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Alumni Network Centrality and Competitive Aggressiveness

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This paper examines the role of external resources and information advantages embedded in a firm's alumni network in the adoption of aggressive competitive strategies. We extend the competitive dynamics literature and social network theory by analysing the effect that the acquisition of external resources and information advantage has on corporate competitive strategy. We hypothesize that more central firms in alumni networks are associated with more aggressive competitive actions and better performance. We introduce extensive data from China and find strong support for our central hypothesis. Further, the data indicate that the effect is stronger in firms with high product market competition, high input–output network centrality, and during periods of high economic policy uncertainty. The results are robust to several endogeneity tests.

Introduction

Existing studies show that competitive aggressiveness is most advantageous in dynamic competitive environments, such as newly developed markets and hypercompetitive (Chen, Lin and Michel, 2010), high-velocity (Nadkarni, Chen and Chen, 2016) and high-growth industries (Andrevski *et al.*, 2014). Competitive dynamics and the resource-based view (RBV) emphasize the important role of internal resources in facilitating competitive action as well as sustaining competitive advantage (Barney, 1991). Firms do not just adopt competitive strategies based on their own limited resources as individual entities, but exist in a network of relationships that may influence their competitive behaviour. However, few studies have focused only on the role of cooperative networks in enhancing corporate competitive aggressiveness and market performance (Sanou, Le Roy and Gnyawali, 2016), with limited attention has been paid to the role of resources and information embedded in social networks formed by corporate executives.

Drawing from the competitive dynamics literature (e.g. Bouncken *et al.*, 2018; Han *et al.*, 2023; Kald, Nilsson and Rapp, 2000; McGee, Thomas and Pruett, 1995; Peng *et al.*, 2012; Ritala, 2012; Thomas and Pollock, 1999) and social network literature (Granovetter, 1992; Nahapiet and Ghoshal, 1998; Amin *et al.*, 2020; Renneboog and Zhao, 2011), we fill this gap by proposing and testing a plausible explanation based on the enhanced corporate competitive aggressiveness brought by the executive alumni network. Specifically, we analyse the effects of a firm's position in the executive alumni network on corporate competitive aggressiveness (i.e. competitive volume, complexity and similarity), using hand-collected data from the listed firms in the largest emerging market (i.e. China).

Unlike most existing studies on this topic, which cover mainly developed countries, we focus on China in this paper for several reasons. First, China is the largest emerging market and the second largest economy in the world, but is seriously under-researched relative to the Western world. Second, the effects of alternative

A free video abstract to accompany this article can be found online at: https://youtu.be/zQzbXRzAvSM non-market channels such as social networks are likely to be more pronounced in China than in the Western world, as in China the legal system and law enforcement are weaker, and hence transaction costs in standard market channels are higher (Allen, Qian and Qian, 2005). Furthermore, the term '*guanxi*' in China has been criticized in the literature (Rui and Bruyaka, 2021; Su *et al.*, 2023; Wong and Tjosvold, 2010). Third, the sources for social networks in China are more clear-cut than those in the Western world, as in China social networks are mainly generated from three sources only: hometown (i.e. prefecture) ties, college ties and past employment relationships (Guan *et al.*, 2016; Rui and Bruyaka, 2021; Su *et al.*, 2023; Wong and Tjosvold, 2010). Fourth, frequent policy shocks in China allow us to address potential endogeneity problems from different perspectives, which adds robustness to our results.

We focus on alumni relationships based on college ties for the following reasons. First, individuals' choices of undergraduate and graduate programmes align with their interests and abilities, which makes alumni relationships stronger, longer lasting and more influential (see, e.g., Cohen, Frazzini and Malloy, 2008). Second, existing studies suggest that alumni relationships tend to be more homogeneous, facilitating effective communication through shared background (Cohen, Frazzini and Malloy, 2008). Third, alumni are influenced by the values instilled during their college experience, which impact their decision-making even years after graduation (Shue, 2013). Ongoing alumni reunions reinforce this influence, resulting in corporate executives from the same alma mater having similar management philosophies and being susceptible to each other's influence. Fourth, prior research demonstrates that alumni relationships create about four times more value than coworker and other social relationships (Engelberg, Gao and Parsons, 2013), and, furthermore, alumni networks are significant channels for disseminating private information in China (Chen *et al.*, 2022; Gu *et al.*, 2019).

Our intuition is simple. First, alumni networks are potential channels for the transfer of resources between the connected parties (Nohria, 1992), and firms with alumni connections have a higher likelihood of cooperation. The process of cooperation often involves the movement of money, equipment, technology and organizational skills between firms. External resources obtained through alumni networks can often serve as a complement to the internal resources of firms (Langlois, 1992), facilitating the adoption of a large combination of different competitive actions by firms. Second, firms with alumni connections are more likely to exchange and transmit valuable information related to competition. Thus, firms that are centrally located in alumni networks have access to new information faster, and may learn more about trends, best practices and current challenges earlier than their peers, which gives these firms stronger information advantages that can empower them to adopt aggressive competitive strategies.

Following the literature on social networks (e.g. Fracassi, 2017; Larcker, So and Wang, 2013), we construct four network centrality measures as our key independent variables to measure a firm's position in the alumni network: degree centrality, closeness centrality, betweenness centrality and eigenvector centrality. Drawing from the competitive dynamics literature in the management discipline (e.g. Ferrier, Smith and Grimm, 1999; Young, Smith and Grimm, 1996) and using content analysis of six categories of new competitive actions captured by news headlines,[1] we build three measures of corporate competitive aggressiveness as our dependent variables, namely the firm's action volume (the total number of competitive actions), competitive complexity (the range of competitive actions) and competitive similarity (the degree of conforming to industry norms).

Our baseline results show that one standard deviation increase in the executive alumni network centrality (i.e. *Degree*) in the current year may enhance the corporate competitive aggressiveness (i.e. *Volume*) by about 3% in the next year. To help mitigate concerns about omitted variable bias and other forms of endogeneity, we use a variety of techniques to examine the robustness of our results. First, following Oster (2019), we estimate effects after removing potential bias arising from unobservables. Second, we exploit the issuance of *Rule 18* as a quasi-natural experiment to identify the causal effect of alumni network centrality on competitive strategy (Hope, Yue and Zhong, 2020). Third, we attempt to capture exogenous variation in executive alumni network centrality by using the number of individuals in the management team who were admitted into universities after 1999 (Che and Zhang, 2018) and provinces' policies to attract highly skilled emigrants (Giannetti, Liao and Yu, 2015) as instrumental variables (IVs). Fourth, we exclude the effect of executive human capital and other types of social networks, for example hometown and colleague networks. Finally, we strengthen the basic logic in the paper that firms compete in more aggressive ways owing to the advantage of information communication and resources exchange via the alumni network, rather than to the power and influence derived from the network, by considering the performance implications.

Further, we explore the cross-sectional and time-series variations in the effect of alumni network centrality on competitive aggressiveness. First, if the executive alumni network enhances the competitive advantages of participating firms by allowing them to acquire critical resources that are not otherwise easily available, then we expect such an effect to be more prevalent among firms

[1]Examples of new competitive actions include new product action, new pricing action, new marketing action, new capacity action, new legal action and new signalling action.

operating in industries facing fierce competition. Second, firms that are more central in the input-output network are more vulnerable to shocks. This vulnerability provides them with stronger incentives to take competitive actions and allows them to benefit more from the dissemination of information through executive alumni relations. Third, if the executive alumni network is an important channel to exchange and disseminate information and thus reduce uncertainty, we predict that the effect of the alumni network centrality on competitive aggressiveness is more pronounced in high-uncertainty periods. Consistent with the above predictions, we find that the effect of the alumni network centrality on competitive aggressiveness is more pronounced in firms with higher product market competition and higher input–output network centrality, as well as in periods with high economic policy uncertainty.

We contribute to the extant literature in several ways. First, we contribute to social network embeddedness theory by focusing on both structural embeddedness and relational embeddedness. Prior studies focus mainly on the structural dimension of network embeddedness and find that social network among executives improves characteristic-adjusted stock returns (Larcker, So and Wang, 2013), capital investment similarity (Fracassi, 2017), financial reporting quality (Omer, Shelley and Tice, 2020) and firm risk (Fan *et al.*, 2021, 2023). We analyse the effect of alumni networks on corporate competitive aggressiveness by distinguishing among four network positions (degree, closeness, betweenness and eigenvector centrality) to show the role of information quantity and focusing on the nature of alumni relationships to show, in turn, the role of information quality. Our findings suggest that alumni relationships among executives may help firms to access new information faster and be more credible in implementing aggressive competition strategies.

Second, our paper adds to the literature on competitive dynamics and RBV that emphasizes the important role of internal resources in facilitating competitive action as well as sustaining competitive advantage (Barney, 1991). There have been recent calls for researchers to identify new drivers for corporate competitive aggressiveness from an external resource perspective (e.g. Connelly *et al.*, 2019; Hughes-Morgan and Ferrier, 2017; Hughes-Morgan, Ferrier and Labianca, 2010; Nadkarni, Chen and Chen, 2016). It is increasingly important to understand how external resources embedded in social networks among executives affect corporate competitive aggressiveness, given that in recent years there has been an increasing consensus that social networks among executives have many corporate consequences that have not been fully discovered in the extant literature.

Third, our study echoes the call of Jiang and Kim (2020) for research on the bright side of *guanxi* in China. Owing to the costs *guanxi* incurs, social networks in China have been heavily criticized in the literature (Rui and Bruyaka, 2021; Su *et al.*, 2023; Wong and Tjosvold, 2010). Our results in this paper suggest that *guanxi* may help executives gain an information advantage so that they can implement more aggressive competition strategies.

The remainder of the paper unfolds as follows. The next section discusses the relevant literature and develops our hypothesis. Thereafter, we discuss the data and methodology. The causal link between executive alumni network centrality and competitive aggressiveness is established in empirical sections, which also investigate the cross-sectional and time-series variations in the effect of alumni network centrality on competitive aggressiveness via sub-sample analyses. The final section concludes.

Theory and hypothesis

Resource-based view and competitive aggressiveness

Competitive dynamics and the RBV of the firm became prominent subfields within strategic management research more than three decades ago. Competitive dynamics research focuses on describing, explaining and predicting competitive interactions among firms (Chen and MacMillan, 1992; Grimm, Lee and Smith, 2005). As one of the core concepts in the study of competitive dynamics, competitive aggressiveness has received wide attention from scholars (e.g. Bouncken *et al.*, 2018; Han *et al.*, 2023; Kald, Nilsson and Rapp, 2000; McGee, Thomas and Pruett, 1995; Peng *et al.*, 2012; Ritala, 2012; Thomas and Pollock, 1999). The RBV emphasizes the important role of internal resources in facilitating the adoption of competitive action by the firm as well as sustaining competitive advantage (Barney, 1991). Thus, early studies mainly focused on the effect of corporate internal resources, including firm size (Chen and Hambrick, 1995; Young, Smith and Grimm, 1996), past performance (Gnyawali, He and Madhavan, 2006; Miller and Chen, 1994) and the heterogeneity and experience of the executive team (Ferrier, 2001; Hambrick, Cho and Chen, 1996; Hughes-Morgan, Ferrier and Labianca, 2010), on the adoption of aggressive competitive strategy.

Lavie (2006) extended the RBV by showing that external network resources can also enable firms to gain a competitive advantage. Network resources refer to ‘external resources embedded in a firm’s alliance network that provide strategic opportunities and affect firm behaviour and value’ (Lavie, 2006, p. 638). Based on existing research, a central location in a network provides firms with informational advantages that increase their chances of accessing resources from the network (Wasserman and Faust, 1994). Firms will also become more competitive and aggressive (Andrevski and Ferrier, 2019). Based on data about the competitive and cooperative actions of firms in the mobile telephone industry, Sanou, Le Roy and Gnyawali (2016) show that the centrality of a firm in a cooperative network increases the volume and variety of competitive actions. However, there are still many unexplored questions regarding why and how firms undertake aggressive competitive strategies in the context of different social networks.

Competitive dynamics involves multiple levels of interaction, including the effect of individual firms, peer-to-peer pairs and industry-level factors on competitive behaviour and responses to the behaviour of rivals. The advantage of social network analysis as applied to the study of competitive dynamics is that this approach allows for the simultaneous analysis of multiple levels of individuals, pairs and networks (Wasserman and Faust, 1994). Moreover, social network analysis can observe not only the interaction between peer firms but also the interaction effects of competitive behaviour among non-peer firms. Therefore, the use of social network analysis can help to contribute to existing competition dynamics studies that focus on peer firms, further advance research in this field, and lead to a better understanding of the competition phenomenon in product markets.

Network embeddedness

Existing studies introduce the concept of network embeddedness to capture the structure of relationships between firms (Granovetter, 1992; Nahapiet and Ghoshal, 1998). Moran (2005) points out that network embeddedness provides an opportunity for accessing information and resources through relationships between firms, which creates social capital for firms embedded in the network. Granovetter (1992) establishes the distinction between network embeddedness through two dimensions: structural embeddedness and relational embeddedness. Structural embeddedness focuses on the configuration of the network, whose key structural features are connectivity, centrality and hierarchy. The second dimension, relational embeddedness, indicates the quality of these relationships, with key dimensions including interpersonal trust and trustworthiness, overlapping identities, and feelings of closeness or interpersonal solidarity. Nahapiet and Ghoshal (1998) redefined Granovetter's (1992) initial categorization by stating that structural embeddedness is 'the impersonal configuration of linkages between people or units', and relational embeddedness is 'personal relations people have developed with each other through a history of interactions' (Nahapiet and Ghoshal, 1998, p. 244). Both the quantity and the quality of network ties may matter for information diffusion. Thus, we focus on both the structural and the relational dimensions of network embeddedness (Granovetter, 1992; Moran, 2005; Nahapiet and Ghoshal, 1998) to show its effects on corporate competitive aggressiveness.

Structural embeddedness and information quantity. Gulati (1995, 1998) emphasizes that structural embeddedness provides information about the firm's structural position in the network, while Grewal, Lilien and Mallapragada (2006) emphasize the firm's position in the network, pointing out that not all positions in the network affect the firm's performance in the same way owing to the differential information availability. The network embeddedness of firms affects their performance through the flow of information generated by interactions in the network (Grewal, Lilien and Mallapragada, 2006). Regarding this, existing studies distinguish between four network positions (degree, closeness, betweenness and eigenvector centrality). Larcker, So and Wang (2013) find that, as measured by all four network centrality proxies, firms that are more centrally located in the network have higher returns. Arranz, Arroyabe and Fernandez de Arroyabe (2020) find that each of the social network dimensions (degree, betweenness and eigenvector centrality) has a different impact on the exploration and exploitation of R&D. First, degree centrality emphasizes the amount of information a firm can access and obtain by virtue of its network of relationships (Ahuja, 2000). A larger value indicates that the firm has more direct connections, which makes the firm highly interconnected with other firms, and, as a result, there are relatively more channels for information and resource exchange.

Second, closeness centrality emphasizes a firm's reachability to every other firm with the fewest number of intermediate firms, reflecting the speed and ease with which the firm is connected to other firms (Gulati and Gargiulo, 1999; Riccaboni, Wang and Zhu, 2021). A larger value means that the firm has relatively closer ties with other firms, which makes information and resource exchange faster and easier. Faster and more timely access to information and resources is important for adopting competitive strategies to cope with the rapidly changing competitive environment.

Third, betweenness centrality emphasizes the extent to which a firm connects to other firms (Gilsing *et al.*, 2008; Grewal, Lilien and Mallapragada, 2006). Firms with greater betweenness centrality play an important role in connecting with other firms. Gilsing *et al.* (2008) state that a larger value of betweenness centrality provides an intermediary as well as access to new information. Thus, when betweenness centrality is larger, the firm can access more diverse and novel information through the network of other firms that are not connected (Gilsing and Nooteboom, 2006; Gulati, 1995).

Finally, eigenvector centrality emphasizes the extent to which a firm connects to other firms structurally embedded in the network (Borgatti and Halgin, 2011). Firms with higher eigenvector centrality are more closely associated with the network centre and have better access to information that has value, content and meaning (Bonacich, 1987; Grewal, Lilien and Mallapragada, 2006). Uzzi (1996) notes that information exchanges in this position are rich in detailed product-market characterization, are oriented towards common problem solving, and emphasize the richness of the information that a firm can obtain through its network of relationships.

Relational embeddedness and information quality. In China, relationships are interwoven into everyone's social life and deeply embedded in Chinese culture. Confucius proposed five basic forms of relationships, namely ruler and subject, father and son, brother, husband and wife, and friend. The gradual expansion of family relationships that include emotions and obligations from the family to the community, a trend Fei, Hamilton and Zheng (1992) called 'the pattern of differential order', suggests that traditional Chinese society is a society of acquaintances and that the mechanism of trust is 'kinship and trust', that is, trust due to familiarity. Lin (1989) conceptualized social relationships as 'family-like relations'. Relationships work in concentric circles, with close family members at the centre, and distant relatives, classmates, friends and acquaintances in that order outwards, based on relational distance and trust (Yang, 2016).

The interpersonal relationships that build social networks exist in many forms, and alumni relationships based on a common educational background are an effective basis for forming social networks for the following reasons. First, individuals' choice of undergraduate and graduate programmes aligns with their interests and abilities, which makes alumni relationships stronger, longer lasting and more influential (McPherson et al., 2001; Cohen, Frazzini and Malloy, 2008). Hence, interactions embedded in alumni relationships are more likely to promote trust and cooperation.

Second, existing studies suggest that alumni relationships tend to be more homogeneous, facilitating effective communication through shared background (Cohen, Frazzini and Malloy, 2008). Cohen, Frazzini and Malloy (2008) emphasize that alumni networks are a particularly effective form of social network, owing to shared interests and higher homogeneity among alumni, which allows alumni to generate higher levels of communication and more enduring relationships.

Third, alumni are influenced by the values instilled during their college experience, which impacts their decision-making even years after graduation (Shue, 2013). Ongoing alumni reunions reinforce this influence, resulting in corporate executives from the same alma mater sharing similar management philosophies and being susceptible to each other's influence.

Fourth, prior research demonstrates that alumni relationships create about four times more value than coworker and other social relationships (Engelberg, Gao and Parsons, 2013), and alumni networks are significant channels for disseminating private information in capital markets. This holds in both developed stock markets (Cheong *et al.*, 2022; Cohen, Frazzini and Malloy, 2008, 2010) and China (Gu *et al.*, 2019; Chen *et al.*, 2022). In China, the dissolution of various old associations, such as hometown associations, chambers of commerce and charitable associations, after 1949 and the fragmentation of society into atomized individuals have reinforced the value of alumni relationships. Moreover, this value is particularly important for executives in management positions (Brown *et al.*, 2012).

Social resources embedded in relationship networks are often referred to as 'social capital' and include information, trust and reciprocity (Woolcock, 1998). Alumni networks influence corporate decision-making through information sharing, enhanced trust and cooperative channels. First, through information-sharing channels, alumni networks facilitate information sharing and reduce information asymmetry (Rui and Bruyaka, 2021; Su *et al.*, 2023; Wong and Tjosvold, 2010). If information is obtained from acquaintances, this information is given a higher value and credibility. Moreover, information in alumni networks is less costly to obtain, and relevant information can be obtained simply by interacting socially. Second, reputation is particularly important in alumni networks, limiting opportunistic behaviour and strengthening trust among individuals in the network. Third, trust among individuals owing to their familiarity with each other promotes cooperation and efficient behaviour among individuals in the networks.

Hypotheses

Studies of competitive dynamics and RBV have shown that intra-firm resources have a significant effect on a firm's competitive behaviour. Firms are more likely to act aggressively when they have stronger resource and information advantages (Chen, 1996). However, firms do not just take aggressive competitive strategies in the form of a single entity with limited resources, but exist in a network of relationships that influence their competitive behaviour. The value of executive alumni networks is often reflected in the quantity and quality of information and resources embedded in them, which have an effect as important as internal resources on the firm. First, the executive alumni network is a potential channel for the transfer of resources within the connected parties (Nohria, 1992). Firms with alumni relationships are more likely to collaborate because of their trust and ability to communicate, to convey implicit information or to make joint decisions in a more timely and effective manner. The process of collaboration often involves the transfer of currency, equipment, technology and organizational skills between firms.

Second, existing studies examine the effect of executive alumni relationships between information providers, such as firm managers, and information demanders, such as fund managers (Cohen, Frazzini and Malloy, 2008), analysts (Cohen, Frazzini and Malloy, 2010) and auditors (Guan *et al.*, 2016), on information transfer and find that executive alumni relationships can enable the information-demand side to obtain private information about the firm. The flow of information between firms with executive alumni relationships includes relevant information and knowledge obtained from connected firms about their competitive intentions, strategies, required resources and so on. Owing to their unique characteristics, alumni relationships give such information a higher level of credibility and value. Thus, in the alumni network, firms with a larger degree centrality can access and obtain more such information, those with a larger closeness centrality can access and obtain such information faster and more easily, those with a larger betweenness centrality can access and obtain extra non-redundant information, and those with a larger eigenvector centrality can access and obtain more abundant information, which collectively gives these firms a stronger resource and information advantage and encourages them to adopt a more aggressive competitive behaviour. Based on the above analysis, we hypothesize the following:

H1: Alumni network centrality can encourage firms to adopt more aggressive competitive strategies.

Data and methodology

Data and sample

The data used in this study come from several sources. We obtained educational background information about executives and directors from the Figure Characteristic Database of Listed Firms via the China Stock Market and Accounting Research (CSMAR) database. The data included in this database come from listed firms' annual reports, interim announcements, IPO data, Sina.com, China Economic Net and so on. Although there is still some missing data on the educational background of executives and directors, obtaining data on the educational background of executives and directors from multiple sources can maximize the completeness and representativeness of the data. Firms' financial and accounting data were retrieved from the CSMAR database, and financial news headlines data were retrieved from the Chinese Financial News Database (CFND) via the Chinese Research Data Services (CNRDS) platform.

We identify whether the executives (including CEOs and CFOs) and directors of two firms are alumni-connected by exploiting their educational background information and using social network analysis to examine the effect of firms' positions in the alumni network on their competitive aggressiveness.[2] To eliminate the concern that changes of coverage in the educational backgrounds of executives and directors might affect the results, in line with existing studies (Fan *et al.*, 2023; Fang *et al.*, 2022) we first identify 9126 unique executives and directors for 2989 firms with non-missing educational background information between 2007 and 2018 from the Figure Characteristic Database of Listed Firms via the CSMAR database. The sample period starts in 2007 because it is the first year that the educational background information of corporate executives and directors is disclosed in detail in the database. Second, we exclude firms in the financial and insurance industries (owing to their special reporting requirements) and construct firm–executive-pairs year-level data based on college name, resulting in 13,259,555 firm–executive pairs. Third, we collapse the data to firm-pairs year level, resulting in 3,212,948 firm pairs. Finally, we compute the network centrality of each firm based on firm-pairs year-level data. This process yields 18,476 firm-year observations of 2896 unique firms. Finally, we merge our network centrality data with competitive aggressiveness data and other control variable data based on the ticker symbol, resulting in a total of 14,725 firm-year observations of 2634 unique firms in our final sample. All continuous variables are winsorized at the top and bottom 1% levels. To control for heteroscedasticity, we cluster the robust standard errors at the firm level.

Measures

Competitive aggressiveness. According to whether the news headlines contain the corresponding keywords, as shown in Appendix A, each competitive action was classified into six mutually exclusive activity categories: pricing actions, marketing actions, product actions, capacity actions, legal actions, and signalling actions (Basdeo *et al.*, 2006; Ferrier, Smith and Grimm, 1999; Young, Smith and Grimm, 1996).

Following existing studies (Ferrier, Smith and Grimm, 1999; Basdeo *et al.*, 2006; Nadkarni and Chen, and Chen, 2016), we use the volume (Volume), complexity (Complexity) and similarity (Similarity) of competitive behaviour to measure firms' competitive aggressiveness. Volume is measured by the natural logarithm of the total number of competitive actions

[2]We conducted a robustness test to examine the effect of the networks based on executives and all directors on the board, respectively. The results are basically unchanged.

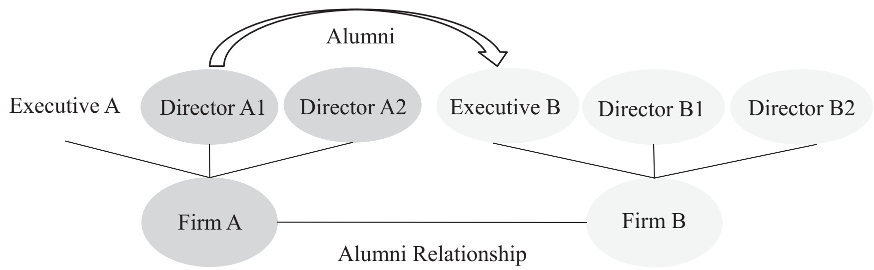

Figure 1. An illustrative example for the construction of alumni relationships. Alumni is defined as two individuals who attended the same college at the same time or at different times

taken by the firm each year. In general, the more competitive actions a company takes, the more aggressive its competitive strategy. The specific formula for the competitive volume indicator is as follows:

$$\text{Volume} = \ln(1 + p_{it}), \tag{1}$$

where p_{it} is the number of competitive actions taken by firm i in year t.

It is worth noting, however, that competitive behaviour is not homogeneous. For example, the release of a new marketing strategy is different from the competitive behaviour of suing a competitor. Firms are more likely to be more competitive when they adopt a combination of competitive behaviours from many different categories than when they adopt the same category of competitive behaviour repeatedly (Ferrier, Smith and Grimm, 1999). Therefore, we construct the second competitive indicator (Complexity) by taking the combination of competitive behaviours of a firm into account, where higher complexity means a more aggressive competitive strategy of the firm. The specific formula for the competitive complexity indicator is as follows:

$$\text{Complexity} = 1 - \sum_{n=1}^{6} (p_{int}/T_{it})^2, \tag{2}$$

where p_{int} is the number of competitive actions in the nth category taken by firm i in year t, T_{it} is the total number of all competitive actions taken by firm i in year t, and n is the number of competitive action categories.

Legitimacy refers to the degree to which an organization's actions are considered consistent with existing institutional logics, norms and beliefs (Suchman, 1995). Firms are perceived as more legitimate when their actions conform to industry norms and are, therefore, similar to those of other firms in the industry (DiMaggio and Powell, 1983). Thus, although firms strive to adopt different competitive actions because such differences enable them to gain a competitive advantage (Young, Smith and Grimm, 1996), they also need to ensure that they are sufficiently similar because the similarity ensures that their actions are perceived as legitimate (Deephouse, 1999). We measure Similarity by the difference between the proportion of actions of a given type for the focal firm and its peers. The specific formula for the competitive similarity indicator is as follows:

$$\text{Similarity} = 2 - \sum_{n=1}^{6} [(p_{int}/T_{it}) - (p_{pnt}/T_{pt})]^2, \tag{3}$$

where p_{pnt} is the sum of the number of competitive actions in the nth category taken by all firms in the industry that firm i belongs to in year t, and T_{pt} is the sum of the number of all competitive actions taken by all firms in the industry that firm i belongs to in year t.

Alumni network centrality. We consider two firms as alumni-connected if any of their executives and directors attended the same college at the same time or different times. For example, in Figure 1, if any of the executives or directors from Firm A (e.g. Director A1) and Firm B (e.g. Executive B) attended the same college at the same time or different times, we consider these two firms as alumni-connected. Then, we use network centrality to measure a firm's position in the alumni network. Consistent with existing studies (Fracassi, 2017; Larcker, So and Wang, 2013), we select four network centrality measures commonly used in social network analysis: degree (Degree), closeness (Closeness), betweenness (Betweenness), and eigenvector (Eigenvector) centrality. The detailed calculations are shown in Appendix B. Each of the four standard network centrality measures represents one aspect of the firm's connectedness in the alumni network of its executives.

Specifically, the first measure, degree centrality (Degree), counts the number of other firms directly connected to the focal firm. The larger the degree centrality, the more channels firms possess to communicate with others. The second measure, closeness centrality (Closeness), reflects how quickly and easily a firm can reach other firms through executive alumni relationships. The larger the closeness centrality, the closer the ties the focal firm has with other firms. The third measure, betweenness centrality (Betweenness), examines the positioning

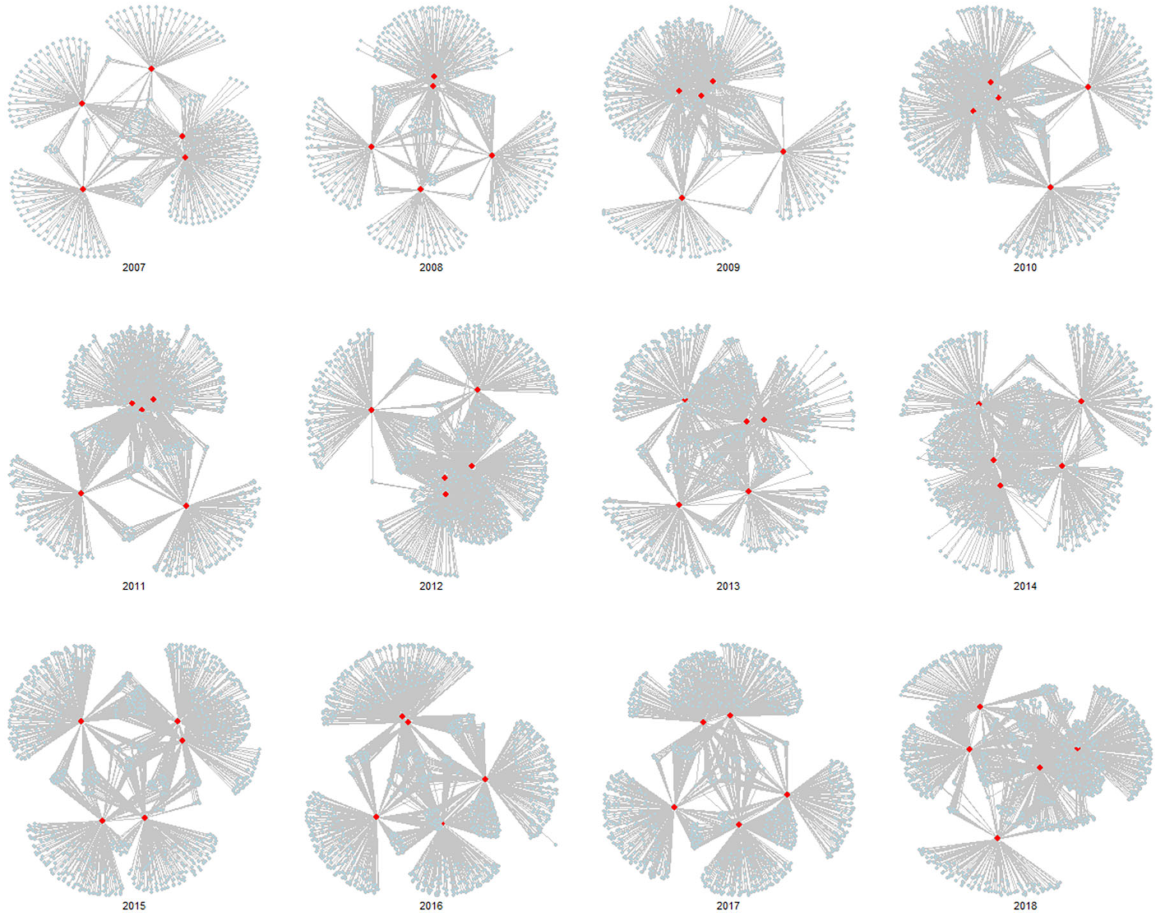

Figure 2. Alumni network in five representative listed firms in China from 2007 to 2018. The large red circles indicate the five listed firms we selected, and the small blue circles indicate other listed firms that have at least one executive who is connected to these five firms by alumni relationships [Colour figure can be viewed at wileyonlinelibrary.com]

advantage of a firm in the entire executive alumni network. The larger the betweenness centrality, the more geodesic paths there are between pairs of other firms. The fourth measure, eigenvector centrality (Eigenvector), evaluates how many other firms are connected to the focal firm and the relative importance of the firms directly connected to the focal firm via the executive alumni network. A larger value indicates that the firm has more direct connections, and such connections can reach or influence more other firms.

The executives in the listed firms in China are widely interconnected via the alumni network. Figure 2 plots the alumni network of five randomly selected listed firms from 2007 to 2018. The large red circles represent the five listed firms we selected randomly, and the small blue circles represent firms connected to them by executive alumni relationships.

Control variables. Based on the literature, we control for many factors that potentially affect firm-level competitive aggressiveness, including firm characteristics, top management team (TMT) characteristics, and industry characteristics.

Finally, we include year- and industry-fixed effects to control for the effects of macro-environmental changes over time and any time-invariant industry-level factors that affect firms' propensity to take competitive actions, respectively.

A detailed description of control variables and variable definitions are given in Appendix C.

Analytical models

Following existing studies (Ferrier, Smith and Grimm, 1999; Nadkarni, Chen and Chen, 2016), we estimate the following baseline regression model for firm i in industry s:

$$\begin{aligned}\mathrm{CA}_{i,t+1} = {} & \beta_0 + \beta_1 \mathrm{Centrality}_{i,t} + \beta_2 \mathrm{Size}_{i,t} + \beta_3 \mathrm{Growth}_{i,t} \\ & + \beta_4 \mathrm{Current}_{i,t} + \beta_5 \mathrm{Debt/equity}_{i,t} + \beta_6 \mathrm{SG\&A}_{i,t} \\ & + \beta_7 \Delta\mathrm{ROA}_{i,t} + \beta_8 \Delta\mathrm{ROS}_{i,t} + \beta_9 \mathrm{TMTSize}_{i,t} \\ & + \beta_{10} \mathrm{TMTAge}_{i,t} + \beta_{10} \mathrm{TMTHeterogeneity}_{i,t} \\ & + \beta_{11} \mathrm{Unpredictability}_{s,t} + \beta_{12} \mathrm{Homogeneity}_{s,t} \\ & + \beta_{13} \mathrm{HHI}_{s,t} + \mathrm{YearFE}_t + \mathrm{IndustryFE}_s + \varepsilon_{i,t}, \quad (4)\end{aligned}$$

Table 1. Descriptive statistics

Panel A: Descriptive statistics for the main variables

	Obs	Mean	SD	Min	P25	Median	P75	Max
Competitive aggressiveness								
Volume	14,725	1.9210	0.9553	0.0000	1.3863	1.9459	2.5649	4.9200
Complexity	14,725	0.4066	0.2333	0.0000	0.2778	0.4800	0.5926	0.7769
Similarity	14,725	1.7884	0.2495	0.5501	1.7099	1.8742	1.9525	2.0000
Network centrality								
Degree	14,725	0.0987	0.0808	0.0005	0.0350	0.0850	0.1374	0.4481
Closeness	14,725	0.5053	0.0449	0.0023	0.4887	0.5101	0.5286	0.6421
Betweenness	14,725	0.0005	0.0011	0.0000	0.0000	0.0001	0.0004	0.0143
Eigenvector	14,725	0.0182	0.0154	0.0000	0.0057	0.0144	0.0271	0.0827
Firm characteristics								
Size	14,725	7.6215	1.2705	3.0834	6.7493	7.5196	8.3774	13.1717
Growth	14,725	0.2203	0.5981	−0.9484	−0.0035	0.1302	0.3035	12.4619
Current	14,725	2.3285	2.5404	0.1616	1.0812	1.5661	2.5104	31.8109
Debt/equity	14,725	1.1942	1.3518	−19.2583	0.3749	0.7814	1.5088	15.7399
SG&A	14,725	0.1781	0.1728	0.0030	0.0840	0.1363	0.2176	4.3564
ΔROA	14,725	−0.5352	3.9821	−115.3304	−0.4892	−0.1061	0.1756	40.3576
ΔROS	14,725	−0.5030	3.5421	−83.6721	−0.4202	−0.0778	0.1537	33.5962
TMT characteristics								
TMTSize	14,725	7.3711	2.7576	2.0000	5.0000	7.0000	9.0000	24.0000
TMTAge	14,725	46.6790	3.6338	36.0000	44.2000	46.7500	49.2857	56.1667
TMTHeterogeneity	14,725	0.0414	0.4409	−1.2221	−0.2653	0.0537	0.3651	1.5913
Industry characteristics								
Unpredictability	14,725	0.0289	0.0241	0.0046	0.0136	0.0266	0.0362	0.2880
Homogeneity	14,725	0.0067	0.0346	0.0001	0.0004	0.0007	0.0020	0.6688
HHI	14,725	0.0607	0.0947	0.0077	0.0144	0.0161	0.0640	0.7269

Panel B: Correlation coefficients for centrality variables

	Degree	Closeness	Betweenness	Eigenvector
Degree	1.0000	0.9877	0.8147	0.9710
Closeness	0.8557	1.0000	0.8002	0.9465
Betweenness	0.7262	0.5333	1.0000	0.7634
Eigenvector	0.9428	0.8048	0.6673	1.0000

Panel C: Principal component analysis of centrality variables

	Comp. 1	Comp. 2	Comp. 3	Comp. 4
Degree	0.5401	−0.0901	−0.2279	−0.8051
Closeness	0.4900	−0.5040	0.6850	0.1912
Betweenness	0.4396	0.8465	0.2742	0.1226
Eigenvector	0.5243	−0.1459	−0.6353	0.5479
Eigenvalue	3.2827	0.4902	0.1824	0.0447
% Var explained	82.07%	12.26%	4.56%	1.12%
Cumulative %	82.07%	94.32%	98.88%	100.00%

Table 1 Panel A reports the descriptive statistics for the main variables used in this study, including industry-, firm- and TMT-level variables. The sample of baseline consists of 14,725 firm-year observations from 2007 to 2018. The sample period for *Volume*, *Complexity* and *Similarity* is from 2008 to 2019. To mitigate the effect of outliers, all continuous variables are winsorized at the top and bottom one percentile. All variables are defined in Appendices A–C. Panel B shows the correlation coefficients for *Centrality* variables, and Panel C shows the principal component analysis of *Centrality* variables.

where $\mathrm{CA}_{i,t+1}$ indicates the competitive aggressiveness for firm i in year $t+1$ (measured by Volume, Complexity and Similarity of competitive actions). $\mathrm{Centrality}_{i,t}$ measures the firm's alumni network centrality for firm i in year t (i.e. Degree, Closeness, Betweenness and Eigenvector centrality).

Descriptive statistics

Table 1 Panel A reports descriptive statistics for the main variables. The average number of competitive actions taken by listed firms is about 7 each year, and the means of Complexity and Similarity are 0.4024 and 1.7856, respectively. For the centrality variables, the mean (median) of Degree centrality is 0.0987 (0.0850), the mean (median) of Closeness centrality is 0.5053 (0.5101), the mean (median) of Betweenness centrality is 0.0005 (0.0001), and the mean (median) of Eigenvector centrality is 0.0182 (0.0144). The summary statistics of all variables are generally consistent with prior studies (i.e. Nadkarni, Chen and Chen, 2016).

Panel B reports a correlation analysis for the four proxies of centrality. The results show that in the alumni network, if a firm has direct connections to more firms (more connections), the firm is also closer to other firms, is more likely to be located in a key intermediary position (at the centre), and is more likely to be connected to the firms with more connections (higher quality).

The principal component analysis allows for the extraction of the principal components of the four centrality variables, namely the linear combinations that maximize the variance of the original centrality variables. This process allows us to identify the most important 'common components' of the four centrality variables in terms of their potential effects on corporate competitive aggressiveness. Panel C reports the results of the principal component analysis of the four centrality variables. The first principal component (the only component with eigenvalues >1) captures more than 80% of the variance of the four centrality variables. Because the factors for each variable are essentially the same, we use the first principal component PC1 as an overall measure of whether a firm is centrally located in the alumni network.

Empirical results

Executive alumni network centrality and competitive aggressiveness

Table 2 presents the results relating to the effect of our conjectured executive alumni network centrality on competitive aggressiveness as shown in Equation (4). Results yielded by models in which Volume, Complexity and Similarity are treated as key dependent variables are reported in Panels A–C, resepctively. The findings reported in columns (1)–(5) of each panel are obtained when Degree, Closeness, Betweenness, Eigenvector and PC1 are adopted as the independent variable, respectively.

As shown in Panel A, the estimated coefficients for all four measures of network centrality and their first principal component PC1 are positive and statistically significant (p-values are all smaller than 0.01), indicating that executives' alumni network centrality is associated with a higher volume of competitive actions adopted by firms. This effect is also economically significant in percentage terms. For example, the coefficient on Degree in column (1) is 0.723, indicating that a one standard deviation increase in degree centrality will increase the volume of competitive actions by about 3% [=(0.723 × 0.0808)/1.9210]. Concerning the complexity dimension (Complexity), results reported in Panel B show that the estimated coefficients on network centrality measures continue to be statistically significant at the 10% level or better, with economic magnitudes similar to those in Panel A. The test of similarity of competitive action appears in Panel C. As can be seen, the similarity of competitive actions increases with the alumni network centrality, suggesting that firms tend to compete using similar strategies, namely with an increase in aggressiveness.

As expected, several of our control variables are significant predictors of the competitive aggressiveness of firms. For example, competitive aggressiveness increases with firm size, sales growth and current ratio, probably because these firms process resources to experiment with a wide range of competitive moves. A larger TMT size fosters a diversity of opinions and perspectives, broader specialization of skills increase, and greater awareness of alternatives, so these firms are more likely to initiate many complex and unique competitive actions (Ferrier, 2001; Hambrick, Cho and Chen, 1996; Wiersema and Bantel, 1992). Consistent with expectations, younger TMTs are inclined to increase their competitive aggressiveness incrementally owing to their higher risk tolerance.

Overall, the results in Table 2 indicate that executive alumni network centrality is indeed associated with higher corporate competitive aggressiveness. That is, firms with higher alumni network centrality would compete aggressively by taking a higher volume, more complexity and more similar competitive actions. These results lend support to our conjectures.

Endogeneity

The positive relationship between executive alumni network centrality and competitive aggressiveness could be biased by potential endogeneity issues. For example, unobservable firm or management characteristics could affect both management alumni network centrality and competitive strategy, resulting in a spurious correlation between the two. Another possibility is that certain types of firms may purposely seek out high-centrality executives because these firms need the information and resources embedded in the alumni networks, resulting in selection bias. Hence, we implement the following tests to mitigate these concerns.

Omitted variable bias. One way to examine the potential effect of omitted variable bias is to construct bias-adjusted coefficients following recent work by Oster (2019), a method that has been used in the recent literature (Hills, Kubic and Mayew, 2021). The bias adjustment in Oster (2019) is derived by comparing the coefficient on Centrality and the resulting R^2 of a 'short' regression without control variables with an

Table 2. Effect of alumni network centrality on competitive aggressiveness

Panel A: Alumni network centrality and the volume of competitive actions

Dependent variable	Volume$_{t+1}$				
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector	(5) PC1
Centrality	0.723***	0.879***	64.603***	3.830***	0.035***
	(3.85)	(2.81)	(4.10)	(3.98)	(4.01)
Size	0.159***	0.160***	0.157***	0.159***	0.158***
	(10.80)	(10.91)	(10.53)	(10.83)	(10.73)
Growth	0.067***	0.067***	0.067***	0.067***	0.067***
	(3.92)	(3.94)	(3.98)	(3.92)	(3.93)
Current	0.013***	0.014***	0.013***	0.013***	0.013***
	(2.99)	(3.12)	(2.87)	(3.01)	(2.94)
Debt/equity	0.004	0.004	0.005	0.004	0.004
	(0.33)	(0.32)	(0.37)	(0.32)	(0.35)
SG&A	0.213**	0.217**	0.216**	0.211**	0.213**
	(2.51)	(2.58)	(2.54)	(2.52)	(2.52)
ΔROA	−0.000	−0.000	−0.000	−0.000	−0.000
	(−0.07)	(−0.07)	(−0.07)	(−0.05)	(−0.09)
ΔROS	0.000**	0.000**	0.000**	0.000*	0.000**
	(1.98)	(2.00)	(2.01)	(1.96)	(2.00)
TMTSize	0.044***	0.044***	0.043***	0.044***	0.044***
	(8.63)	(8.63)	(8.62)	(8.58)	(8.63)
TMTAge	−0.025***	−0.025***	−0.025***	−0.025***	−0.025***
	(−6.62)	(−6.57)	(−6.61)	(−6.58)	(−6.64)
TMTHeterogeneity	−0.042	−0.025	−0.037	−0.038	−0.047*
	(−1.51)	(−0.92)	(−1.35)	(−1.38)	(−1.66)
Unpredictability	1.126**	1.108**	1.083**	1.127**	1.114**
	(2.16)	(2.12)	(2.08)	(2.16)	(2.14)
Homogeneity	−0.212	−0.212	−0.205	−0.225	−0.216
	(−0.90)	(−0.90)	(−0.86)	(−0.95)	(−0.91)
HHI	0.170	0.155	0.173	0.159	0.165
	(0.76)	(0.69)	(0.78)	(0.71)	(0.74)
N	14,725	14,725	14,725	14,725	14,725
Adj. R^2	0.127	0.125	0.128	0.127	0.127
Oster bias-adjusted Centrality coeff.	0.723	0.879	64.603	3.830	0.035
Oster δ	3.20	2.12	5.23	4.87	3.54

Panel B: Alumni network centrality and the complexity of competitive actions

Dependent variable	Complexity$_{t+1}$				
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector	(5) PC1
Centrality	0.061*	0.047	5.189**	0.349*	0.003*
	(1.77)	(0.79)	(2.23)	(1.93)	(1.82)
Size	0.026***	0.027***	0.026***	0.026***	0.026***
	(10.61)	(10.68)	(10.53)	(10.60)	(10.59)
Growth	0.007*	0.007*	0.007*	0.007*	0.007*
	(1.75)	(1.76)	(1.76)	(1.74)	(1.75)
Current	0.003***	0.004***	0.003***	0.003***	0.003***
	(3.48)	(3.54)	(3.44)	(3.48)	(3.46)
Debt/equity	0.000	0.000	0.000	0.000	0.000
	(0.13)	(0.12)	(0.15)	(0.13)	(0.14)
SG&A	0.050***	0.051***	0.051***	0.050***	0.050***
	(2.97)	(3.01)	(2.99)	(2.97)	(2.98)
ΔROA	0.000	0.000	0.000	0.000	0.000
	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)
ΔROS	0.000	0.000	0.000	0.000	0.000
	(0.08)	(0.08)	(0.09)	(0.08)	(0.09)

Table 2. (Continued)

Panel B: Alumni network centrality and the complexity of competitive actions

Dependent variable	Complexity$_{t+1}$				
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector	(5) PC1
TMTSize	0.006***	0.006***	0.006***	0.006***	0.006***
	(6.48)	(6.53)	(6.41)	(6.46)	(6.47)
TMTAge	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***
	(−5.12)	(−5.08)	(−5.10)	(−5.11)	(−5.12)
TMTHeterogeneity	−0.004	−0.001	−0.003	−0.004	−0.004
	(−0.62)	(−0.23)	(−0.54)	(−0.61)	(−0.64)
Unpredictability	0.002	0.001	-0.001	0.003	0.001
	(0.02)	(0.01)	(−0.01)	(0.02)	(0.01)
Homogeneity	0.100**	0.100**	0.101**	0.099*	0.100*
	(1.97)	(1.97)	(1.98)	(1.94)	(1.96)
HHI	0.009	0.008	0.009	0.008	0.009
	(0.18)	(0.16)	(0.19)	(0.17)	(0.18)
N	14,725	14,725	14,725	14,725	14,725
Adj. R^2	0.059	0.058	0.059	0.059	0.059
Oster bias-adjusted Centrality coeff.	0.061	0.047	5.189	0.349	0.003
Oster δ	2.19	0.81	3.41	7.24	2.49

Panel C: Alumni network centrality and the similarity of competitive actions

Dependent variable	Similarity$_{t+1}$				
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector	(5) PC1
Centrality	0.081**	0.151**	5.843***	0.479**	0.004***
	(2.34)	(2.36)	(2.64)	(2.53)	(2.69)
Size	0.023***	0.023***	0.023***	0.023***	0.023***
	(9.21)	(9.23)	(9.10)	(9.21)	(9.14)
Growth	0.017***	0.017***	0.017***	0.017***	0.017***
	(4.71)	(4.71)	(4.73)	(4.70)	(4.71)
Current	0.003**	0.003**	0.003**	0.003**	0.003**
	(2.50)	(2.52)	(2.48)	(2.49)	(2.47)
Debt/equity	−0.006*	−0.006*	−0.006*	−0.006*	−0.006*
	(−1.81)	(−1.80)	(−1.80)	(−1.82)	(−1.80)
SG&A	0.012	0.013	0.013	0.012	0.012
	(0.84)	(0.87)	(0.87)	(0.82)	(0.84)
ΔROA	0.000	0.000	0.000	0.000	0.000
	(0.71)	(0.69)	(0.72)	(0.71)	(0.70)
ΔROS	0.000	0.000	0.000	0.000	0.000
	(1.39)	(1.42)	(1.40)	(1.39)	(1.41)
TMTSize	0.005***	0.005***	0.005***	0.005***	0.005***
	(5.30)	(5.34)	(5.25)	(5.27)	(5.27)
TMTAge	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***
	(−5.10)	(−5.11)	(−5.07)	(−5.08)	(−5.11)
TMTHeterogeneity	−0.008	−0.008	−0.006	−0.008	−0.009
	(−1.16)	(−1.19)	(−0.97)	(−1.19)	(−1.30)
Unpredictability	0.186	0.184	0.181	0.186	0.184
	(1.45)	(1.43)	(1.41)	(1.45)	(1.44)
Homogeneity	−0.012	−0.013	−0.012	−0.014	−0.013
	(−0.20)	(−0.21)	(−0.19)	(−0.23)	(−0.21)
HHI	0.098*	0.096*	0.098*	0.097*	0.098*
	(1.92)	(1.89)	(1.92)	(1.90)	(1.91)
N	14,725	14,725	14,725	14,725	14,725
Adj. R^2	0.058	0.058	0.058	0.059	0.059
Oster bias-adjusted Centrality coef.	0.081	0.151	5.843	0.479	0.004
Oster δ	2.52	2.01	4.59	9.38	3.30

This table reports the regression results of the impact of alumni network centrality on competitive aggressiveness. Panels A–C show the results of the volume, complexity and similarity of competitive actions, respectively. All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We always control for both industry- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

'intermediate' regression that contains observable control variables. The bias adjustment also requires an assumption about the importance of observables relative to unobservable variables (δ) and an assumption about the explanatory power of a regression that contains both observable and unobservable variables (R^2max). Following Oster (2019), we assume that observable and unobservable variables are of equal importance ($\delta = 1$) and that the inclusion of omitted, unobservable variables would result in R^2max equal to 1.3 times the R^2 of the intermediate regression.

When applying these conditions via the *psacalc* command in STATA provided in Oster (2019), we obtain a bias-adjusted Centrality coefficient of 0.723, which is consistent with the Centrality coefficient we originally observed of 0.723 (column 1 of Table 2 Panel A). Using the same approach in columns (2)–(5) as well as in Panels B and C yields bias-adjusted Centrality coefficients that are again consistent with the original estimates. Assuming an R^2max equal to 1.3 times the R^2, for the omitted variable bias to render our original Centrality results statistically insignificant, unobservable factors (δ) would have to be between 2.12 and 5.23 times larger than observable factors (Panel A). Panels B and C give similar results. As shown by the above results, the unobservable missing variables hardly affect the results of our paper.

Difference-in-difference (DID) estimator. In line with Hope, Yue and Zhong (2020), we adopt the DID methodology by exploiting an exogenous shock to executive alumni network centrality. The phenomenon of politically connected directors (PCDs) has drawn the attention of the Chinese government over the years. On 19 October 2013, the Central Organization Department of the Central Committee in the Chinese Communist Party released the document '*Advice on Further Standardizing the Issue of the Party and Government Leading Cadres Taking Part-time or Full-time Jobs in Firms*' (hereafter, *Rule 18*). This document imposes strict and specific restrictions on the Party and government-leading cadres who take part-time or full-time jobs in terms of the types of jobs they can take and the durations, numbers and age limits for different job positions. Not surprisingly, the issuance of *Rule 18* triggered a wave of PCD resignations from listed firms in China.[3] As Figure 3 shows, the number of official directors who resigned from their independent director positions increased sharply by about 300% after *Rule 18* issuance. To some extent, network ties among directors would be destroyed owing to the departure (destruction) of official directors (nodes) of some corporations, thus creating an exogenous regulatory shock to the alumni network centrality of executives. Thus, by exploiting the issuance of *Rule 18* as a quasi-natural experiment, we performed the following multivariate DID test:

$$\begin{aligned}
\mathrm{CA}_{i,t+1} = {} & \beta_0 + \beta_1 \mathrm{IDirector(Treat)}_i \times \mathrm{Post}_t + \beta_2\,\mathrm{Size}_{i,t} \\
& + \beta_3\,\mathrm{Growth}_{i,t} + \beta_7\,\mathrm{Current}_{i,t} + \beta_8 \mathrm{Debt/equity}_{i,t} \\
& + \beta_9 \mathrm{SGA}_{i,t} + \beta_{10} \Delta\mathrm{ROA}_{i,t} + \beta_{11} \Delta\mathrm{ROS}_{i,t} \\
& + \beta_{12} \mathrm{TMTSize}_{i,t} + \beta_{13} \mathrm{TMTAge}_{i,t} \\
& + \beta_{14} \mathrm{TMTHeterogeneity}_{i,t} + \beta_4 \mathrm{Unpredictability}_{s,t} \\
& + \beta_5 \mathrm{Homogeneity}_{s,t} + \beta_6 \mathrm{HHI}_{s,t} + \mathrm{YearFE}_t \\
& + \mathrm{FirmFE}_i + \varepsilon_t, \qquad (5)
\end{aligned}$$

where $\mathrm{CA}_{i,t+1}$ is one of three competitive aggressiveness measures (i.e. Volume, Complexity or Similarity). IDirector is the number of other firms that connected with the focal firm through official directors' alumni relationships before the issuance of *Rule 18*. A larger value of Idirector implies that there are more firms disconnected from the focal firm owing to official director departures after the issuance of *Rule 18* and thus that firms are highly exposed to *Rule 18*. Meanwhile, we construct the dummy variable Treat based on whether the variable Idirector is >0. Specifically, we classify a firm into the treated group when it has direct ties through official directors' alumni relationships over the pre-event period, and into the control group otherwise. Post is a dummy variable, which equals 1 after issuance of *Rule 18* (i.e. 2013 and 2014), and 0 otherwise.

When exploiting the issuance of *Rule 18* as a quasi-natural experiment to identify the causal effect of alumni network centrality on competitive strategy, an underlying assumption is that *Rule 18* indeed affects alumni network centrality. Thus, we first conduct tests to validate the setting. According to Panel A of Table 3, the estimated coefficients of the interaction terms Idirector × Post and Treat × Post are negative and statistically significant at the conventional level (at least 10%) in all columns, which indicates that, compared with firms less directly exposed to *Rule 18*, firms that are more exposed suffer a large decline in alumni network centrality. These results lend support to the conjecture that *Rule 18* is a potential shock to executive alumni network centrality.

Then we use a DID estimation strategy to identify the causal linkages between alumni network centrality and firms' competitive strategy. In columns (1)–(3) of Panel B, the estimated coefficient of the interaction term Idirector × Post is negative and statistically significant at the 10% level or better, showing that, relative to less-exposed firms, more-exposed firms decreased their

[3]See http://finance.sina.com.cn/stock/s/20140307/015318431403.shtml, http://www.chinanews.com/gn/2014/06-03/6238320.shtml and http://finance.people.com.cn/money/n/2014/0423/c42877-24930194.html. Because the potential penalties for noncompliance are severe, it is unlikely that officials would take a risk to get the benefits of serving as directors. Empirically, we found that almost all official directors resigned within a very short period.

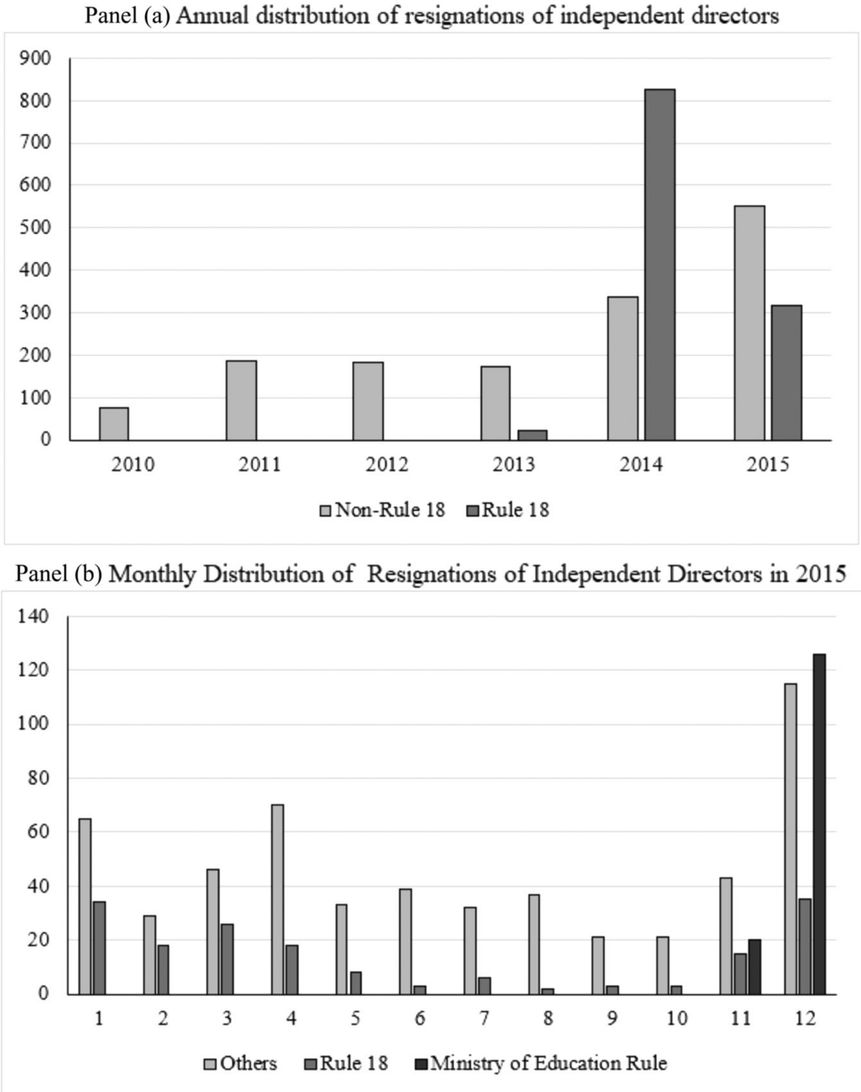

Figure 3. The distribution of resignations of independent directors. Panel A shows the annual distribution of resignations of independent directors due to Rule 18 and other reasons from 2010 to 2015, respectively. Panel B shows the monthly distribution of resignations of independent directors due to Rule 18, the Ministry of Education Rule and other reasons in 2015, respectively

competitive aggressiveness following the issuance of *Rule 18*. Replacing Idirector with Treat, we find that the estimated coefficient of the interaction term in columns (4)–(6) remains negative and statistically significant, with magnitudes similar to those in the first three columns. Given that the issuance of *Rule 18* may have a direct impact on firm characteristics, using time-varying controls would potentially bias our coefficients of interest. We address this problem by using the pre-event value of these controls interacted with Post in the model. Overall, these results are consistent with our prediction that treatment firms, relative to control firms, experienced significant decreases in competitive aggressiveness after *Rule 18*.

We next undertake additional robustness tests. First, we examine whether the parallel trends assumption behind the DID analysis is justified. Specifically, we construct a dynamic model including the interaction of the treated variable (Idirector or Treat) with a set of dummies for the years surrounding the year of issuance of *Rule 18*, using the previous 2 years as the reference group. Before1, Current and Post, which are respectively set to 1 for (i) a firm-year observation 1 year before the issuance of *Rule 18*, (ii) an observation in the year of issuing *Rule 18* and (iii) an observation 1 year after the issuance of *Rule 18*. Panel A of Table 4 shows that coefficients on Before1 × Idirector (Treat) are insignificant in all regressions, suggesting that there is no discernible difference in the pre-treatment competitive aggressiveness trends between treatment and control firms.

Second, we conduct a placebo test to ensure the validity of our DID analysis. Specifically, we move the event

Table 3. Difference-in-difference estimation

Panel A: The impact of *Rule 18* on alumni network centrality

Dependent variable	Degree (1)	Closeness (2)	Betweenness (3)	Eigenvector (4)	Degree (5)	Closeness (6)	Betweenness (7)	Eigenvector (8)
IDirector × Post	−0.115**	−0.130***	−0.002***	−0.038***				
	(−2.31)	(−5.11)	(−3.31)	(−4.04)				
Treat × Post					−0.004*	−0.005***	−0.000***	−0.001***
					(−1.81)	(−4.22)	(−3.38)	(−2.84)
N	5039	5039	5039	5039	5039	5039	5039	5039
Adj. R^2	0.840	0.811	0.866	0.838	0.839	0.810	0.866	0.838

Panel B: The impact of *Rule 18* on competitive aggressiveness

	Competitive aggressiveness $_{t+1}$					
Dependent variable	Volume (1)	Complexity (2)	Similarity (3)	Volume (4)	Complexity (5)	Similarity (6)
IDirector × Post	−2.438***	−0.505*	−0.434			
	(−2.90)	(−1.92)	(−1.59)			
Treat × Post				−0.098***	−0.020*	−0.021*
				(−2.60)	(−1.71)	(−1.67)
N	5039	5039	5039	5039	5039	5039
Adj. R^2	0.575	0.276	0.238	0.575	0.276	0.238

This table reports the regression results of the difference-in-difference estimation based on *Rule 18* in China. As in Hope, Yue and Zhong (2020), we exploit *Rule 18*, released in October 2013, which caused many official independent directors of listed firms to resign as an exogenous shock to the firm's alumni network, and use the difference-in-difference method to estimate the causal relationship between alumni network centrality and competitive aggressiveness. *IDirector* is a continuous variable, measured by the pre-event number of firms connected to the focal firm by the alumni relationships of official independent directors who resigned owing to *Rule 18*, *Treat* is an indicator variable that takes the value of 1 if *IDirector* is above the median, and 0 otherwise. *Post* is defined as 1 when the year is after the issuance of *Rule 18* (i.e. 2013 and 2014), and 0 otherwise (i.e. 2011 and 2012). Panels A and B show the regression results of the impact of *Rule 18* on the firm's alumni network centrality and competitive aggressiveness, respectively. All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, firm- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

year back by 4 years (to avoid overlap with our analysis window) and repeat the DID analysis mentioned above. In Panel B of Table 4, we find insignificant coefficients on Idirector × Post and Treated × Post. These results suggest that no significant treatment effects exist surrounding the pseudo-issuance years, which reinforces our main inference and further mitigates endogeneity concerns.

Third, we employ propensity score matching (PSM) to construct a matched sample and use a combined PSM/DiD design for our tests. While the issuance of *Rule 18* creates an exogenous regulatory shock to the alumni network centrality of corporate management, potential selection issues may still exist because firms voluntarily appoint government officials as directors. By pairing each treated firm (Treat = 1) with a firm from the control group (Treat = 0), we aim to control for 'other' dimensions of firm characteristics that contributed to the selection bias originally. Specifically, we start by retaining all observations for treated and control firms in the year 2012 (the year before the issuance of *Rule 18*) and require that firms in both groups have at least one observation both before and after the regulatory change. We use logistic regressions to estimate the propensity of a firm being in the treated group based on a set of variables controlled in Equation (5). Then, we use the propensity score to match each firm in the treated group with a firm in the control group. This procedure yields a matched sample of 3290 firm-year observations, involving 1645 pairs of treated and control firms.

Panel C of Table 4 presents the statistical differences of the matching covariates between treated and control groups after the matching algorithm to confirm matching effectiveness. As shown, except for SG&A (SG&A) cost, there is little significant difference in the matching variables between the treatment and the control group, which to some extent affirms the validity of the matching process. Panel D reports regression results using the matched samples based on propensity score to reaffirm our baseline results. In column (1), the coefficient on Treat × Post is negative and statistically significant at the 1% level (t = 3.31). This indicates that *Rule 18* reduces the volume of competitive actions adopted by the treated group relative to the control group. In columns (2) and (3), we find consistent results that treated firms reduced the complexity and similarity of competitive

Table 4. Robustness checks for the difference-in-difference estimation results

Panel A: Parallel trend test

	Competitive aggressiveness$_{t+1}$					
Dependent variable	Volume (1)	Complexity (2)	Similarity (3)	Volume (4)	Complexity (5)	Similarity (6)
IDirector × Before1	−0.525	−0.183	−0.187			
	(−0.44)	(−0.47)	(−0.47)			
IDirector × Current	−2.791**	−0.389	−0.560			
	(−2.29)	(−1.02)	(−1.42)			
IDirector × Post1	−2.668**	−0.840**	−0.516			
	(−2.14)	(−2.14)	(−1.22)			
Treat × Before1				0.013	−0.009	−0.003
				(0.24)	(−0.49)	(−0.16)
Treat × Current				−0.089	−0.014	−0.021
				(−1.61)	(−0.81)	(−1.19)
Treat × Post1				−0.093*	−0.037**	−0.024
				(−1.66)	(−2.09)	(−1.22)
N	5039	5039	5039	5039	5039	5039
Adj. R^2	0.575	0.276	0.238	0.574	0.276	0.238

Panel B: Placebo test

	Competitive aggressiveness$_{t+1}$					
Dependent variable	Volume (1)	Complexity (2)	Similarity (3)	Volume (4)	Complexity (5)	Similarity (6)
IDirector × FPost	−0.619	0.146	0.393			
	(−0.50)	(0.36)	(0.80)			
Treat × FPost				−0.014	0.010	0.013
				(−0.26)	(0.53)	(0.61)
N	2352	2352	2352	2352	2352	2352
Adj. R^2	0.571	0.307	0.296	0.571	0.307	0.296

Panel C: Covariate balance diagnostics

	Pre-match			Post-match		
	Treatment	Control	Mean difference (p-value)	Treatment	Control	Mean difference (p-value)
Size	7.6779	7.4854	0.00***	7.6556	7.5971	0.18
Growth	0.1816	0.1924	0.48	0. 1535	0.1639	0.42
Unpredictability	0.0364	0.0356	0.21	0. 0326	0. 0326	1.00
Homogeneity	0.0072	0.0051	0.00***	0.0056	0.0056	1.00
HHI	0.0692	0.0701	0.78	0. 0491	0. 0491	1.00
Current	2.5601	2.7194	0.07*	2.7061	2.6771	0.78
Debt/equity	1.2905	1.1782	0.01***	1.2160	1.1755	0.39
SG&A	0.1705	0.1694	0.79	0.1696	0.1781	0.09*
ΔROA	−0.5701	−0.4496	0.25	−0.4127	−0.4140	0.99
ΔROS	−0.4683	−0.4382	0.72	−0.3927	−0.3639	0.73
TMTSize	7.5308	7.4438	0.26	7.5544	7.5495	0.96
TMTAge	46.5992	46.3355	0.01***	46.5896	46.4226	0.16
TMTHeterogeneity	0.0571	−0.0056	0.00***	0.0591	0.0677	0.53

Panel D: Regression results with propensity-score-matched sample

	Competitive aggressiveness$_{t+1}$		
Dependent variable	(1) Volume	(2) Complexity	(3) Similarity
Treat × Post	−0.206***	−0.029	−0.064***
	(−3.43)	(−1.38)	(−3.15)
N	3290	3290	3290
Adj. R^2	0.667	0.392	0.378

Table 4. (*Continued*)

This table reports the regression results of the robustness tests for difference-in-difference estimation based on the release of *Rule 18* in China. Panel A shows the results of tests to verify the parallel trend assumption, which suggests that the treatment and control groups are not significantly different before the release of *Rule 18*. Specifically, we replace the *Post* variable with the following variables: *Before1*, *Current* and *Post1*. *Before1* is a dummy variable indicating 1 year before *Rule 18* release, and *Current* is a dummy variable indicating the year when *Rule 18* was released, and so on. The variables of interest are these time-indicator variables interacting with *IDirector* and *Treat*. Panel B shows the results using the fictitious-event year that occurred 4 years before the actual year of *Rule 18* release (i.e. 2009). Specifically, we re-estimate Equation (4) using 2007–2008 as the pre-event period and 2009–2010 as the post-event period. This fictitious-event indicator variable is defined as *FPost*. The variable of interest is the interaction term, *IDirector* × *FPost* and *Treat* × *FPost*. Panel C shows the covariate mean differences before and after matching. Panel D shows the results for competitive aggressiveness based on the sample formed by propensity score matching. The variable of interest is the interaction term, *Treat* × *Post*. All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, firm- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

actions following the issuance of *Rule 18*. Baseline results are robust to the combined PSM/DiD design.

Instrumental variable method. To further address the endogeneity problem, we attempt to capture exogenous variation in executive alumni network centrality using an IV approach. We choose the number of the management team who were admitted into universities after 1999 as the first instrument. The rationale is as follows. In the 1990s, the central government implemented a series of reforms in the higher education sector to improve its efficiency and role in local economic development. One particularly notable reform was the higher education expansion programme. In January 1999, the Ministry of Education in China announced an admission plan of 1.3 million for 3- and 4-year college programmes, a 20% increase over 1998. The following June, it revised the admission plan to 1.56 million, an unprecedented increase of 44% over the previous year. Relative to annual admission growth averaging 4.7% between 1995 and 1998, the growth rate after the expansion programme increased sharply. Higher education admissions grew annually by more than 40% in both 1999 and 2000, and by about 20% over the next 5 years (Che and Zhang, 2018). Given that the expansion programme enlarged the size of alumni networks by allowing more people to attend college, the more management team members who entered college after the expansion plan, the more links they have with alumni of their college. Thus, we construct the variable College expansion plan, which is the number of management team members who enrolled in regular colleges and universities after the 1999 expansion plan.

Additionally, we use provinces' policies to attract highly skilled emigrants as our second IV (Giannetti, Liao and Yu, 2015). The flow of students from China towards universities in the developed world to acquire master's or higher degrees became sizable in the early 1990s. To lure highly skilled individuals with foreign experience to return, different provinces begin to introduce incentives at different times. By the end of 2019, 29 provinces had implemented this policy. The introduction of provincial policies led to an exogenous change in the supply of management team members with alumni relationships but did not influence a firm's competitive position directly. Thus, we construct the indicator variable Hiring returnee policy, which takes a value of 1 in years following the implementation of a policy that attracted highly skilled emigrants in each province and 0 otherwise.

Table 5 presents the estimated results based on IV regressions. The results of the first stage are reported in Panel A. As expected, the coefficient on the College expansion plan is positive and statistically significant in all columns, indicating that firms with more management team members who enrolled into colleges after 1999 are more central in the alumni network. Similarly, the coefficient on the Hiring returnee policy is positive and statistically significant in two of four columns at the conventional significance level (i.e. 5%). Our Cragg–Donald Wald F-statistic from the first-stage regression is much larger than the conventional threshold (e.g. 10% critical value of 16.38 as reported by Stock and Yogo, 2005), which rejects the null hypothesis that the instruments are weak and supports the alternative hypothesis of the relevance condition.

Panels B–D present the second-stage regressions. The estimated coefficients on the instrumented alumni network centrality measures are positive and statistically significant. This test further mitigates endogeneity concerns. The Hansen J statistics in Panels B and D are statistically insignificant, which provides supporting evidence for the exclusion restriction.

Alternative explanations

In this subsection, we consider alternative explanations for the positive association between alumni network centrality and firms' competitive aggressiveness.

Executive human capital. One possible concern about our alumni network centrality variable is that it captures the ability and human capital of TMTs and firms led by such management teams with more information and resources to adopt a more aggressive competitive strategy.

Table 5. Instrumental variable estimation

Panel A: Regression results for the first stage

Dependent variable	Centrality			
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector
College expansion plan	0.273***	0.111***	0.004***	0.043***
	(17.83)	(17.32)	(12.47)	(16.94)
Hiring returnee policy	0.059**	0.039***	0.000	0.008
	(2.25)	(3.15)	(1.40)	(1.60)
N	14,725	14,725	14,725	14,725
Kleibergen–Paap Wald F-statistic	163.959	156.633	79.206	146.644

Panel B: Regression results for the second stage

Dependent variable	$Volume_{t+1}$			
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector
Centrality	1.701***	4.052***	106.488***	10.882***
	(4.15)	(3.99)	(4.47)	(4.17)
N	14,725	14,725	14,725	14,725
Adj. R^2	0.121	0.106	0.126	0.116
Hansen J statistic	2.409	3.050	1.872	2.237

Panel C: Regression results for the second stage

Dependent variable	$Complexity_{t+1}$			
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector
Centrality	0.163**	0.367**	10.691**	1.055**
	(2.30)	(2.12)	(2.47)	(2.34)
N	14,725	14,725	14,725	14,725
Adj. R^2	0.057	0.055	0.058	0.057
Hansen J statistic	6.896	7.416	6.414	6.770

Panel D: Regression results for the second stage

Dependent variable	$Similarity_{t+1}$			
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector
Centrality	0.115*	0.280*	7.106*	0.735*
	(1.80)	(1.79)	(1.82)	(1.80)
N	14,725	14,725	14,725	14,725
Adj. R^2	0.058	0.058	0.058	0.058
Hansen J statistic	0.008	0.026	0.000	0.005

This table reports the results of the impact of alumni network centrality on competitive aggressiveness using a 2-Stage Least Squares (2SLS) approach. The first instrumental variable is based on the college expansion plan released in 1999. Specifically, we use the number of executives in listed firms who enrolled in higher education after 1999 scaled by the number of executives in listed firms as the first instrumental variable. The second instrumental variable is the hiring returnee policy released in 2008. Specifically, we use an indicator variable that takes the value of 1 if the provinces where listed firms are located release policies for the introduction of high-level overseas talents, and 0 otherwise. This is used as the second instrumental variable. Panel A shows the regression results for the first stage, where the dependent variable is the firm's alumni network centrality. Panels B–D show the regression results for the second stage, where the dependent variables are the volume, complexity and similarity of competitive actions, respectively. All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, industry- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

To address this concern, we construct additional centrality variables to remove the impact of the human capital of the management team. To do so, we first follow Ferris, Javakhadze and Rajkovic (2017) to construct the executive human capital index, which is defined as the sum of the following five indicator variables. The first indicator variable takes the value of 1 if at least one executive has an academic degree from an 'elite' college, and 0 otherwise. The second indicator variable takes the value of 1 if at least one executive has a PhD, and 0

Table 6. Filtering out the impact of executive human capital

Panel A: Alumni network centrality and the volume of competitive actions				
Dependent variable	$Volume_{t+1}$			
	(1) $Degree_{Excess}$	(2) $Closeness_{Excess}$	(3) $Betweenness_{Excess}$	(4) $Eigenvector_{Excess}$
$Centrality_{Excess}$	0.607***	0.710**	52.080***	3.315***
	(3.17)	(2.25)	(3.20)	(3.38)
N	14,193	14,193	14,193	14,193
Adj. R^2	0.128	0.127	0.129	0.128

Panel B: Alumni network centrality and the complexity of competitive actions				
Dependent variable	$Complexity_{t+1}$			
	(1) $Degree_{Excess}$	(2) $Closeness_{Excess}$	(3) $Betweenness_{Excess}$	(4) $Eigenvector_{Excess}$
$Centrality_{Excess}$	0.059*	0.040	4.379*	0.334*
	(1.70)	(0.67)	(1.86)	(1.83)
N	14,193	14,193	14,193	14,193
Adj. R^2	0.059	0.059	0.059	0.059

Panel C: Alumni network centrality and the similarity of competitive actions				
Dependent variable	$Similarity_{t+1}$			
	(1) $Degree_{Excess}$	(2) $Closeness_{Excess}$	(3) $Betweenness_{Excess}$	(4) $Eigenvector_{Excess}$
$Centrality_{Excess}$	0.069**	0.134**	4.259*	0.428**
	(2.01)	(2.10)	(1.83)	(2.25)
N	14,193	14,193	14,193	14,193
Adj. R^2	0.059	0.059	0.059	0.060

This table reports the regression results of the impact of alumni network centrality on competitive aggressiveness after filtering the human capital out of executive alumni network centrality measures. Specifically, we use excess alumni network centrality – *Centrality* $_{Excess}$, estimated as the residuals from the regression of alumni network centrality on the executive human capital index – as the alternative measure of alumni network centrality. The executive human capital index is estimated as the sum of the following indicator variables: an indicator variable that takes the value of 1 if at least one executive has an academic degree from an 'elite' college and 0 otherwise; an indicator variable that takes the value of 1 if at least one executive has a PhD, and 0 otherwise; an indicator variable that takes the value of 1 if at least one executive has legal experience, and 0 otherwise; an indicator variable that takes the value of 1 if at least one executive has finance experience, and 0 otherwise; an indicator variable that takes the value of 1 if at least one executive has political experience, and 0 otherwise. Panels A–C show the regression results for the volume, complexity and similarity of competitive actions, respectively. All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, industry- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

otherwise. The third indicator variable takes the value of 1 if at least one executive has legal experience, and 0 otherwise. The fourth indicator variable takes the value of 1 if at least one executive has finance experience, and 0 otherwise. The fifth indicator variable takes the value of 1 if at least one executive has political experience, and 0 otherwise. Then, we regress alumni network centrality on the executive human capital index and use the estimated residuals from this regression as the excess centrality variable, $Centrality_{Excess}$. As shown in Table 6, the estimated coefficients on $Centrality_{Excess}$ are positive and statistically significant in all columns. The positive relationship between $Centrality_{Excess}$ and competitive aggressiveness measures, Volume, Complexity and Dissimilarity, corroborates the notion that our main results are less likely to be driven by the omitted variable of the human capital of the TMT.

Hometown network and colleague network. Another concern is that there is an overlap between alumni connections and hometown connections or colleague connections. That is, the observed effects of alumni networks on competitive aggressiveness might be driven by other possible connections. We rule out this alternative explanation by controlling for the hometown network centrality (Centrality_Hometown) and past employment colleague network centrality (Centrality_Colleague) of TMTs in our baseline regression model. Similar to the calculation of alumni network centrality, we compute the hometown network centrality and colleague network centrality for executives. As presented in Panels A–C of Table 7, the estimated coefficients on alumni network centrality measures continue to be positive and statistically significant after adding Centrality_Hometown and Centrality_Colleague as

Table 7. *Filtering out the impact of executive hometown and colleague connection*

Panel A: Alumni network centrality and the volume of competitive actions				
Dependent variable	$Volume_{t+1}$			
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector
Centrality	0.682***	0.793**	67.335***	3.563***
	(2.91)	(2.10)	(3.75)	(3.06)
Centrality_Hometown	0.117	0.210	−8.422	0.549
	(0.55)	(0.37)	(−0.74)	(0.52)
Centrality_Colleague	1.834	0.263	23.131*	0.947
	(0.64)	(0.52)	(1.94)	(0.77)
N	9996	9996	9996	9996
Adj. R^2	0.140	0.138	0.144	0.140

Panel B: Alumni network centrality and the complexity of competitive actions				
Dependent variable	$Complexity_{t+1}$			
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector
Centrality	0.069*	0.034	5.192**	0.455**
	(1.66)	(0.47)	(2.02)	(2.15)
Centrality_Hometown	0.034	0.104	−0.219	0.221
	(0.88)	(1.02)	(−0.11)	(1.13)
Centrality_Colleague	−0.565	−0.120	−0.446	−0.442**
	(−1.08)	(−1.19)	(−0.20)	(−2.11)
N	9996	9996	9996	9996
Adj. R^2	0.064	0.063	0.064	0.065

Panel C: Alumni network centrality and the similarity of competitive actions				
Dependent Variable	$Similarity_{t+1}$			
	(1) Degree	(2) Closeness	(3) Betweenness	(4) Eigenvector
Centrality	0.077*	0.127*	6.599***	0.409*
	(1.83)	(1.70)	(2.69)	(1.89)
Centrality_Hometown	−0.006	−0.015	−4.255*	0.034
	(−0.14)	(−0.13)	(−1.84)	(0.17)
Centrality_Colleague	−0.080	−0.071	1.108	0.141
	(−0.17)	(−0.71)	(0.51)	(0.79)
N	9996	9996	9996	9996
Adj. R^2	0.055	0.055	0.056	0.056

This table reports the regression results of the impact of alumni network centrality on competitive aggressiveness after excluding the impact of executive hometown and colleague network centrality measures. Specifically, based on whether any executives in two firms share a hometown or past employment connection, we compute the firms' hometown network centrality (*Centrality_Hometown*) and colleague network centrality (*Centrality_Colleague*) according to Appendix B. Then we add these two network centrality measures into the baseline model. Panels A–C show the regression results for the volume, complexity and similarity of competitive actions, respectively. All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, industry- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

additional controls. So, it is unlikely that the documented results can be attributed to the explanation of hometown connections or colleague connections of the TMT.

Moderating effects

In this section, we further investigate the cross-sectional and time-series variations in the effect of alumni network centrality on competitive aggressiveness. Examining this heterogeneous effect can further alleviate the concern that some omitted variables are driving our results because such variables would have to be uncorrelated with all control variables included in the regression models. The moderating effects would also explain under which scenarios the alumni network centrality plays a more pronounced role. We conduct three sets of tests here, aiming to provide stronger empirical support for the prediction that alumni network increases firms' capacity to take aggressive competitive actions via increased access to valuable information and resources.

High versus low product market competition

First, we explore whether the positive effect of executive alumni network centrality on competitive aggressiveness varies with the intensity of product market competition. If the executive alumni network has significant competitive implications, that is, it enhances the competitive advantages of participating firms by allowing them to acquire critical resources that are not otherwise easily available, then we expect that such an effect will be more prevalent among firms operating in industries facing fierce competition. This is because in situations of fierce competition, firm networks via executive alumni connections could be an important mechanism to exchange knowledge and to gain (information) advantages and thus allow firms to engage in more aggressive competitive actions. We use the Herfindahl index (HHI) to measure the intensity of product market competition and classify firms into two groups based on the median value. Then, we conduct separate analyses for the high and low product market competition groups.

The results in Table 8 are consistent with this conjecture, in which Panels A–C correspond to the volume of competitive actions (Volume), the complexity of competitive actions (Complexity) and the similarity of competitive actions (Similarity), respectively. Specifically, the results of Panel A show that the coefficient on alumni network centrality variables is positive and statistically significant for the group facing a high level of product market competition (in columns 1, 3, 5 and 7) but insignificant for the group facing a low level of product market competition (in columns 2, 4, 6 and 8). That is, the executive alumni network centrality significantly increases the competitive aggressiveness of firms in industries facing a high level of product market competition but has little effect on firms in low-competition industries. In all compared pairs, the empirical p-value indicates that the coefficient difference between the high and low product market competition groups is statistically significant at the 1% level. In Panels B and C, we find qualitatively similar results.[4]

High versus low input–output network centrality

Second, we explore the role of input–output network centrality. Firms are also connected along the value chain in customer–supplier relationships. Input–output networks have recently attracted a considerable amount of research attention (Carvalho and Gabaix, 2013). The effect of the executive alumni network might vary with the input–output network ranking. First, firms that are more central in the input–output network are more susceptible to shocks, regardless of whether those are upstream technology shocks or downstream demand shocks (Gabaix, 2011). That is, firms more exposed to value-chain shocks may have more uncertain asset valuations. Thus, they may have stronger incentives and benefit more from information dissemination through executive alumni relationships regarding taking competitive actions. Second, contractual links on intermediate goods are most likely to take place through long-term relationships, which require knowledge and trust in subcontractors. The trust embedded in alumni relationships enables executives to share and disseminate information over the supply chain and lubricate the formation of contractual linkages.

To test the above conjecture, we first compute the input–output network centrality for each firm and then divide firms into high and low groups based on the median value. Specifically, we construct a production network between listed firms based on whether they are in a related industry and compute four input–output network centrality measures. The results, reported in Panels A–C of Table 9, show that the coefficient on alumni network centrality variables is positive and statistically significant in columns (1), (3), (5) and (7). In contrast, in columns (2), (4), (6) and (8), the coefficient on alumni network centrality variables is insignificant. The empirical p-value further indicates that the effect of executive alumni network centrality is economically more relevant among firms with high centrality in the production network. The evidence is consistent with our predictions.

High versus low economic policy uncertainty

Third, we consider the dimension of economic policy uncertainty. Economic policy is an effective means for the government to shape the business environment (e.g. Gulen and Ion, 2016; Jens, 2017). A constantly changing international environment and economic recession result in economic policy uncertainty, which affects firms' cost of capital (Kwabi *et al.*, 2022) and strategic development (Jens, 2017). The uncertainty of economic policy will increase the fluctuations in future cash flows of investment projects and thus exacerbate the operating risks. Therefore, when uncertainty is very high, managers tend to take conservative financial policies (e.g. reduce investment, increase cash holding) owing to reduced transparency in the future business environment (Gulen and Ion, 2016). In this case, if the executive alumni network is an important channel to exchange and disseminate information and thus reduce uncertainty, then we predict that the effect of the alumni network centrality on competitive aggressiveness is more pronounced in high-uncertainty periods.

[4] We further examine the effect of firms' alumni network centrality on aggressive competitive strategies focusing on peer firms. We find that the magnitude of the coefficients of centrality is larger for the peer firms, which shows that alumni network centrality can improve corporate competitive aggressiveness mainly through stronger peer pressure. To save space, we omit the regression results here.

Table 8. High versus low product market competition

	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)	High (7)	Low (8)
Panel A: Alumni network centrality and the volume of competitive actions ($Volume_{t+1}$)								
Degree	0.945***	0.388						
	(4.44)	(1.20)						
Closeness			1.370***	0.112				
			(3.86)	(0.20)				
Betweenness					67.294***	56.547**		
					(3.68)	(2.32)		
Eigenvector							4.554***	2.675
							(4.14)	(1.64)
Adj. R^2	0.150	0.115	0.148	0.115	0.150	0.118	0.149	0.116
Empirical p-value	0.000***		0.000***		0.049**		0.000***	
Panel B: Alumni network centrality and the complexity of competitive actions ($Complexity_{t+1}$)								
Degree	0.044	0.071						
	(0.99)	(1.33)						
Closeness			0.023	0.065				
			(0.30)	(0.68)				
Betweenness					4.070	5.637*		
					(1.26)	(1.76)		
Eigenvector							0.125	0.543*
							(0.54)	(1.95)
Adj. R^2	0.053	0.068	0.052	0.068	0.053	0.068	0.052	0.068
Empirical p-value	0.107		0.150		0.143		0.000***	
Panel C: Alumni network centrality and the similarity of competitive actions ($Similarity_{t+1}$)								
Degree	0.114***	0.029						
	(2.60)	(0.53)						
Closeness			0.192**	0.085				
			(2.50)	(0.78)				
Betweenness					6.509**	4.571		
					(1.99)	(1.54)		
Eigenvector							0.536**	0.363
							(2.28)	(1.20)
Adj. R^2	0.045	0.072	0.045	0.073	0.045	0.073	0.045	0.073
Empirical p-value	0.000***		0.008***		0.078*		0.078*	
N	8311	6414	8311	6414	8311	6414	8311	6414

This table reports the results of tests on whether the impact of alumni network centrality on competitive aggressiveness varies with product market competition. We use the Herfindahl index (HHI) to measure the degree of product market competition faced by a firm, and according to the median of product market competition, we divide the sample into two groups with high product market competition and low product market competition. Panels A–C show the results of the volume, complexity and similarity of competitive actions, respectively. We compare the different coefficients across two sub-samples using the empirical p-values from the simulation procedure in Cleary (1999). All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, industry- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

We apply the measure of economic policy uncertainty from Davis, Liu and Sheng (2019) and then examine the effect on competitive aggressiveness in the periods of high and low economic policy uncertainty, respectively. We classify the sample as a period of high (low) economic policy uncertainty if the value of the uncertainty proxy in December of the prior year is higher (lower) than its median value in the previous 36 months. The results are presented in Table 10. In Panel A when using Volume as a competitive aggressiveness proxy, we find that the coefficient on alumni network centrality variables is positive and statistically significant both for the group with high uncertainty (columns 1, 3, 5 and 7) and for the group with low uncertainty (columns 2, 4, 6 and 8). Further tests show that the coefficient difference between the two groups is statistically significant at the 5%

Table 9. High versus low input–output network centrality

	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)	High (7)	Low (8)
Panel A: Alumni network centrality and the volume of competitive actions ($Volume_{t+1}$)								
Degree	1.211***	0.203						
	(4.54)	(0.90)						
Closeness			1.840***	-0.207				
			(4.47)	(−0.50)				
Betweenness					92.009***	35.471**		
					(4.12)	(2.03)		
Eigenvector							6.582***	0.578
							(4.91)	(0.49)
Adj. R^2	0.128	0.135	0.133	0.128	0.130	0.134	0.130	0.133
Empirical p-value	0.000***		0.000***		0.000***		0.000***	
Panel B: Alumni network centrality and the complexity of competitive actions ($Complexity_{t+1}$)								
Degree	0.084*	0.036						
	(1.87)	(0.77)						
Closeness			0.103	−0.014				
			(1.33)	(−0.17)				
Betweenness					5.312	5.155*		
					(1.64)	(1.85)		
Eigenvector							0.485**	0.185
							(2.04)	(0.73)
Adj. R^2	0.067	0.048	0.068	0.047	0.073	0.042	0.067	0.047
Empirical p-value	0.031**		0.004***		0.467		0.014**	
Panel C: Alumni network centrality and the similarity of competitive actions ($Similarity_{t+1}$)								
Degree	0.110**	0.046						
	(2.49)	(0.95)						
Closeness			0.235***	0.050				
			(2.79)	(0.53)				
Betweenness					5.889**	4.672		
					(2.08)	(1.64)		
Eigenvector							0.692***	0.199
							(2.98)	(0.74)
Adj. R^2	0.056	0.062	0.059	0.060	0.067	0.053	0.062	0.058
Empirical p-value	0.010***		0.000***		0.251		0.001***	
N	7643	7081	7733	6991	7776	6948	7966	6759

This table reports the results of tests on whether the impact of alumni network centrality on competitive aggressiveness varies with the firm's position in the production network. We construct a production network between listed firms through industry-level input–output relationships. Similarly, we compute four input–output network centrality measures, and, according to the median of these proxies, we divide the sample into two groups with high input–output network centrality and low input–output network centrality. Panels A–C show the results of the volume, complexity and similarity of competitive actions, respectively. We compare the different coefficients across two sub-samples using the empirical p-values from the simulation procedure in Cleary (1999). All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, industry- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

level (columns 5 and 6; columns 7 and 8). When using the other two competitive aggressiveness proxies (Complexity and Similarity), we obtain results similar to those shown in Panels B and C. Thus, the effect of executive alumni network centrality on firms' competition strategy is more pronounced in high, versus low, policy uncertainty groups.

Economic consequences

Existing studies have shown that high-centrality executives and directors may exploit the power and influence derived from social networks for private gain, for example by making value-reducing acquisitions and riskier initial public offerings (El-Khatib, Fogel and Jandik,

Table 10. High versus low economic policy uncertainty

	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)	High (7)	Low (8)
Panel A: Alumni network centrality and the volume of competitive actions ($Volume_{t+1}$)								
Degree	0.962***	0.663***						
	(3.93)	(3.26)						
Closeness			1.255***	0.790**				
			(2.60)	(2.38)				
Betweenness					110.986***	55.300***		
					(5.35)	(3.37)		
Eigenvector							5.433***	3.500***
							(3.70)	(3.47)
Adj. R^2	0.105	0.135	0.102	0.134	0.109	0.137	0.104	0.136
Empirical p-value	0.000***		0.000***		0.000***		0.000***	
Panel B: Alumni network centrality and the complexity of competitive actions ($Complexity_{t+1}$)								
Degree	0.158***	0.035						
	(2.87)	(0.92)						
Closeness			0.260**	−0.003				
			(2.37)	(−0.05)				
Betweenness					18.442***	2.572		
					(4.18)	(1.05)		
Eigenvector							0.743**	0.267
							(2.24)	(1.39)
Adj. R^2	0.041	0.066	0.041	0.066	0.043	0.066	0.040	0.066
Empirical p-value	0.000***		0.000***		0.000***		0.000***	
Panel C: Alumni network centrality and the similarity of competitive actions ($Similarity_{t+1}$)								
Degree	0.166***	0.056						
	(2.97)	(1.45)						
Closeness			0.362***	0.098				
			(3.18)	(1.42)				
Betweenness					16.100***	3.730		
					(3.62)	(1.53)		
Eigenvector							0.836**	0.406**
							(2.46)	(1.97)
Adj. R^2	0.041	0.067	0.041	0.067	0.041	0.067	0.040	0.068
Empirical p-value	0.000***		0.000***		0.000***		0.000***	
N	3247	11,478	3247	11,478	3247	11,478	3247	11,478

This table reports the results of tests on whether the impact of alumni network centrality on competitive aggressiveness varies with economic policy uncertainty. We use economic policy uncertainty in China as developed by Davis, Liu and Sheng (2019), who quantify the policy-related economic uncertainty in China over the past 70 years, as filtered through the lens of two leading mainland newspapers: the Renmin Daily and the Guangming Daily. According to whether the value of the uncertainty proxy in December of the prior year is higher than its median value in the previous 36 months, we divide the sample into two groups of a high economic policy uncertainty period and low economic policy uncertainty period. Panels A–C show the results of the volume, complexity and similarity of competitive actions, respectively. We compare the different coefficients across two sub-samples using the empirical p-values from the simulation procedure in Cleary (1999). All continuous variables are winsorized at the top and bottom one percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, industry- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

2015), which is detrimental to firm performance. However, stronger resources and information advantages obtained from a more central location in alumni networks can help firms improve performance (Granovetter, 2005). Existing studies have provided evidence that valuable information and resources transmitted through the network of high-centrality executives and directors can create high firm value (Engelberg, Gao and Parsons, 2013) and superior firm performance (Larcker, So and Wang, 2013). Therefore, it is useful to consider the performance implications, which can strengthen the basic logic in this paper that firms compete in more aggressive ways owing to the advantage of information communication and resources exchange via alumni networks, rather than through the power and influence derived from social networks.

Table 11. The effect of alumni network centrality on firm performance

Panel A: Alumni network centrality and changes in market share

	$MktShareGrow_{t+1}$				$MktShareGrow_{t+2}$			
	Degree (1)	Closeness (2)	Betweenness (3)	Eigenvector (4)	Degree (5)	Closeness (6)	Betweenness (7)	Eigenvector (8)
Centrality	0.170**	0.268*	5.059	0.893**	0.108	0.116	6.304	0.692
	(2.13)	(1.90)	(1.22)	(2.09)	(1.21)	(0.77)	(1.35)	(1.42)
Lnasset	−0.052***	−0.051***	−0.051***	−0.052***	−0.082***	−0.082***	−0.082***	−0.083***
	(−8.28)	(−8.33)	(−8.07)	(−8.28)	(−10.65)	(−10.66)	(−10.59)	(−10.64)
Tobin q	0.036***	0.036***	0.036***	0.036***	0.029***	0.029***	0.029***	0.029***
	(4.47)	(4.47)	(4.48)	(4.47)	(2.99)	(2.99)	(2.98)	(2.98)
PPEGrowth	0.000	0.000	0.000	0.000	−0.000	−0.000	−0.000	−0.000
	(0.66)	(0.68)	(0.70)	(0.68)	(−0.53)	(−0.49)	(−0.48)	(−0.51)
Capex	0.023	0.023	0.022	0.023	−0.008	−0.008	−0.007	−0.007
	(0.18)	(0.18)	(0.17)	(0.18)	(−0.05)	(−0.05)	(−0.04)	(−0.04)
R&D	−2.352***	−2.339***	−2.310***	−2.349***	−1.921***	−1.905***	−1.899***	−1.926***
	(−5.85)	(−5.84)	(−5.78)	(−5.84)	(−4.45)	(−4.43)	(−4.41)	(−4.46)
Cash	−0.021	−0.019	−0.017	−0.021	0.012	0.014	0.013	0.011
	(−0.35)	(−0.33)	(−0.28)	(−0.36)	(0.16)	(0.19)	(0.18)	(0.15)
LDebt	0.261***	0.261***	0.261***	0.261***	0.282***	0.282***	0.284***	0.283***
	(3.04)	(3.04)	(3.04)	(3.04)	(3.09)	(3.08)	(3.11)	(3.09)
ROA	0.162**	0.162**	0.162**	0.162**	-0.060	-0.060	-0.060	-0.060
	(2.37)	(2.38)	(2.38)	(2.37)	(−0.48)	(−0.48)	(−0.48)	(−0.48)
N	16,092	16,092	16,092	16,092	13,967	13,967	13,967	13,967
Adj. R^2	0.024	0.024	0.023	0.024	0.030	0.030	0.030	0.030

Panel B: Alumni network centrality and changes in profitability

	ΔROA_{t+1}				ΔROA_{t+2}			
	Degree (1)	Closeness (2)	Betweenness (3)	Eigenvector (4)	Degree (5)	Closeness (6)	Betweenness (7)	Eigenvector (8)
Centrality	0.015***	0.023**	0.518	0.073**	0.011**	0.021**	0.805**	0.049*
	(2.63)	(2.00)	(1.32)	(2.50)	(2.07)	(1.99)	(2.19)	(1.78)
ΔROA	−0.379***	−0.379***	−0.379***	−0.379***	−0.072***	−0.072***	−0.072***	−0.072***
	(−22.05)	(−22.04)	(−22.04)	(−22.04)	(−3.71)	(−3.71)	(−3.71)	(−3.71)
Return	0.163***	0.162***	0.163***	0.163***	0.004	0.004	0.004	0.004
	(8.43)	(8.42)	(8.42)	(8.43)	(0.20)	(0.19)	(0.21)	(0.20)
LBM	−0.001	−0.001	−0.001	−0.001	0.013	0.012	0.012	0.013
	(−0.09)	(−0.11)	(−0.11)	(−0.10)	(1.55)	(1.54)	(1.54)	(1.54)
LnMV	−0.005	−0.005	−0.005	−0.005	−0.006*	−0.006*	−0.006*	−0.006*
	(−1.34)	(−1.33)	(−1.31)	(−1.34)	(−1.77)	(−1.77)	(−1.78)	(−1.76)
R&D	0.054	0.055	0.057	0.054	0.051	0.051	0.053	0.051
	(1.40)	(1.42)	(1.48)	(1.41)	(1.45)	(1.45)	(1.50)	(1.46)
LDebt	0.010*	0.010*	0.010*	0.010*	−0.009	−0.009	−0.009	−0.009
	(1.68)	(1.68)	(1.67)	(1.68)	(−1.40)	(−1.38)	(−1.37)	(−1.40)
Lnasset	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
	(0.11)	(0.11)	(0.12)	(0.11)	(0.22)	(0.22)	(0.23)	(0.23)
Lnsales	0.003***	0.003***	0.002***	0.003***	0.003***	0.003***	0.003***	0.003***
	(2.61)	(2.60)	(2.58)	(2.60)	(2.92)	(2.93)	(2.92)	(2.91)
Age	0.003***	0.003***	0.003***	0.003***	0.002***	0.002***	0.002***	0.002***
	(5.11)	(5.06)	(5.03)	(5.13)	(3.13)	(3.11)	(3.11)	(3.12)
N	14886	14886	14886	14886	13400	13400	13400	13400
Adj. R^2	0.112	0.112	0.112	0.112	0.013	0.013	0.013	0.013

This table reports the regression results of the impact of alumni network centrality on firm performance. Panel A shows the results of the impact of alumni network centrality on firm 1- and 2-year-ahead changes in market share. In line with the existing literature, we calculate a firm's market share growth as the difference in market share between the current year and the previous year, where a firm's market share is measured by its sales in a year divided by the industry's total sales in that year. We also add the following control variables: the logritham of total asset (*Lnasset*), *Tobin q* equals the ratio of market value to book value of total assets, *PPEGrowth* equals the percentage changes in fixed assets, *Capex* equals capital expenditures scaled by total assets, *R&D* is research and development scaled by total sales, *Cash* is the ratio of cash to total assets, *LDebt* is long-term debt scaled by total assets, and *ROA* is the ratio of net income to total assets. Panel B shows the results of the impact of alumni network centrality on firm 1- and 2-year-ahead changes in ROA. In line with Larcker, So and Wang (2013), we add the following control variable: Δ*ROA* equals a firm's change in

Table 11. (Continued)

industry-adjusted *ROA*, where *ROA* is the firm's net income scaled by lagged assets, *Return* is the firm's market-adjusted returns over the 12 months prior to portfolio formation, *LBM equals one plus the firm's book-to-market ratio*, *LnMV* equals the log of market capitalization, *Lnsale* is the log of total sales and firm *Age*. All continuous variables are winsorized at the top and bottom percentile. Standard errors are clustered by firm, and t-statistics are shown in parentheses. We omit the estimates for control variables, industry- and year-fixed effects, and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Specifically, we examine the effect of alumni network centrality on firm product market performance, including changes in future market share and profitability. We calculate the 1-year-ahead and 2-year-ahead changes in product market share and Return on Assets (ROA) and present the regression results in Panels A and B of Table 11, respectively. Results show that executive alumni network centrality is positively associated with changes in market share and ROA, indicating that alumni network centrality has a positive effect on improvements in product market share and operating profitability. The results are consistent with our conjecture that the executive alumni network provides information and resource advantages and net economic benefits.

Concluding remarks

In a relational society such as China, where formal institutions are relatively weak, relational networks are particularly important. However, there is a lack of relevant empirical evidence to support whether resources and information embedded in social networks can play an important role in corporate competitive strategy. In this paper, we incorporate the resources and information embedded in alumni networks into the consideration of firm value and examine the important role of alumni relationships among corporate executives from the perspective of corporate competitive aggressiveness.

We construct four network centrality measures as our key independent variables to measure a firm's position in the alumni network: degree centrality, closeness centrality, betweenness centrality and eigenvector centrality, and build three measures of corporate competitive aggressiveness as our dependent variables: competitive volume, complexity and similarity. The results show that firms with higher executive alumni network centrality are more likely to adopt aggressive competitive strategies. Our results survive several endogeneity tests. Further, we have found that the effect of executive alumni network centrality on corporate competitive aggressiveness is stronger in firms with higher product market competition and more central in the input–output network, as well as in periods with high economic policy uncertainty. Overall, executive alumni network centrality enhances corporate competitive aggressiveness.

On a practical note, we expect that our study could be useful for a wide range of audiences. Managers are constantly looking for ways to stay one step ahead of their rivals, so it will be important for them to access new information, ideas and opportunities, which promotes a firm's abilities to acquire competitive capabilities and outperform their rivals. We find that a firm's position in the executive alumni network gives it stronger resource and information advantages, which will improve its ability to enact an aggressive competitive strategy. The findings in the paper inform executives of the importance of maintaining existing social relationships as well as establishing new ones.

By establishing a causal relationship between executive alumni networks and corporate competitive aggressiveness, our study has important implications for studies on the interaction of social networks and for the competitive dynamics literature, suggesting that future research on corporate behaviours should carefully examine the potential channel via which firms' interconnectedness may affect corporate strategies.

Author contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Shenglan Chen, Xiaoling Liu and Hui Ma. The first and final drafts of the manuscript were written by Cheng Yan and Douglas Cumming, respectively. All authors read and approved the final manuscript.

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Conflict of interest statement

All authors declare that they have no conflict of interest.

Ethical approval

This paper does not contain any studies with human participants or animals performed by any authors.

Informed consent

Informed consent was obtained from all individual participants included in the study.

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