skewness, and variance) calculated on the observed data and simulated distributions for the pre- and post-European models.

# Discussion

A striking finding in our results is the change in network properties of Kiwulan burials from a more cohesive network with multiple subgroups toward a more centralized network with concentration of connections among fewer burials after the European arrival in the 17th century. This supports our pericolonial impact model that Kiwulan changed from a more corporate-based to a more networked-based society, as indicated in the grave goods and burial attributes. A corporate-based society, as we interpret the pre-European situation at Kiwulan, stresses shared power between individuals, communal rituals, and social inequality, if any, would be associated with groups (Drennan et al., 2010; Feinman, 2000; Feinman et al., 2000). In contrast, a network-based society, as we interpret the post-European data from Kiwulan, presents wealth accumulation through individual networks, prestige goods manipulation, and trade monopolization (Blanton et al., 1996). It should be noted that the corporate-network continuum represents a dynamic process with different degrees of hierarchical complexity instead of static ideal-type stages (Feinman, 2000).

Network covariates give insights into the socio-cultural factors that were associated with the acquisition and distribution of foreign prestige goods. Our results indicate that the major factor contributing to burial networks for the pre-European network was ritual, and for the post-European network was wealth. We interpret these results as illustrating different social and economic mechanisms influencing relations between burials for the two periods. Before European arrival, ritual behaviors were important factors that structured the interconnections of prestige goods in the burial contexts. This might imply that ritual could be a status indicator at the time before many foreign goods were introduced to Indigenous societies. After the European presence was established, status indicators shifted from ritual to wealth differences. Geographical proximity of burials, implying kinship association, has no effect on sharing similar prestige items between burials for both phases. This may suggest that the use of prestige items is more individual-oriented instead of kinship-based. Demographic information, such as age and sex, do not have any effects on network formation for both networks. We also note that no effects could be due to the unavailability of age (30 out of 78 burials) and sex (52 out of 78 burials) values in our sample.

We used burial data as a proxy to explore social relations reflected by interconnections of prestige goods based on assumptions that burials can represent social structures (Binford, 1971; Saxe, 1970), and individuals with similar prestige goods reflect similar access to trade, exchange, and gifting networks (eg. Coward, 2013, p. 252). We argue that the social relations at Kiwulan changed because of contact with European colonial powers and associated foreign trade. This argument is supported by changes in burial network structures through time. It should be noted that manipulation of burial rituals by the living can cause a disconnect between a person’s status in life and their status represented by burial contexts (Hodder, 1980; Pearson, 1982). However, this issue can be reduced by comparing the results with evidence from other archaeological contexts, such as residential areas (Chapman, 2003). Previous studies of trade ornaments from the residential area of Kiwulan suggests an uneven spatial distribution when the Europeans were active in northern Taiwan that hints at an increased social differentiation (Wang and Marwick, 2020). This is consistent with the result of a more centralized burial network after the presence of Europeans, that supports a connection between a burial and the social role of the living person. Also, ethnographic records support our interpretation of burial goods as prestige goods or status items in the local Indigenous culture (Borao, 2009; Li and Wu, 2006), so the interrelations represented by the flow of these goods observed in the burial data likely reflect social contexts of the living people at Kiwulan.

# Conclusion

We presented a novel approach for studying burials to interpret social structures using ERGMs within a Bayesian framework. This case study demonstrates the methodological benefits of Bayesian inference on ERGMs to inform and enhance studies of relational data in archaeology. A Bayesian framework can reduce the effects of small sample size or missing data commonly present in archaeological data and incorporating prior information and MCMC estimations to quantify uncertainty and provide interpretable output. An important feature of Bayesian network modeling is the ability to set prior values to evaluate competing anthropological models, enabling a comparison of anthropologically-relevant models, rather than testing a hypothesis of no difference or randomness. Bayesian network modeling can be applied to a wide range of archaeological data to examine the formation of relationships using robust probabilistic inference. This enables insights into the dynamic processes of relationship formation and the underlying factors of historical trajectories of socio-cultural phenomena.

Our case study examined social changes in a European pericolonial context in northeastern Taiwan. We tested a hypothesis of changes in burial networks at Kiwulan with the evaluation of both endogenous and exogenous network effects. The results support our model that the relationship between burials changed after the European colonization period in the 17th century. Before the arrival of Europeans, the burial network has a tendency of more clustered subgroups with pottery as ritual practice as the key formation mechanism. After European arrival, the network has a tendency of centralization relative to the rarity of goods. We interpret the changes in formation mechanisms of networks, observed as a change from ties formed by ritual to wealth, as an increase in wealth accumulation behaviors, stimulated by the European presence and its associated long-distance trade network. This aligns with changes in horizontal hierarchy represented by corporate-network societies, that demonstrates different degrees of social inequality in relation to different strategies for achieving power (Feinman, 2000). Using burial data with historical documents, we can better understand indirect European impacts in understudied pericolonial contexts of East Asia (e.g. Acabado, 2017; Trabert, 2017).

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#> P statnet \* 2019.6 2019-06-14 [?] CRAN (R 4.0.2)  
#> P statnet.common \* 4.4.1 2020-10-03 [?] CRAN (R 4.0.2)  
#> P stringi 1.5.3 2020-09-09 [?] CRAN (R 4.0.2)  
#> P stringr \* 1.4.0 2019-02-10 [?] CRAN (R 4.0.2)  
#> P systemfonts 0.3.2 2020-09-29 [?] CRAN (R 4.0.2)  
#> P tergm \* 3.7.0 2020-10-15 [?] CRAN (R 4.0.2)  
#> testthat 3.0.2 2021-02-14 [1] CRAN (R 4.0.2)  
#> tibble \* 3.0.6 2021-01-29 [1] CRAN (R 4.0.2)  
#> P tidygraph \* 1.2.0 2020-05-12 [?] CRAN (R 4.0.2)  
#> P tidyr \* 1.1.2 2020-08-27 [?] CRAN (R 4.0.2)  
#> P tidyselect 1.1.0 2020-05-11 [?] CRAN (R 4.0.2)  
#> P tidyverse \* 1.3.0 2019-11-21 [?] CRAN (R 4.0.2)  
#> P tmvnsim 1.0-2 2016-12-15 [?] CRAN (R 4.0.2)  
#> P trust 0.1-8 2020-01-10 [?] CRAN (R 4.0.2)  
#> P tsna \* 0.3.1 2020-01-20 [?] CRAN (R 4.0.2)  
#> P tweenr 1.0.1 2018-12-14 [?] CRAN (R 4.0.2)  
#> P units 0.6-7 2020-06-13 [?] CRAN (R 4.0.2)  
#> P usethis 2.0.0 2020-12-10 [?] CRAN (R 4.0.2)  
#> P uuid 0.1-4 2020-02-26 [?] CRAN (R 4.0.2)  
#> P vctrs 0.3.6 2020-12-17 [?] CRAN (R 4.0.2)  
#> P viridis 0.5.1 2018-03-29 [?] CRAN (R 4.0.2)  
#> P viridisLite 0.3.0 2018-02-01 [?] CRAN (R 4.0.1)  
#> withr 2.4.1 2021-01-26 [1] CRAN (R 4.0.2)  
#> P xfun 0.20 2021-01-06 [?] CRAN (R 4.0.2)  
#> P xml2 1.3.2 2020-04-23 [?] CRAN (R 4.0.2)  
#> P yaml 2.2.1 2020-02-01 [?] CRAN (R 4.0.2)  
#> P zip 2.1.1 2020-08-27 [?] CRAN (R 4.0.2)  
#>   
#> [1] /Users/EmilyWang/Desktop/School document/LW-Papers/kwl-burials-2020/renv/library/R-4.0/x86\_64-apple-darwin17.0  
#> [2] /private/var/folders/gd/flx6648926xgtkrpp55bl7200000gn/T/RtmpDjHXAq/renv-system-library  
#> [3] /Library/Frameworks/R.framework/Versions/4.0/Resources/library  
#>   
#> P ── Loaded and on-disk path mismatch.

The current Git commit details are:

#> Local: master /Users/EmilyWang/Desktop/School document/LW-Papers/kwl-burials-2020  
#> Remote: master @ origin (https://github.com/LiYingWang/kwlburials.git)  
#> Head: [f6d112a] 2021-03-02: revised the SI and the table in it

Word count: 2258