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EY and KPMG merger: How strong are relationships among board members and their audit partners? A network perspective

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Abstract This study investigates the avenue of outcomes that followed up the process of joining the operations between two audit firms in Denmark - KPMG and Ernst & Young - in 2014, under the EY label. In this research, we study clients' behavior to audit staff defection in the auditor selection context in order to identify the impact of the change that occurred in the market for audit services on engagement partner selections. Company behaviors to the newly formed situation are examined against the tendency towards each of the following three behavioral patterns: (a) staying with the same audit firm; (b) following the engagement partner's switch to another audit firm; and (c) selecting a third auditor. Utilizing the cutting-edge methodology for social network analysis called exponential random graph models (ERGMs), we study the relevant reactions in the period from 2012 to 2017. Results show that, at the audit firm level, earlier KPMG clients preferred to stay with the newly established KPMG. On the other hand, at the audit partner level, former KPMG clients had a strong tendency to follow their incumbent partners who had decided to switch to EY. Finally, those KPMG clients that decided to rotate audit firms did not commit this rotation in order to follow their incumbent partners.

Key words: The Big-Four; KPMG; Ernst & Young; auditor selection; auditor-client relationship; social network analysis

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1. Introduction

Sporadic occurrence of audit firm mergers has substantial implication on auditor selection process at the audit service markets. This study sets out to determine whether the strength of auditor-client relationships (Blouin et al., 2007) has influence on re-selection of incumbent auditors after the merger between two Big-4 audit firms in Denmark despite of the cooling-off clauses introduced to motivate auditor rotation.

It was a major event for the Danish audit market in 2014 when most of KPMG's audit partners and staff defected to Ernst & Young (henceforth EY) due to an agreement achieved between the two audit firms to join their operations. The agreement resulted in closing down of the Danish KPMG subsidiary, which caused disruptions on a clients' side by prompting them to select new auditors (De Martinis et al., 2008) and exposing them to forced auditor switch. This case was specific because the merger did not imply natural follow of incumbent audit partners to the new audit firm (Chang et al., 2019). The reason for that was the legislation brought up by The Danish Competition and Consumer Authority (DCCA), who issued a *client clause* to restrict the former KPMG partners to re-engage their clients for a period of two-and-a-half years after the merger. This period is formally called a *cooling-off period* which, in this case, aimed at serving as a safeguard not only to prevent the auditors from losing independence and professional skepticism, but also to ensure fair market rivalry among competitors after the merger.

When it comes to forced auditor switch (also known as *forced rotation regime*), literature argue that clients either follow auditors to reduce switching costs, or switch to new auditor due to agency benefits (Blouin et al., 2007). Here, we adopt the theoretical perspective developed by Chang et al. (2019) who argue that, when an audit partner switches to another audit firm, clients would choose to pursue one of the following three behavioral patterns: (1) to *follow* the departing auditor (in our case to EY); (2) to *stay* with the same audit firm (in our case KPMG 2014[1]); or (3) to *change* (to another audit firm not involved in the merger case) (Chang et al., 2019)[2]. We use this merger as a case to investigate how clients commit auditor selection under the forced rotation regime to identify the presence of dominant behavioral patterns and use it as a proxy for discussion about the strength of auditor-client relationships.

By utilizing a recently developed method for social network analysis called exponential random graph models (ERGMs) for multilevel networks (Lusher et al., 2013; Wang et al., 2013; 2016), we address the following research question:

How do clients select auditors in situations of forced auditor rotation regime?

Including the data covering the period from 2012 to 2017[3], we model the networks representing auditor selection process by estimating probabilities for emergence of each of the three behavioral patterns (Chang et al., 2019). We rely on ERGMs (Lusher et al., 2013; Kacanski & Lusher, 2017; Kacanski et al., 2020) as they account on the condition of *interdependency* (Lusher et al., 2013; Wang, 2013; 2016), which enables us to examine network structures without preconditioning their statistical independence (Lusher et al., 2013).

Our empirical results yield the following findings. First, we find that audit firm mergers tend to reconstruct audit markets, but their oligopolistic nature prevents them from increasing the market concentration level regardless of a reduced number of audit firms on the market.

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[1] After the staff defection and closing down of KPMG in Denmark, a brand-new subsidiary of KPMG with new governance has been established and named KPMG 2014 to distinguish from the former subsidiary.

[2] Although we do not pursue this possibility audit fee changes are possible when a partner switches firms and the client follows the partner. Whether the new firm will give a fee discount to induce the client to follow the switching partner or they will extract rents because the client values this particular partner is a relevant question to be addressed in future research.

[3] 2012 – a year before the merger, 2013 and 2014 – merger years, 2015 – 2017 after the merger period.

Second, we find that the strength of auditor-client relationships has the capacity to prevail the expected effects of stipulated cooling-off periods by making them inefficient in such proposed lengths. Third, we find that studying auditor selection at an interorganizational level might galvanize the outcomes gained from interpersonal levels, indicating that auditor selection is mainly driven by auditor's affiliation. Lastly, auditor selection outside the merged firms occurs in disregard with the potential for re-engaging of incumbent partners.

Our study makes several important contributions. First, to the best of our knowledge, our study is the first to examine the implications of audit firm mergers on the strength of auditor-client relationships using exponential random graph models, which is a cutting-edge social network analysis methodology. Prior studies have investigated various aspects of auditor selection processes using different research methods while conditioning the setup of the cases on stable market circumstances. From a methodological perspective our results suggest that scalability of social actors in account is an important consideration for theoretical inferencing as it might lead to conclusions that auditor selection is portrayed by disparate behavioral patterns. Moreover, our study enhances understanding on how auditor-client relationships might serve as a tool for reduction of various consequences of by merger affected audit markets. Additionally, we consider country-level characteristics that may affect the relationship between auditors and clients and find that auditor selection is both driven by the strength of auditor-client relationship, as well as the auditors' characteristics, which can affect how that relationship might be perceived by the client.

Second, our findings may be of an interest to regulators and policymakers, particularly ministries, competition authorities, and other governmental bodies responsible for dealing with consolidations in audit industry. The results here shed light on the consequences that the decisions regarding the length of the cooling-off periods and mandatory rotations might be on market efficiency, auditor independency protection, and market competition. Our findings may also be of interest to practitioners, particularly audit firms contemplating a merger as a strategy for overcoming challenges associated with revenue streams and/or client networks. We suggest that small-scale mergers (between non-Big 4, and between Big 4 and non-Big 4 audit firms) may also benefit from these findings because of an oligopolistic nature of audit markets and high market concentration level in both regulatory and practical sense. This implies that even small-scale market changes might have important impact on restructuring the audit markets. We suggest that the validity of our results and arguments should be further tested in other voluntary-switch-related audit merger contexts.

The remainder of the article is organized as follows. The next section discusses the extant literature surrounding the issues examined and develops hypotheses. This is followed by a methodology section that explains the sample, case, and methods used in the study. We then report our empirical findings. The final section discusses the findings and concludes the paper by offers suggestions for future research.

2. Literature review and development of hypotheses

The market for audit services has long been characterized as oligopolistic—i.e., few rivals, stable market share among competitors, and medium- to high-entry barriers (Beattie and Fearnley, 1994). The National Economic Research Associates (NERA, 1992) stated that audit firm oligopolistic competition would remain healthy as long as no further mergers occurred among the biggest audit firms.[4]

The history of audit firm mergers is relatively rich. Most cases have involved the adoption of a structural approach to horizontal mergers (Liu, 2014). On September 1, 1989, Arthur Young merged with Ernst & Whinney to establish Ernst & Young, which became the

[4] Big8 audit firms include Arthur Anderson, Arthur Young & Company, Coopers & Lybrand, Ernst Whinney, Deloitte Haskins & Sells, Peat Marwick Mitchell, Price Waterhouse, and Touche Ross.

largest international audit firm. Later on October 4th of the same year, Deloitte, Haskins & Sells merged with Touche Ross, becoming the third largest audit firm at the global level. These two mergers aimed at empowering the U.S.-based audit firms to enhance their market share overseas (Cowan, 1989), which reduced competition from Big8 to Big7. In 1998, PricewaterhouseCoopers was established as a result of merger between Price Waterhouse and Coopers & Lybrand (Wang, Liu & Chang, 2011). The competition among the audit firms intensified even more when Big7 shrunk to Big6, and then Big6 to Big5 with the reestablishment of PriceWaterhouseCoopers in 1998. The last significant global market change occurred when Arthur Andersen collapsed in 2002 as a result of Enron scandal, reducing the total number of the biggest international audit firms to what we know today as Big4.

Mergers have different benefits for the audit market. They strengthen market share, increase revenues, and enable better price control (Hubbard, 2016). Moreover, they expand and diversify client networks and enable the enhancement of economies of scale (Berton, 1989; Waller, 1989). Mergers strengthen industry specialization and improve quality of assurance services (DeFond, 1992). To our best knowledge, audit firm merger literature has mainly focused on discussing the consequences of mergers on market concentration and audit fee levels from the perspective of the assurance service context (Iyer & Iyer, 1996; Baskerville & Hay, 2006; Gong et al., 2016; McMeeking et al., 2005; Ding & Jia, 2012; Wang, Liu & Chang, 2011).

In this study, we apply the client perspective to theoretical discussion of audit firm mergers in order to scrutinize the implications of market structure changes on auditor selection processes. This perspective is significant for the literature, as mergers could cause changes of audit firm staff assembly, in this situation clients might be forced to switch their auditor as the incumbent partner may have considered departure (Thavapalan et al., 2006). Introducing a social network analysis methodology to auditor selection mechanism investigation is further relevant to the literature, as auditor-client ties that emerge through auditor selection processes are attributed both to the characteristics of interpersonal and inter-organizational levels of auditor-client relationships (Xue et al., 2013). We argue that further investigation of the structures of these interpersonal and inter-organizational relations might enable us to understand underlying processes that lead towards establishing specific network configurations. Therefore, it will enable us to understand client behavioral patterns that may benefit from current market disruptions in the case of audit firm mergers.

Chang et al. (2019) argued that, in audit firm merger situations, clients are compelled to carry out auditor selection by following one of three behavioral patterns: (i) following the departing partner to the new audit firm (*followers*); (ii) staying with the incumbent audit firm (*stayers*); or (iii) changing to a third-party audit firm (*changers*). This study investigates social networks to estimate the statistical propensity of emergence for each of the three scenarios in the particular research context in order to understand the characteristics of client behavioral patterns and client-auditor relational patterns that unfold as a result of audit firm merger.

To date, literature has primarily focused on *following* behavior to inspect the implications of auditor selection mechanisms in the Arthur Andersen case (Basioudis & Papadimitriou, 2007; Blouin et al., 2007; Vermeer, 2008; Martinis et al., 2008; Barton, 2005; Bewley, Chung & McCracken 2008; Chang et al. 2003; Krishnamurthy et al. 2006). These studies have been executed at both interpersonal and inter-organizational levels. However, Xue et al. (2013) indicated that the interpersonal level should be the preferred level for the investigation of behavioral patterns, since the length of audit engagement is principally contingent on the strength of the client-partner and not the client-audit firm relationship (Ye et al., 2011). Accordingly, we argue that the strength of the client-partner relationship reflects the propensity of clients to follow a partner to another audit firm in the event that the engagement partner decides to depart.

Furthermore, the literature has demonstrated that the strength of client-partner relationship is contingent upon the cost of switching (Blouin et al., 2007; Lim & Tan, 2008; DeAngelo, 1981; Arrunada and Paz-Ares, 1997; Beattie and Fearnley, 1995), which is referred to audit engagement start-up costs (Blouin et al., 2007). Although the literature conceptualizes these costs as a one-dimensional construct (Greiger et al., 2012), it is rather multi-faceted since they include procedural, financial, and relational elements. From a broader perspective, these costs involve money, time, effort, and uncertainty in the business-to-business context (Lam et al., 2004) – such as is auditor-client relationship. More specifically, in the auditing context, these costs encompass auditor selection costs (GAO, 2003), costs of educating the auditors, and risks of failures in the early years of engagement (Geiger & Raghunandan, 2002; Myers et al., 2003). Furthermore, these costs are subjective in nature, as they are subordinate to client perception of a magnitude of additional costs that are required to conclude current relationships and establish alternative engagements (Blut et al., 2015). As a result, they are intangible and could be material for clients (Martinis et al., 2008).

Studies show that, when an incumbent partner decides to switch to another audit firm, clients tend to switch to that same audit firm in order to circumvent switching costs (Martinis et al., 2008). In this event, the switch arguably occurs due to the strength of interpersonal and not inter-organizational relationships, albeit the auditor choice decision has repercussions on both levels. They also demonstrate that high-quality boards of directors and audit committees are more prone to expressing following behavior due to the strong ties established with the audit partners and the high switching costs (Martinis et al., 2008), which might further negatively affect company market value and reputation level.

In addition, auditor industry expertise is also a predictor for clients' following behavior (Blouin et al., 2007). Lim & Tan (2008) demonstrated that industry specialized audit partners are capable of producing higher quality audits because of their capacity to assess risk with higher accuracy than their non-industry specialized partners. The reason is that these auditors more efficiently exploit their knowledge (Moroney, 2007), which allows them to detect mistakes and frauds through industry specialized knowledge, as compared to how their non-industry specialized colleagues would conduct the same procedures (Solomon et al., 1999). Moreover, Lin (2015) did not identify audit quality differences among departing and non-departing audit partners in terms of whether the affiliation change correlates to the audit quality level.

To summarize, the literature demonstrated that partner following behavior characterizes situations when cost saving and industry expertise are important factors that clients account for while selecting an audit partner. However, previous literature only implicitly accounts for the strength of auditor-client relationships in the discussion of following behavioral mechanism. Our empirical case provides us with a unique opportunity to enrich this discussion by more explicitly making an investigation into the strength of interpersonal relationships, wherein we will utilize the cooling-off period as a regime to measure the strength of the auditor-client relationship. The cooling off period applied to all former engagement partners of KPMG regardless of the audit firm they have affiliated themselves to after the merger, even though this included KPMG 2014.

Accordingly, we would expect KPMG clients to follow their switching partners to EY in order to re-select them after the cooling-off period due to the switching cost reductions and minimization of audit failure risks. Since the Danish corporate governance context is specific for a strong relationship among boards and auditors, we argue the following scenario:

H1: Former KPMG clients will follow their incumbent partners who switched to EY in order to re-engage with them again after the cooling-off period.

On the other side, studies have argued that the inter-organizational level of the client-auditor relationship should not be neglected, as mechanisms that underpin social selection processes could also be predicted by attributes at an organizational level (Lusher et al., 2013). Studies demonstrate that companies consider brand, costs, and the length of engagement as the most important audit firm selection determinants when the effects of audit partner defection are observed at the inter-organizational level of analysis (Riel et al., 2005; Bendixen et al., 2014). They further show that, when client companies and audit firms are attached to each other, the client will rather stick to the same audit firm if its incumbent partner commits to switching to another audit firm, instead of to following that partner. Moreover, research demonstrates that companies would also rather choose to stay with the same audit firm because of the negative signal that audit firm switch sends to the public, which might further affect their corporate image and stock price (Beatty, 1989; Barber et al., 1995; Ashtana et al., 2010).

Studies argue that, if a client company perceives that the audit firm switch will incur high switching costs, even though this might mean re-engagement with the incumbent partner, it is less likely that the client company will decide to change the audit firm (Blut et al., 2015). Such a behavior enables client companies to strengthen brand-driven inter-organizational relationships, implying that brand equity and brand loyalty may be more important determinants of audit firm selection than interpersonal relationships with engagement partners (Beidenbach et al., 2015). In this way, brand equity and brand loyalty are perceived as a proxy for audit quality (Riel et al., 2005; Bendixen et al., 2004), as they represent overall buyer attachment and commitment to different products and service provider values (Oliver, 1999). As a result, such a staying behavior might lead to a locking-in effect, wherein clients use the same service provider for each subsequent purchase. The length of an engagement is a precondition for the development of strong relationships among audit firms and their clients. It might be ascribed to the time that audit firms need to learn about their client accounting practices, which will further lead to better efficiency and audit quality (Aydin et al., 2005).

Based on these considerations, we argue that the auditor selection process is, from the inter-organizational perspective, characterized by a staying behavior. By this, we refer to a mechanism according to which the client companies of former KPMG decide to switch to the newly established KPMG 2014 and, in such a way, stay with the same brand, instead of following their incumbent partner to the new audit firm and thereby increase risk of negative market repercussions. Therefore, we propose the following hypothesis:

H2: Former KPMG clients will switch to the newly established KPMG 2014 subsidiary.

Based on the categories of behavioral scenarios developed by Chang et al. (2019), clients who were affected by the audit firm merger are, in one way or another, forced to make auditor selection, regardless of whether the mandatory rotation period has legally expired. However, in addition to the two previous behavioral patterns, Chang et al. (2019) also suggested that clients may choose to switch to a third-party audit firm and, in that way, commit changing behavior. By third-party audit firm, we mean PwC and Deloitte, which were not involved in the audit firm merger, and all other non-Big Four audit firms that provide assurance services for public companies. However, we also take into account the possibility that an incumbent audit partner that has not switched to EY after the merger might have decided to join a third-party audit firm. We account for this as a following behavior, but from a change behavior perspective, due to post-merger affiliation differences.

To summarize, we argue that companies are, in this way, attempting to stay away from any negative repercussion that the merger might have brought regarding corporate reputation, even though the switching costs were considered low as compared to the effects that following and staying behaviors could have given to clients. We also argue that the switch to a third-party audit firm is not incentivized by the idea of increasing proximity with the former incumbent partner or possibility for re-engagement, if the previous partner switched to another audit firm.

Accordingly, we propose the following hypothesis to argue for a possible third behavioral pattern:

H3: Former KPMG clients will decide to switch to a third-party audit firm after the merger, but not to re-engage their incumbent partner.

3. Case, data, and methodology

In this section we provide case descriptions together with the details about data collection and data analysis. Furthermore, the methodological approach used in this study, which is called exponential random graph models (ERGMs) is explained together with the selected variables, network parameters, and measurements, are explained.

3.1. A brief history of the KPMG and Ernst & Young merger – A case description[5]

The history of the audit profession in Denmark shows an increasing concentration during the 1980s and 1990s, when the big international networks established a dominant position (Christiansen & Loft, 1992; Jeppesen, 2010). However, Ernst & Young was a minor player relative to KPMG, who dominated the audit market for listed companies.

In 2013, these two audit firms decided to join their operations. Audit staff defection occurred when KPMG and Ernst & Young in Denmark merged under the EY name, with most of the KPMG staff moving to Ernst & Young. The push for the merger was chiefly made by KPMG clients, who were interested in engaging with partners affiliated with an audit firm with stronger client and partner networks, which KPMG did not have at the time. The entire process around the merger was initiated by the CEO of KPMG Denmark who argued that the joining

[5] Source: Børsen and Jyllands-Posten newspaper articles.

of the operations would enlarge the companies' employee and client networks more effectively than the organic growth of the competing entities.

Among all of the KPMG partners, only 48 decided to switch to Ernst & Young, together with their staffs. The other 23 KPMG partners chose not to be involved in the merger, stating their resistance to adopting a new business model and to what they feared would be negative client reactions to the merger. As a result, they decided to either join the new KPMG subsidiary or switched to another audit firm not involved in the merger.

Regarding market share at the time, KPMG competed with BDO for fourth place in the audit market. On the other hand, Ernst & Young Denmark was perceived as the weakest link in the global Ernst & Young network and the least enticing workplace in the industry. EY was forced to report the loss of almost one-third of its audit partners when 11 of the 36 partners decided to resign due to financial challenges (a drop of revenue of 2 mil. EUR and net incomes by 0.7 mil. EUR). This loss was the result of both deficient governance by Ernst & Young Sweden (which administered its Danish subsidiary) and a number of the partners moving to firms outside the Big Four network (e.g., Beierholm, BDO, etc.). This situation enhanced the extent of the difficulties facing Ernst & Young in holding onto new audit partners, which meant that joining operations with KPMG was an acceptable remedy for overcoming challenges on both sides.

KPMG and Ernst & Young commenced negotiations in 2013, which were finalized by a formal approval issued by the DCCA. On November 20, 2013, the two firms announced that they would continue operations under the EY name. The DCCA formally approved the decision on May 29, 2014 and categorized this scenario as a merger under the Competition Law (§ 12 a, stk. 1, nr. 2.). The overall cost of the merger reached 150 mil. EUR, which was credited to EY. These monies were mainly used to compensate contracting partners who decided to switch from KPMG. From a leadership perspective, the former KPMG CEO became the new CEO of EY, relegating the former Ernst & Young CEO to an audit partner position.

As a result, it was perceived that the Danish audit market became highly oligopolistic, which triggered KPMG International to establish a new subsidiary in Denmark. Despite the complexity of the process that was finally chosen and suggestions to form the new KPMG office by merging BDO and Beierholm, the new subsidiary took the name KPMG 2014,[6] with a former CEO of a listed company as its CEO. This subsidiary of KPMG had nothing in common with the previous KPMG and was distinguished by "2014" in the firm name for a short time before it was removed. The aim for the newly established KPMG 2014 was to reach revenue of 7 mil. EUR with around 500 staff members within the first three years of operation.

3.2. Data collection

To investigate the effect of merger on client behavior in audit partner selection context, we utilize *social selection, which is* a theoretical concept borrowed from social network theory (Lusher et al., 2013). This concept suggests that when the structure of ties in networks is what matters for the study, the patterns[7] based on which the network is structured may be self-organized, in which the tie formation, or dissolution, is driven by individuals' attributes (Robins et al., 2007). The social selection is primarily concerned with the role that actors' characteristics, to which we afterwards refer as attributes, take on those combined actor/tie locales. In this perspective, attributes[8] are used to explain the patterns. According to this process, actors are more likely to form ties with those who embody a specific attribute, than with those who are missing that attribute (for similar approach see more Kacanski et al., 2021).

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[6] This paper uses "KPMG 2014" to refer to the discussion related to the new KPMG office in order to avoid possible misinterpretations. The "2014" was a part of the official audit firm's name at the time of its establishment, but was afterwards deleted, meaning that the firm retained the same name it had before the audit staff defection at the time of the merger commencement.

[7] Networks are comprised of substructures representing mechanisms that explain the presence of ties and models describe patterns in the networks (Lusher et al., 2013).

[8] Table 2 lists out network parameters that are used in measuring the influence of actor's attributes on selection mechanisms.

In order to cover the period both before and after the merger we selected a timeframe of six years (2012 – 2017). The pre-merger period (2012 and 2013) was included in order to control for the market effects that took place during the main period of observation (2015 – 2017). The main period for which we measure behavioral effects includes these last three years. We chose this period because of the clause in the DCCA's approval document aimed at prohibiting switching partners from re-engaging with their pre-merger clients for a period of two-and-a-half years after the merger. This period was considered to be a mandatory cooling-off period applicable only to switching audit partners. Since the merger implementation was completed in May 2014, that month and year was the moment when this cooling-off period commenced. This period ended in 2016, and beginning in 2017 those partners were again permitted to re-engage their clients from the period before the merger.

To test the hypotheses, we used annual reports from Danish public companies[9] that were listed during the entire timeframe of the observation. The list of companies was identified using interim reports on equity trading published by the stock exchange on December 31st of each year of observation. These reports provide listing and delisting disclosures, which formed the basis for delineating the sample. The annual reports were collected through *Virk.dk*[10], through company websites, and/or through direct contact with investor relations personnel if they could not be retrieved through one of the other two methods.

We identified a total of 196 public interest entities. The following steps were applied to complete the sample selection in order to exclude entities whose presence in the selection may disturb the results. First, we excluded all entities that were not listed during the entire timeframe. Second, we excluded banks and other financial organizations for the following reasons: (1) it is relatively difficult to compare the financial statements of banks and financial

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[9] The Danish stock exchange is called Nasdaq OMX Copenhagen
[10] Virk.dk is a registry of all business entities in Denmark in which annual and interim reports and other public disclosures may be retrieved.

organizations with those of non-financial firms; and (2) the cost structure and audit fee pricing of banks and financial organizations are different from those of all other industries (McMeeking et al., 2007; Wang et al., 2011; Iyer and Iyer, 1996; Simunic, 1980). Lastly, we excluded those companies whose corporate governance is based in other countries, as we assumed that the interpersonal and inter-organizational relationships were not relevant if the audit firm selection was made in another country.[11] Finally, we retained extreme observations with respect to total assets, since the measurement results were not materially different when the extreme observations were included or excluded from the sample. We provide a description of the final sample comprised of 74 public business entities in Table 1.

Table 1 - Description of sampling procedure

Total number of companies listed on the Danish stock exchange (NASDAQ OMX Copenhagen) during the observation period 2012-2017	196
Less: Companies not listed during the entire period	(83)
Less: Banks and other financial organizations	(23)
Less: Danish subsidiaries of companies governed abroad	(16)
Final sample size:	**74**

Data on audit fees and total assets for all of the sampled companies were collected through the Thompson Reuters Eikon database. This data was used to calculate the market concentration index and market share audit fee change indices. Indices set forth in descriptive statistics were normalized by logarithmic transformations based on the data on total assets. The normalization was administered not only to mitigate the potential for large auditees to dominate the results (McMeeking, 2005), but also to enable comparability of the presentation of the descriptive statistics with previous research, making the descriptive statistics reliable and comparable. These transformation procedures reduce the extent of skewness in the distribution of total assets by audit firms.

[11] E.g.: TopDenmark, Tryg, Victoria Properties, SAS, Scandinavian Private Equity, etc., are governed from abroad (e.g., Sweden, Faroe Islands, etc.)

We collected data on audit partner selection by extracting data on signing-off auditors/audit firms from annual reports for each company in the sample. The statements of auditor's reports in the annual reports include independent auditor's reports, in which the engagement partners and the audit firm information are disclosed. It is mandatory for all public entities in Denmark to disclose this independent auditor's report together with the names of signing-off partners and their affiliations. As a result, we collected 444 annual statements from 74 companies that were audited by, in total, six audit firms (the Big Four and two non-Big Four), out of which 151 unique engagement partners were identified for the selected timeframe.

Those data were used to map out networks comprised of two groups of actors (companies and auditors/audit firms). These two groups of actors are represented by nodes, while ties connecting them represent audit partner/audit firm selection made by the companies. To understand the principles behind the complexity of the network structure, we also extracted data about personal characteristics (attributes) of audit partners, such as affiliation and industry specialization. This is because in social network theory, social selection considers actors' attributes (i.e., affiliations, industry specialization, etc.) to be exogenous predictors of network structure (Lusher et al., 2013).

To prepare network data for statistical modeling, we extracted all the relational data among the social actors (companies and audit partners/audit firms) and put it into a single spreadsheet. Data files are further converted into .csv files readable by the network visualization tool Visone (Brandes & Wagner, 2004), and adjacency matrices[12] in .txt format readable by MPNet software (Wang et al., 2018) in order to estimate the ERGMs.

[12] In graph theory adjacency matrix is a 2D array of a size A x B where in two-mode networks A and B are a number of nodes of two kinds in a graph. Matrix is used to indicate whether pairs of nodes are connected by a tie or not. It is a binary construct where 1 indicates the presence of ties, and 0 if otherwise, unless the ties are weighted.

3.3. Market concentration

We use concentration ratios as a descriptive statistical indicator to demonstrate the tendency for monopolistic behavior among audit firms with respect to pricing aspects of the market for audit services. We use both C_n and the Herfindahl-Hirschman index (HHI) because they enable us to take into account, on the one hand, the size of the market sector taken over by the largest actors, and on the other, variances in activity levels among these actors. These two measures demonstrate whether auditors and their clients should be concerned about possible anti-competitive pricing in the audit market (McMeeking et al., 2007), and have been used broadly by academics (Beattie & Fearnley, 1994; McMeeking et al., 2007; Moizer & Turley, 1989; Pong, 1999).

C_n measures the size of a market sector taken over by the largest actors in the industry and considers the proportionate size of the industry (Thavapalan et al., 2006). We calculate the size by using the square root of the clients' total consolidated assets (A) (Tai & Kwong, 1997):

$$C_n = \frac{\sum_1^n A_i}{\sum_1^k A_i} \tag{1}$$

In this formula, n is the sample size of the large companies considered, and k is the total number of public entities in the industry. The numerator is the sum of the square roots of the consolidated total assets (Tai & Kwong, 1997) of clients audited by the Big4, while the denominator is an extension of the value of the numerator by the asset values of those clients audited by non-Big4 audit firms.

The *HHI* is defined as the sum of the squares of the share of industry activity possessed by the k most active companies in the industry. It is a more comprehensive market concentration measure, because it accounts for variances in the activity levels across the audit firms (Pong, 1999), and it is expressed as follows:

$$HHI = \frac{\sum_1^k A_i^2}{(\sum_1^k A_i)^2} = \sum_1^k S_i^2 \tag{2}$$

In this formula, S_i indicates the size of an audit firm i as a percentage of the size of the entire market (McMeeking et al., 2007).

3.4. Variables, measures, and analytical framework

To isolate behavioral patterns that characterize clients' reactions to audit firm mergers, we use social network analysis, particularly exponential random graph models (ERGMs). In the following, we provide further details on ERGMs as social network methodology, and emphasize the importance of accounting for network endogeneity to avoid spurious modeling results.

3.4.1. The network data

We characterize our networks as bipartite (Robins, 2015). These are two-mode networks comprised of two fundamentally different types of actors without ties connecting the same types of nodes. The condition for classifying a network as bipartite is that there should be no logical higher-order category that encompasses the two types of nodes (Robins, 2015, p. 43); in our case, companies and auditors/audit firms. Although ties in bipartite networks connect only nodes of different types, ties connecting nodes of the same type are essentially possible, but they are not observed since they are outside the scope of the research problem (see more in e.g., Kacanski, 2020). However, we decided to include ties connecting audit partners[13] to control for the social selection process because it enriches our findings regarding how joint partner engagements unfold, i.e., how partner attributes drive partner appointment to individual engagements.

To prepare that data for analysis, we developed 27 binary adjacency matrices:[14] 13 matrices for *H1*, 7 for *H2*, and 7 for *H3*. For each of the hypotheses, we estimated seven models,

[13] It is common that the financial statements of listed Danish companies are signed off by two audit partners from the same audit firm.

[14] Intersections between nodes of different types were recorded as 1 if the tie exists between the two nodes, and 0 if otherwise. In each matrix, $x = \{x_{ij}\}$ cells x_{ij} correspond to i's relation with inventory j. If a company i chooses an audit firm or an engagement partner j, or if audit partner i, then the cell $x_{ij} = 1$, $x_{ij} = 0$ otherwise.

one for each year in the timeframe of observation, and one to calculate the likelihood of repeated collaboration (the perennial models).

To measure the propensity for ties to emerge, we utilize the social selection process to account for nodal attributes (industry specialization and affiliation of audit partners) as exogenous predictors of network structural parameters (Lusher et al., 2013). Those variables are integrated into all of the models, as well as into the perennial model in *H2*.

In the rest of perennial models, particularly in *H1* and *H3*, we used dyadic covariates to denote repeated collaborations. Dyadic covariates are similar to nodal attribute files, but they constitute networks on their own. Their function is to assign attributes to network ties (instead of nodes). In a similar fashion to nodal attributes, dyadic covariates are exogenous predictors of tie emergence, and serve as tie attributes that explain the social selection. In the perennial models (*H1* and *H3*) we use dyadic covariates to weight those company–partner ties from 2017, which also existed in the control year. This approach enabled us to identify whether clients chose to re-engage their incumbent partners after the mandatory cooling-off period.

In Figure 1, we visualize a simplified network[15] to apprehend the nodes and ties included in the estimation of the network statistics corresponding to the particular hypothesis. We used squares to denote companies, small circles to represent audit partners, and large circles to indicate the audit firms of audit partners' affiliation. We distinguished between small and large circles according to the scope of the hypotheses. *H1* and *H3* observe relationships among companies and audit partners, while *H2* accounts for relationships among companies and audit firms. Ties present relations among the nodes, where full lines denote a company's selection of an audit firm and/or engagement partner for all three hypotheses. Dashed lines demonstrate

[15] Please note that none of the big circles represent particular audit firms, as they are only used here to visualize the types of nodes that are used for parameter estimation purposes.

collaborative ties among the engagement partners, and dotted lines represent partners' affiliations with audit firm.

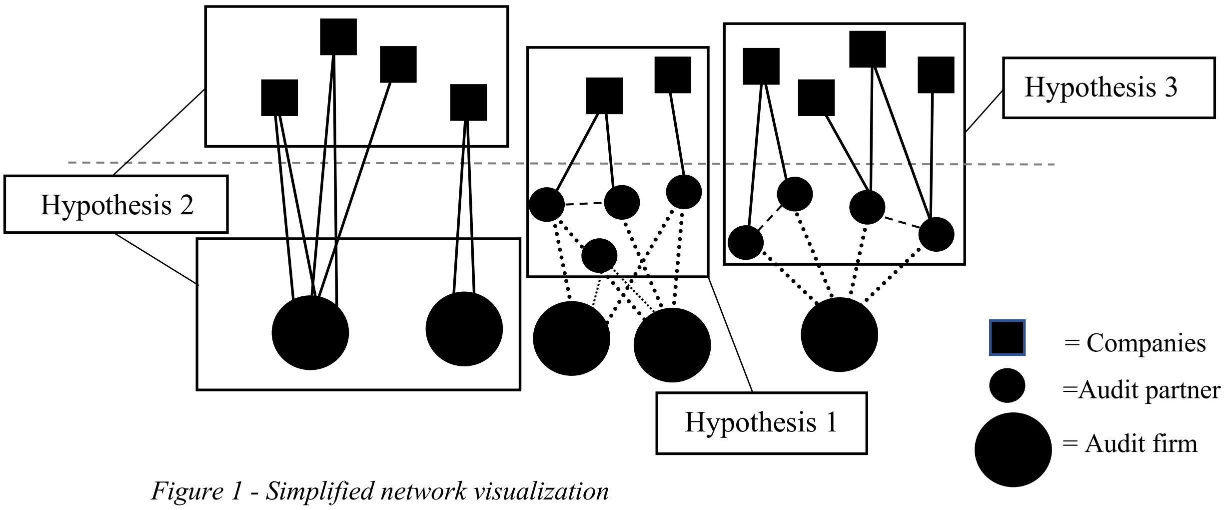


Figure 1 - Simplified network visualization

3.4.2. Exponential random graph models

To analyze the data, we used exponential random graph models[16] for multilevel networks (for introduction to ERGMs see e.g.: Lusher et al., 2013; Wang et al., 2013). ERGMs are one of the most popular tools used by social scientists to understand social networks and test hypotheses about these networks (Robins et al., 2007; Frank and Strauss, 1986, Wassermann & Pattison, 1996; Snijders et al., 2006, and others). ERGMs are generative models that treat network topology as a response variable, which are built to explain global structure of a network while allowing inference on tie prediction on a micro level (Lusher et al., 2013; Robins et al., 2007). This assumption is adequate for answering questions related directly to how and why social associations or interactions occur.

The motivation behind the use of ERGMs is that the complexity of social and economic phenomena is difficult to assess through existing block-models and logistic regressions as they

[16] There have been several generations of network tie dependence assumptions and model specifications for one-mode networks (see more: Erdős & Renyi, 1959; Snijders et al., 2006). Wang et al. (2013, 2016) extended ERGMs to the cases of multilevel networks, in which nodes of two different types are seen as nodes from two different levels, and three types of ties are defined within and across levels.

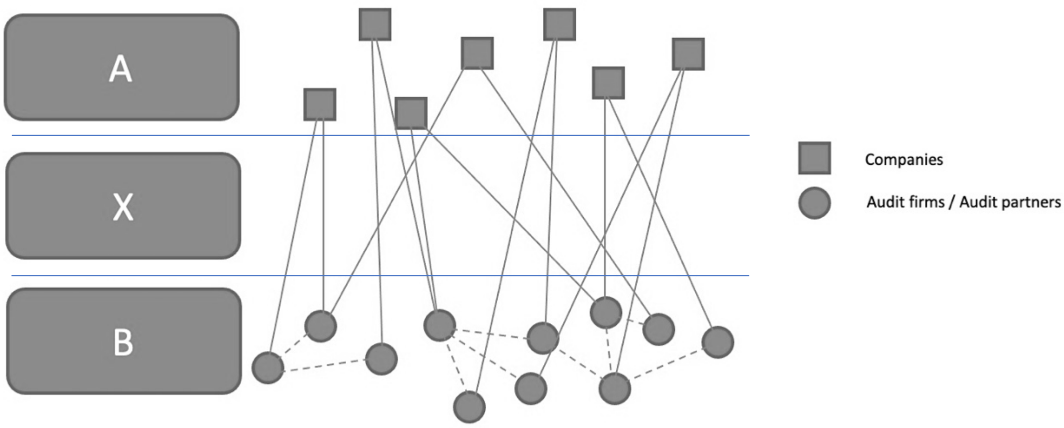
do not allow assessment of all the intricate rules that are at play (van der Pol, 2019). For instance, conventional regression models require assumption of independence between observations and fail to incorporate endogenous structural effects of the observed network (Kim et al., 2016).

A basic idea of ERGMs is that the networks develop through stochastic processes where the presence of one tie is influenced by a presence or an absence of other tie or actor-level attributes (Lusher et al., 2013; Wang et al., 2013). ERGMs treat network ties as dependent variables and account for tie *interdependence* in network structures. The concept of interdependency has been introduced by Frank & Strauss (1986) and Wasserman & Pattison (1996) who argued that the existence of one tie may be dependent on the existence of other ties (conditional dependency). ERGMs assume that dynamics of tie generation affect the overall network formation through the interplay of various local mechanisms (Lusher et al., 2013). By analyzing those stochastic processes, we identify variability in the factors determining tie emergence by capturing local mechanisms whose presence or absence in the network is more likely to occur than by random.

ERGMs measure the overall network probability through parameters associated with those local mechanisms, which are called patterns. Patterns are small substructures contained inside the network, whose presence or absence reflects certain tie formation phenomena (Lusher et al., 2013). The combination of patterns is determined by a theory-based *interdependence* assumption regarding interlocking directorates and auditor selection ties. The selected patterns correspond to particular relational mechanisms within the observed network, where in our case we selected multilevel network type as the most applicable for our research design.

In multilevel networks, ERGMs recognize three network levels denoted as (A), (X) and (B). Levels (A) and (B) indicate network ties between the same types of nodes (single level), while network level (*X*) captures ties between disparate types of nodes (multilevel). In our case, we treat companies as nodes from level (*A*), audit firms or engagement partners as nodes from level (*B*), and the ties among companies and audit partners/audit firms as belonging to level (*X*). Figure 2 demonstrates network levels used in multilevel network analysis.

Figure 2 - A, X, and B network levels used in multilevel ERGMs



We use only the single-level network *(B)* and the multilevel network *(X)* as network random variables, each of which is a collection of network tie variables that are represented by an adjacency matrix. Regarding our hypotheses *H1*, *H2*, and *H3* (reference: Figure 1), ties connecting audit firms/audit partners and companies are accounted as a multilevel network categorized as *(X)* network level, while partner-partner ties[17] belong to the single-level network defined as *(B)* network level. By including single-level and multilevel network patterns we are able to estimate their relative contribution as drivers of local structural patterns while conditioning their occurrence on the likelihood of observing the overall network (Robins et al., 2007).

In technical sense, ERGMs serve as a pattern recognition device. They have the capacity to identify the presence and/or absence of selected network patterns by measuring

[17] Partner-partner ties are representing pairs of audit partners assigned to single client who sign-off the audit reports. In Denmark most audit opinions are signed by two audit partners from the same audit firm.

parameters' propensity of occurrence in the observed network. The parameter estimates further enable drawing conclusions regarding how selected patterns portray underlying processes that create the overall network. We made use of MPNet software (Wang et al., 2013), which implements the Markov chain Monte Carlo maximum likelihood (MCMCML) estimations algorithm proposed by Snijders (2002). This software is used because the study was multi-period and cross-sectional.[18]

Formally stated in the expression (3), let $Y = \{Y_i\}$ denote the vectors of auditing firm attributes, such as binary indicators for KPMG, or industry specialized auditing firms, and $X' = \{X'_{ij}\}$ as dyadic covariates for possible attribute values for each network tie; for example, the previous company-partner ties before the merger. Our ERGMs can be expressed as:

$$Pr(X = x, B = b|Y = y,\ X' = x') = \left(\frac{1}{k}\right) exp\left(\sum_{Q} \Theta_Q Z_Q(x, b, y, x')\right) \quad (3)$$

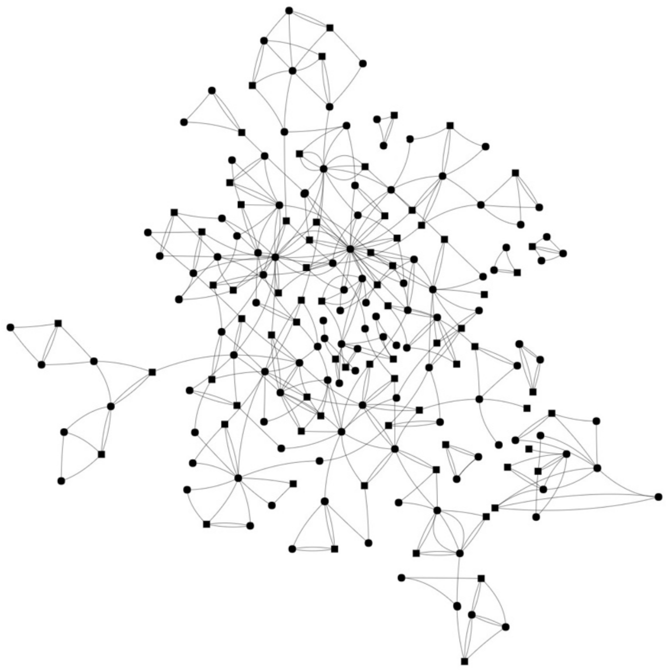
where (i) Z_Q (x,b,y,x') is a network statistic counting the number of network configurations of type Q for the particular network realizations [x,b], the given vector of actor attributes y, and dyadic attributes x'. The choices of Z_Q, or the model specification, are dependent on the dependence assumptions among the network ties and nodal or dyadic attributes, for which all tie- and attribute variables are considered interdependent in each configuration. Moreover, (ii) Θ_Q is the vector of the parameters for the list of statistics Z_Q. A positive and significant parameter estimate suggests that the corresponding configuration happened more often than was expected by chance, while negative parameter estimates mean the opposite.[19] Hence, the underlying social selection process can be seen as prominent in generating the network structure; (iii) k is a normalizing constant included to ensure that (1) is a proper probability distribution.

[18] In the event that the process study was our main interest, we would use RSiena instead (Ripley et al., 2018), because in that case this would fit better.

[19] The statistical significance of the parameter estimates is suggested by the ratio between the estimated parameter value and the estimated standard error. If such ratio is greater than 2.0, we consider the parameter significant.

In Figure 3 we visualize a network assembled of audit partners and their clients on both the (*X*) and (*A*) levels by using VPnet software. The visualization shows the presence of the

Figure 3 Network visualization - containing ties on (X) and (A)levels for both 2012 and 2017



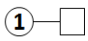
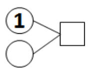
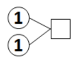
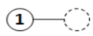
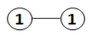
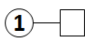
central point of our analysis, which is repeated ties between companies and auditors, represented by the squares and circles. Double ties between the pair of disparate nodes indicate the presence of a tendency toward partner re-engagement, where those ties were used for the development of dyadic covariates to weight ties between clients and partners. An important remark for network visualization is that motivations for tie formation cannot be observed directly from a visual representation of interactions, nor are they clear from glimpsing at a database containing relational data, thus a more in-depth analysis is required (van der Pol, 2019).

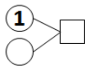
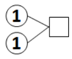
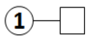
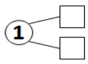
Among many strengths of using ERGMs, we suggest that they are suitable for network studies in this context as they incorporate dependency structures that are integral to social networks, and model network topology as response variable. This is a fundamental feature which makes them be suitable for questions related to interactions or social relationships, as well as any questions for which the structure of the network is of primary interest (van der Pol, 2019).

3.4.3. ERGM specifications - Exogenous and endogenous patterns

Our ERGM specifications consist of both nodal attribute (exogenous) effects and endogenous network structural effects, some of which are directly related to the proposed hypotheses. Exogenous effects are used in our models because ERGMs assume that social actors bring their own capacities, capabilities, and predispositions to a social system. Therefore, it could be argued that the association of a particular attribute with a social actor can be the reason behind the tie formation (Lusher et al., 2013). In the following Table 2 we list the exogenous main and control network effects included in the models.

Table 2 - Network exogenous patterns

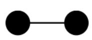
Pattern	Visualization	Interpretation
Following partners from KPMG to EY *(Hypothesis 1)*		
Industry_specialization_XEdgeB (control effect)		Propensity that clients select a partner who is an industry specialist.
Industry_specialization_X2StarB100 (control effect)		Parameter indicates the tendency that clients select two or more engagement partners out of which one is a specialist in the industry that client belongs to.**
Industry_specialization_X2StarB101 (control effect)		Tendency that both selected engagement partners are specialists in the industry that client belongs to.**
Defection_ActivityB (control effect)		General tendency that defected audit partners are involved in audit engagements in EY.***
Defection_InteractionB (control effect)		Parameter measures tendency that defected audit partners collaborate together in the same engagement.***
Repeated_collaboration_XEdge (main effect)	*Dyadic covariate*	Measures propensity that clients will re-engage with the same engagement partner after their defection from KPMG to EY.
Staying with KPMG *(Hypothesis 2)*		
KPMG_Select_XedgeB (control effect)		Measurement of a general tendency for companies to select KPMG.

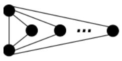
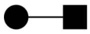
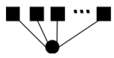
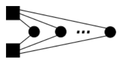
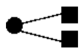
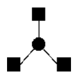
KPMG_Select_X2StarB100 (control effect)		Parameter measures likelihood for pre-merger KPMG clients to switch to another audit firm.
KPMG_Select_X2StarB101 (main effect)		Tendency that pre-merger KPMG clients will stay with the new KPMG (2014) after partner defection.
Following partners outside the KPMG and EY *(Hypothesis 3)*		
Select_other_AuditFirm_XEdge (main effect)		General propensity that former KPMG clients select audit firm outside the KPMG and EY case.
Select_other_AuditFirm_X2StarB010 (control effect)		Parameter measures whether audit firms not involved into the KPMG and EY case are more attractive for former KPMG clients who decided to switch to other audit firms.
*Repeated_collaboration_XEdge (main effect)	*Dyadic covariate*	Measures the tendency that former KPMG clients which decided to switch to another audit firm commit the switch in order to re-engage with the same engagement partner after their defection outside the KPMG and EY case.

* Network exogenous parameters marked with * are the main attribute effects.
** A common practice in Denmark is that clients select two engagement partners who are responsible for their audit reports.
*** These parameters measure tendency for within-audit-firm collaboration ties between the engagement partners.

On the other hand, endogenous effects, and network self-organization, assume that network ties organize themselves into patterns because the presence of some ties encourages others to come into existence (Lusher et al., 2013). Omitting endogenous network effects could eventually lead to invalid findings because they may be attributable to structural mechanisms driving the emergence of ties (Robins et al., 2007). The purpose of using the endogenous effects is to control for the exogenous (attribute parameters). Table 3 provides a summary of each endogenous network effect included in the models that is estimated together with the exogenous (attribute) effects.

Table 3 Network structural parameters – Endogenous network control effects

Pattern	Visualization	Interpretation
Single-level structural parameters among audit partners (endogenous effects – control par.)		
Edge		An edge connecting two nodes (a baseline propensity for tie formation).
Star parameter ASB*		Indicative of the presence of highly central audit partners within the audit partner network.

One-mode level closure parameter ATB*		Within-level closure parameter that models collaborative (triadic closure) relations among the audit partners.
Cross-level structural parameters Between audit partners and clients (endogenous effects – control par.)		
XEdge*		A baseline propensity for a client company to select an audit firm / engagement partner – a control effect.
Multiple auditor selection XASA*		Indicative to clients tendencies to select more than one engagement partner responsible for audits. The parameter models degree distribution.
Auditor popularity effect XASB*		Parameter models the presence of highly central (popular) audit firms / engagement partners.
Two-mode clustering effect XACB*		Parameter measures the likelihood for multiple clients tend to select the same auditor or a common set of auditors.
2-star (Markov) X2Star2B*		Tendency that two companies select the same auditor (used to improve model goodness of fit).
3-Star (Markov) X2Star2B*		Tendency that three companies select the same auditor (used to improve model goodness of fit).
**Indicates name/abbreviation for network parameters according to Wang et al., 2013*		

4. Analysis

We start analysis by presenting descriptive statistics and laying out concentration ratios and Hirschman-Herfindahl indices, together with the description of audit fee change indices to indicate the duality of price change effects on the joint activity formation among the audit firms. Afterwards, we present results from the statistical models by discussing exogenous parameters and endogenous structural effects to analyze client behavioral patterns in the context of the auditor selection process.

4.1. Descriptive statistics

Table 4 outlines the market share of those audit firms that provided assurance services to the sampled companies. Concentration ratios are computed on audit firm revenues only from sampled companies. Revenue distributions are measured as lump sums based on information disclosed in the annual reports reserved for mandatory audits. The ratios were estimated for the

Table 4 - Concentration index on the Danish market for audit/assurance services

Audit firm	Market share											
	2012		2013		2014		2015		2016		2017	
	%	Log transf.	%	Log transf.	%	Log transf.	%	Log transf.	%	Log transf.	%	Log transf.
KPMG	63,45	19,11	62,16	19,01	54,01	18,78	51,75	18,86	11,64	17,99	0,04	14,81
Deloitte	9,08	17,85	9,88	17,82	8,70	17,61	9,33	17,75	8,94	17,82	7,18	18,38
EY	2,38	16,98	3,26	17,10	8,32	17,58	9,03	17,73	10,19	17,90	9,28	18,56
PwC	25,05	18,51	24,66	18,41	28,92	18,38	29,85	18,50	69,19	19,15	83,47	20,05
Grant Thortnton	0,04	14,30	0,04	14,17	0,03	13,96	0,03	13,97	0,02	13,99	0,02	14,49
Beierholm[20]	0,01	13,25	0,01	13,50	0,02	13,67	0,01	13,19	0,01	13,16	0,01	13,72
Total	100.00		100.00		100.00		100.00		100.00		100.00	
C_6	98.43		98.35		98.36		98.67		98.68		98.44	
CR4	1.00		1.00		1.00		1.00		1.00		1.00	
HHI	4,741.60		4,579.50		3,898.29		3,738.14		5,106.29		7,015.32	

sample of 74 companies for six years—i.e., two years before, three years after, and the year of the merger. We included two ratios, one for all audit firms (C_6) and one for the Big Four only (CR4). HHI shows that the Danish audit market is highly concentrated for clients belonging to public companies, as all the index values were over 2.500[21] for all the years. However, HHI fell by 0.07 and 0.02 in the year of the merger and after that, respectively, which could be attributed to the opening of the KPMG 2014 subsidiary, since the market consequently contained the same number of audit firms as it had before the merger. The index continued to increase in the following years by 0.14 in 2016 and 0.2 in 2017. Although the concentration index demonstrates relatively stable values over time, findings showed a slight increase in the years after the merger, though not right from the first year.

Table 5 shows the changes of audit fees to visualize the effects of the merger on the audit market. Audit fees change index is the ratio of audit fee per 1 DKK on total assets adjusted to consumer price index. The column *Change (%)* showcases the decrease of audit fees in the period 2013 - 2015 by 7%, 8%,.and an additional 4% respectively. On the other hand, the fees increased by 3% in 2016, and stayed at the same level in the last year of observation. This

[20] Part of the HLB Network

[21] Hirschman-Herfindahl index categorizes values in a manner such that an index below 1.500 is considered as low concentration, between 1.500 and 2.500 as moderate, and above 2.500 as high.

implies that fees were the lowest in 2015 during the "audit war", as the press called the period right after the merger.

Table 5 - Audit fee change index from 2012-2017

Year	Change in consecutive years	Change (%)	Index year					
			2012	2013	2014	2015	2016	2017
2012	**1.00**	-	1.00	-	-	-	-	-
2013	**0.93**	**-7.00**	**0.93**	1.00	-	-	-	-
2014	**0.92**	**-8.00**	0.86	**0.92**	1.00	-	-	-
2015	**0.96**	**-4.00**	0.83	0.89	**0.96**	1.00	-	-
2016	**1.03**	**3.00**	0.85	0.91	0.99	**1.03**	1.00	-
2017	**1.00**	**0.00**	0.85	0.92	0.98	1.03	**1.00**	1.00

This change may be attributed to the situation wherein the audit firms aimed at attracting more clients, especially those affected by the merger. At the same time, paradoxically, the audit firms were ready to pay higher compensation to employ audit partners in order to attract new clients and win the battle for clients.

4.2. Network analysis - Results from the Exponential Random Graph Models

Table 6 contains statistical model outputs estimated based on a combination of network configurations that delineate the processes that characterize social selection mechanisms in the context of auditor selection. The models were estimated for each year of observation, together with the estimates of integrated models in the last column, which combined relational data from the pre-merger year and after the cooling-off period (indicated as "2012 and 2017 combined" in the table).

Conditional on all other patterns in the model, a positive parameter value indicates that a particular configuration is observed more often in the network than what would be expected if ties emerged randomly, whereas a negative parameter indicates the opposite occurrence (Robins & Daraganova, 2013). Akin to a logistic regression, the size of the parameter estimates can be interpreted through conditional log odds. This implies that, with every increase of a value by one unit, the conditional odds of observing the auditor selection tie as a social selection mechanism increase by a factor that can be obtained by calculating the exponential function of the parameter (Hunter et al., 2008; Robins & Daraganova, 2013).

With regard to our research question, the results of the model estimations show that the networks are characterized by a number of single and multilevel patterns that emerge more or less often than expected from their random occurrences. Though the strengths of selected and estimated network parameters are not fully consistent across the observations, clear trends concerning the attribute-driven structural principles of bipartite and multilevel networks were identified and presented. The results in Table 6 are arranged into horizontal sections for each hypothesis, where the first hypothesis *single* and *meso* sections refer to single- and meso-level structural effects.

Table 6 - Results of the exponential random graph models for the selected years

H1 – Clients following their incumbent partners – "*following*" mechanism

Level	***Network parameters***	2012	2013	2014	2015	2016	2017	2012 and 2017 combined
		Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)	Estimate (S.E.)
Single	Tie formation propensity – one mode- EdgeB	-2.8139* (0.218)	-3.1747* (0.216)	-3.7974* (0.318)	-2.5512* (0.606)	-3.6517* (0.283)	-3.5602* (0.248)	-
	ASB / ATB	-1.5521* (0.67)	-1.7229* (0.603)	-4.1871* (0.907)	-0.1391 (0.339)	-1.1074 (5.343)	-2.3693* (0.637)	-
Meso	Tie formation propensity – two mode- XEdge	5.8727* (2.804)	-1.8841* (0.481)	-1.5622* (0.568)	-1.5315* (0.309)	-1.5979* (0.287)	-1.4376* (0.305)	-2.6204* (0.237)
	XASA	-5.6219* (2.55)	-	-	-	-	-	-1.6303** (0.688)
	XASB	-1.1388* (0.573)	-2.1601* (0.764)	-3.385* (0.965)	-3.379* (0.955)	-	-2.2548* (0.709)	-
	XACB	-0.3038 (0.265)	-1.1456 (1.884)	-	-	-	-	-0.6202 (0.88)
Attribute	Industry_specialization_XEdgeB	2.9181* (0.953)	2.6814* (0.826)	1.9244* (0.796)	1.7125* (0.592)	1.5326* (0.558)	2.3297* (0.811)	-
	Industry_specialization_X2StarB100	-2.2189* (0.518)	-2.1685* (0.48)	-1.53* (0.604)	-2.2593* (0.493)	-2.3872* (0.56)	-2.225* (0.507)	-
	Industry_specialization_X2StarB101	-1.2932 (0.905)	-0.0596 (0.703)	-1.9635 (1.195)	-0.065 (0.663)	0.2314 (0.734)	-0.803 (0.681)	-
	Defection_ActivityB	-	-	-2.5443* (0.264)	-2.8023* (0.235)	-3.8824* (0.416)	-3.5589* (0.392)	-
	Defection_InteractionB	-	-	2.768* (0.662)	3.3475* (0.581)	5.2708* (0.904)	5.0623* (0.905)	-
	Repeated_collaboration_Xedge	-	-	-	-	-	-	0.7161* (0.253)

H2 – Clients staying with KPMG – "*staying*" mechanism

Level	***Network parameters***	2012	2013	2014	2015	2016	2017	2012 and 2017 combined
Meso	Tie formation propensity – two mode - XEdge	-1.9667* (0.144)	-1.9144* (0.138)	-1.4567* (0.14)	-1.4596* (0.136)	-5.1185* (0.537)	-2.468* (0.132)	-13032* (0.123)
	XStar2B	0.0015* (0.001)	0.0457* (0.015)	0.0473* (0.013)	0.0679* (0.004)	0.0491* (0.012)	0.0659* (0.004)	0.0641* (0.003)
	XStar3B	-	0.0017** (0.001)	-	-	-	-	-
	XASA	-	-	-	-	-	-	-2.8755* (0.738)
	XASB	1.5576** (0.235)	0.7699** (0.194)	0.7941** (0.202)	0.7686** (0.167)	0.7886** (0.189)	0.5209*** (0.117)	-
	XACB	-	0.0516* (0.012)	8.9033* (3.484)	0.0529* (0.009)	10.6266* (4.878)	0.0414* (0.012)	0.0531* (0.003)
Attribute	KPMG_SELECT_XEdgeB	0.8014* (0.274)	0.5503** (0.258)	-1.3354** (0.57)	-1.3863*** (0.514)	-1.5577** (0.724)	-1.9274** (0.957)	-4.0446* (1.436)
	KPMG_SELECT_X2StarB101	-	-	-	-	-	-	2.0834** (0.977)

H3 – Clients switching to other audit firms where their incumbent partner potentially switched to – "*changing*" mechanism

Level	***Network parameters***	2012	2013	2014	2014	2016	2017	2012 and 2017 combined
Meso	Tie formation propensity – two mode - XEdge	-1.3056* (0.345)	-5.6022* (1.137)	-3.9612* (1.03)	-4.1482* (0.864)	-2.5652* (0.128)	-2.2341* (0.202)	-2.3372* (0.363)
	XStar3B / XStar2B	-0.0052 (0.003)	-0.005 (.003)	-	-0.0231* (0.007)	0.0691* (0.004) – **2B**	-0.0231* (0.007)	0.1889* (0.067) – **2B**
	XASB	-	2.0126* (0.564)	1.4987* (0.515)	-	-	-	0.5389* (0.21)
	Select_other_AF_XEdgeB	-2.206* (0.599)	-0.077* (0.264)	-1.6232* (0.255)	-1.1107* (0.268)	-0.9958* (0.266)	-0.9904* (0.243)	-
Attribute	Select_other_AF_X2StarB010	0.18* (0.047)	0.0623* (0.006)	0.0696* (0.006)	-0.1124* (0.016)	0.038* (0.017)	0.0559* (0.012)	-
	Repeated_collaboration_XEdge	-	-	-	-	-	-	-0.7823* (0.347)
	Repeated_collaboration_XEdge	-	-	-	-	-	-	-0.7823* (0.347)

* Indicates significant effect at Lambda = 2
** Indicates significant effect at Lambda = 4
*** Indicates significant effect at Lambda = 6

The value of λ = 2 has been used here as an initial value as it has been proven to be reasonable for many ERGMs estimations, however higher values, as indicated (λ = 4) contribute convergence in the case of highly skewed degree distributons (Koskinen & Daraganova, 2013; Robins et al., 2007).

The single-level structural effects refer to network configurations that unfold at the audit partner level, while the meso level refers to a network wherein ties are formed between the nodes of two kinds (companies and auditors). All three horizontal sections are supplemented by a combination of exogenous attribute effects to provide network statistics that delineate the social selection mechanisms. Columns refer to the years or their combinations for which the parameter estimations were modelled.

It remains important to highlight that we included either only the $XEdge$ parameter on level (X), or jointly with $Edge$ parameter on level (B) into all the models (if the single-level network was a part of the model) to control for the other endogenous structural principles that characterize network emergence. Both $XEdge$ and $Edge$ parameters are negative and significant in all models, which indicates that ties on both (X) and (B) levels rarely unfold in configurations that are outside of the selected structural parameters that characterize the patterns in the observed networks.

In the following, we outline the results of network statistics by discussing each parameter before we discuss the goodness of fit analysis of the models.

4.2.1. Network parameter estimations for *following* behavior

The structural parameters demonstrate that, within the auditors at a (B) level, the negative tie centralization effects (ASB) suggest that there are no particularly popular audit partners within the audit partner network who are involved in engagements with a number of other audit partners. This possibly indicates alignment in the engagement distribution among the audit partners in the audit firms. However, this finding should be taken with caution because a pair of partners might be involved in more engagements at the same time and, therefore, be more popular among the clients than what the audit partner network demonstrates. This assumption is further supported by the negative closure (ATB) parameter, which shows that, in the event that two partners collaborate on the same engagement, they tend not to collaborate with the other partners regarding the other engagements. On the (*X*) network level among clients and audit partners, the structure parameters were included into the models to control for attribute effects. In addition, ($negative\ XASB$) also confirms that there are no audit partners who are more popular and possess more engagements relative to the others in the same network. They also show that clients tend not to cluster by engaging with the same pair of other partners in the partner network ($negative\ XACB$).

Regarding the exogenous (attribute) effects that determine the *following* behavior, we tested the effect of industry specialization on the propensity for audit partner selection. Findings demonstrated that industry specialization plays an important role in auditor selection, implying that clients choose audit partners who are industry specialists in industries to which the focal company belongs ($positive\ Industry\_specialization\_XEdgeB$). As most of the companies in our case engage two audit partners, our findings indicate that companies do not find it inevitable that both engagement partners should be industry specialists, as the parameter ($Industry\_specialization\_X2StarB100$) is consistently negative and significant.

Furthermore, we measured the extent of defected audit partner integration into the organizational structure of EY. To do this, we estimated the attribute parameter to measure the extent to which defected audit partners who switched to EY from KPMG tend to share collaboration ties with the EY resident partners—i.e., those partners who were affiliated with Ernst & Young before the merger. We measure this effect only for the post-merger period from 2014 onwards. The results showed a strong homophily affiliation-based engagement effect ($Defection\_InteractionB$), which indicates a low partner integration as the partners of the same pre-merger affiliations are more likely to share engagements. This may be explained by the strength of inter-partner relations and the risks of breaking down the current engagements for the sake of partner integration in periods soon after the merger.

Lastly, we estimated a repeated collaboration parameter based on a dyadic covariate as an attribute effect to test the propensity of incumbent partner re-selection after the cooling-off period, which serves as a proxy for the strength of the auditor-client relationship ($Repeated\_collaboration\_XEdge$). A positive and significant parameter indicates that clients tend to return to the incumbent partners with whom they were engaged before the merger. This indicates that the strength of auditor-client relationship before the merger was stronger than what the client clause aimed at attaining with the new engagements. These findings fully support $H1$.

4.2.2. Network parameter estimations for *staying* behavior

The second horizontal subsection in Table 6 lays out the list of endogenous and exogenous structural principles at the meso level in order to estimate the propensity for staying behavior at the client-audit firm level. The exogenous parameters are accompanied with the endogenous to control for the unfolding of social selection (Wang et al., 2016).

Concerning $H2$, we find that the statistics regarding both popularity ($XASB$) and clustering ($XACB$) effects are positive and significant in all models. The star effect ($XASB$) is indicative of the presence of highly central audit firms in the market for assurance services. This is not surprising since audit firms have high degree distributions in respect to the number of clients because the market for audit services is highly oligopolistic and, therefore, attracts more clients than the others. This implies that there are some audit firms that are particularly recognized as sought-after market actors that primarily focus on providing audits, while the others rather focus on consultancy or taxation services. The clustering effect supplements the findings here by demonstrating that many companies tend to select the same audit firm, showing that clients have preferential attachment to particular firms relative to the others. We also included Markov star effects ($X2Star$ and $X3Star$) in some of the years in order to improve the model goodness of fit. These effects are also positive, further enhancing the centralization effects. Furthermore, clustering effect ($XACB$) in this context supplements the findings related to the previous parameter by demonstrating that many companies tend to select or share the same audit firm that corresponds.

Regarding exogenous parameter effects, findings show that, in the years before the merger, KPMG had a higher selection rate among the public companies as compared to the other audit firms. However, starting in 2014, when the audit staff defection occurred and the establishment of KPMG 2014, this subsidiary has become less attractive to the focal group of clients, which is demonstrated by the negative and significant ($KPMG\_Select\_Xedge$) parameter.

Moreover, to measure the propensity for KPMG 2014 re-selection by earlier KPMG clients, we combine the endogenous $XASA$ effect, which indicates the presence of companies that switched audit firms from 2012 to 2017, with the exogenous parameter ($KPMG\_Select\_X2Star101$). Findings show that former KPMG clients have a strong positive tendency to select KPMG 2014, which may be indicative of their propensity to engage another audit partner, while staying under the KPMG label. These findings fully support $H2$.

4.2.3. Network parameter estimations for *changing* behavior

Lastly, we estimated the probability that former KPMG clients might also react in another way and switch to another audit firm that was not involved with the merger for the sake of re-engaging their incumbent partners who had decided not to switch to EY after the merger. To do this, we measured first whether there is a general tendency that earlier KPMG clients will select any other audit firm after the merger. The results indicated positive and significant effect that those pre-merger KPMG clients who decided to switch to another audit firm, in fact, found it rather more attractive to select those other audit firms that were not involved into the merger ($Select\_other\_AuditFirm\_XStarB010$).

In regards to hypothesis $H3$, we estimated the tendency that clients would switch to other audit firms not involved in the merger case in order to re-engage their incumbent partner if the partner moved to another audit firm after the merger ($Repeated\_collaboration\_XEdge$). For this, we used a dyadic covariate to control for ties before the merger. The effect was negative and significant, which suggests that the KPMG clients who decided to switch to outside the firms involved into the merger did not switch in order to increase proximity to their incumbent partners with the aim to re-engage with them. These findings here fully support $H3$.

4.3. Goodness of fit

Based on the procedure suggested by Hunter et al. (2008), we assessed the goodness of fit for each model after the models converged. Goodness of fit (GOF) enables an assessment of how well the model manages to capture features of data that were not explicitly modeled. More concretely, it estimates whether the combination of the selected network parameters is adequate enough to explain the observed network structure. Technically, the GOF analysis requires the inclusion of all statistics, both those that were included and those that were not included in the models. Following the recommendation of Hunter et al. (2008), we simulated 1,000 samples over 100 million iterations to produce a sample of distributions from the fitted models and then compare the simulated graphs with the characteristics of the observed models. In order to assess whether a summary measure $S_k(x_{obs})$ for the observed graph falls far from the expected values under the fitted model, we calculated the t-ratios as $[S_k(x_{obs}) - \bar{s}_k]/SD\big(S_k(x)\big)$, where $\bar{s}_k$ and $SD\big(S_k(x)\big)$ represent mean and standard deviation, respectively. Given that we estimated models based on a combination of 6 to 10 different parameters for which the estimation algorithm converged, we simulated networks from the models to generate the distribution of graphs by including, in total, 54 network statistics.

According to the goodness of fit test, the summary of the corresponding feature in data is not extreme in all the distributions of the graphs for each model. Building on criteria recommended by Wang et al. (2013), the results of our models demonstrated adequate fits, as the GOF analysis for all network parameters included in the models demonstrated that *t*-ratios for the selected parameters were below the threshold of 0.1, and the values for all other parameters not included in the initial models were below 2.0 in their absolute values. In addition, we also measured standard deviation and skewness of the degree distributions for the entire model goodness of fit for each year. Moreover, we also measured standard deviation and skewness of the degree distributions for the entire model goodness of fit for each year of observation. As a result, both of the measures were below 2. Particularly, standard deviations ranged between 0.9 and 1.7, and skewness ranged from 0.6 and 1,7, which suggests a good fit. Based upon this fact, we can assume that observed networks can be adequately reproduced based on the model estimations.

5. Discussion and conclusion

Given the importance of the social processes that underpin auditor selections, as well as of the "primacy of network" prevailing in corporate governance clusters, the aim of this study was to shed light on the following question: *How do clients select auditors in situation of forced auditor switch regime?* Building on theoretical and empirical findings from research in auditing, corporate governance, and organizational networks, we investigate behavioral aspects of three dominant corporate attitudes regarding auditor selection in the context of the Danish audit firm merger between KPMG and Ernst & Young. We took the Danish merger case to examine the strength of client-auditor ties, knowing that, in Denmark, non-executive directors have a tradition of strong relationships with their auditors both legally and in practice (Johansen & Pettersson, 2013). The purpose of this study was to investigate the strength of auditor-client relationships through the measurement of a likelihood for repeated engagement with the incumbent audit partner after the audit firm merger. To model the network parameters, we utilized social network analysis, particularly exponential random graph models to test the hypotheses.

The results of our analysis show that clients' behavioral characteristics in the auditor selection context might be portrayed by disparate mechanisms contingent on the sample scale and on whether the study is conducted on the interpersonal or inter-organizational levels. The introduction of a forced auditor switching regime after audit firm merger does not prevent clients from fostering the tendency to re-engage their incumbent partners. Instead, after-merger partner selection is influenced by the chance to re-engage the incumbent partner after the mandatory cooling-off period termination.

Our results show that this merger has not much affected the market for audit services in terms of the concentration index. It has rather changed the distribution of clients among the extant audit firms. This result falls in line with that of Berton (1989), who argued that the strengthening of the concentration index is not a fundamental incentive for audit firm mergers, as much as it is in terms of audit fees and auditor selection dynamics (Iyer & Iyer, 1996; Baskerville & Hay, 2006; Gong et al., 2016; McMeeking et al., 2005; Ding & Jia, 2012; Wang, Liu & Chang, 2011).

A main part of our research design adheres to the argument of Chang et al. (2019) regarding the determinants and effects of client behavior in situations where the audit partner switches to another audit firm. They proposed three options—*following*, *staying, and changing*—as an indication of a type of behavioral patterns that clients might commit in the particular context. Based on this, we developed three hypotheses to test both interpersonal and inter-organizational tie creation dynamics regarding the presence of disparate processes that lead to auditor selection in the audit firm merger context. We based our study on a discussion of the strength of the auditor-client relationship as a propensity to re-establish audit engagement (Kacanski, et al., 2021; Chang et al., 2019). We modeled the behavioral patterns by utilizing exponential random graph models for multilevel networks based on Wang et al. (2013; 2016).

The study started off by testing clients' propensity for the following behavior, which was conducted at the interpersonal level of the client-partner relationship, as suggested by Xue et al. (2013). Our main finding demonstrated that clients tend to switch back to their incumbent partners after the cooling-off period if the auditor switches affiliation to the audit firm involved in the merger from the firm to which the partner was previously affiliated. This complies with the finding of Martinis et al. (2007) that the client will follow its switching partner to circumvent the switching costs incurred by the forced auditor switching regime. Furthermore, this adheres to the assertion that high-quality boards of directors and audit committees, as their integral parts, are more likely to follow their switching partners due to the strength of ties established with the audit partners (Martinis et al., 2007). To the contrary, if partners switched to other audit firms outside the merger, the clients might still decide to switch, but not to re-engage their incumbent partners. In addition, the findings here suggest that the mandatory cooling-off period introduced by DCCA to prevent client reengagement behavior is inefficient, meaning that companies find aborted audit engagements more valuable and thus are more prone to reinvest in them than to continue developing and investing in new engagements.

Moreover, the models confirmed the assertion that partner selection is also driven by the industry expertise of the engagement partner (Blouin et al., 2007; Moroney, 2007; Solomon et al., 1999). However, the results are only somewhat in line with previous findings, as our models indicate that, when a company engages a pair of audit partners to sign off on an audit report, clients find it is sufficient that only one should be an industry specialist, and not both of them. Even though earlier research shows that investors react positively when clients switch from non- to industry specialists as this may improve earnings quality, our findings could indicate that their combination might limit knowledge spread among the partners in the cases when competitors select the same audit firm.

Regarding the partner level network, our study found that the audit partner integration level tends to be limited in the first years after the merger. This could be a result of the transformation of the organizational structure and the adaptation period needed to establish collaborative ties among the employees.

In addition, our results demonstrated that, at an inter-organizational level, despite the fact that KPMG lost its recognition among the public companies in regards the audit services after the establishment of KPMG 2014, the former KPMG clients were still inclined towards engaging that audit firm. This argument complies with the earlier findings that companies acknowledge brand, costs, and length of engagement to be important determinants for audit firm selection (Riel et al., 2005; Bendixen et al., 2014; Beidenbach et al., 2015). Complementary, they apprehend that the audit firm change might be expensive for its negative impact on a company's reputation level, which could generate stock price shocks (Beatty, 1989; Barber et al., 1995; Ashtana et al., 2010).

This study has several limitations. First, the single national level context has some obvious limitations, as it is difficult to extend conclusion to other contexts. However, such an approach was necessary because both data and analysis are sensitive to the institutional setting. Second, though the central parameter of our statistical models is a dyadic covariate that connects two momentums, we were unable to capture auditor selection mechanism dynamics over the period of time. However, this only partially addressed the problem by using multi cross-sectional modeling, which still lacks parameters that can measure the dynamics between the two cross-sectional measures. Third, this study employs a straightforward binary value to categorize the strength of relationship proxied by repeated engagement and does not differentiate the strength of the relationship on different scales by introducing possible other interpersonal characteristics that might give other values to the strength of relationships. Finally, this study does not take into account the sensitivity of demand mechanisms related to the audit fee effect (Bar-Yosef & Sarath, 2005), which may enrich reflections around the switching costs and the discussion about the trade-off between fees and the strength of interpersonal ties.

Future research should address these issues by exploiting different methodologies regarding capturing the effect of repeated interactions by proposing different approaches to measure the strength of client-auditor relationships. One obvious extension is to see if the attachment of a client to a particular audit partner leads to rent extraction (in terms of extra fees) or is driven by a discount offered by the new firm in order to induce the client to stay with their former audit partner. Moreover, it would be interesting to investigate a similar question in different corporate contexts and different regions in order to increase the generalizability of the study. Lastly, it would be appealing to look deeper into the one-mode network among the audit partners in order to investigate the knowledge management perspectives of audit partner networks after the merger in the same or similar empirical contexts.

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