



Market ranking and network structure: Pathway to dominance

| | |
|------------------|--|
| Journal: | <i>Management Decision</i> |
| Manuscript ID | MD-04-2020-0473.R3 |
| Manuscript Type: | Original Article |
| Keywords: | Network analysis, Boards of Directors, Interlocking directorates, Resource dependency theory |
| | |

SCHOLARONE™
Manuscripts

1
2
3 ABSTRACT:
4

5 The relationship between interlocking directorates and firm performance has been increasingly
6 debated, with a focus on whether firm's centrality in interlock networks is associated with
7 performance. The purpose of this study is to not only examine how a firm's position in this
8 network is associated with performance, but also how the performance of network partners can
9 impact a firm's performance. This study examines how firms effectively utilise the interlock
10 network to achieve the goal of higher market capitalisation – termed market capitalisation rank
11 (MCR).
12
13

14 The premise of the study is the UK FTSE 350 firms from 2014 to 2018. The paper makes use of a
15 temporal network autocorrelation model to examine how firm characteristics, the structural position
16 in the interlock network, and the performance of network partners affect MCR over time.
17

18 The analysis indicates that firms with ties (via the interlock network) to firms with high market
19 capitalisation are more likely to enhance their own MCR, highlighting network partners have the
20 opportunity to play a critical role in a firm's dominance strategy to optimise firm value.
21

22 CUST_RESEARCH_LIMITATIONS/IMPLICATIONS__(LIMIT_100_WORDS) :No data available.
23

24 CUST_PRACTICAL_IMPLICATIONS__(LIMIT_100_WORDS) :No data available.
25

26 CUST_SOCIAL_IMPLICATIONS__(LIMIT_100_WORDS) :No data available.
27

28 The value of this research is that it does not only look at the impact of a firm's position in the
29 network on performance, but the impact of the performance of network partners on a firm's
30 market performance as well.
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3
4 **Title:** Market ranking and network structure: Pathway to dominance
5
6

7 **Abstract**
8

9 **Purpose:** The relationship between interlocking directorates and firm performance has been
10 increasingly debated, with a focus on whether firm's centrality in interlock networks is
11 associated with performance. The purpose of this study is to not only examine how a firm's
12 position in this network is associated with performance, but also how the performance of
13 network partners can impact a firm's performance. This study examines how firms effectively
14 utilise the interlock network to achieve the goal of higher market capitalisation – termed market
15 capitalisation rank (MCR).
16
17
18
19
20
21
22
23
24

25 **Design/methodology/approach:** The premise of the study is the UK FTSE 350 firms from
26 2014 to 2018. The paper makes use of a temporal network autocorrelation model to examine
27 how firm characteristics, the structural position in the interlock network, and the performance
28 of network partners affect MCR over time.
29
30
31
32
33
34

35 **Findings:** The analysis indicates that firms with ties (via the interlock network) to firms with
36 high market capitalisation are more likely to enhance their own MCR, highlighting network
37 partners have the opportunity to play a critical role in a firm's dominance strategy to optimise
38 firm value.
39
40
41
42
43
44

45 **Originality/value:** The value of this research is that it does not only look at the impact of a
46 firm's position in the network on performance, but the impact of the performance of network
47 partners on a firm's market performance as well.
48
49
50
51
52
53
54
55

56 **Keywords:** Boards of directors; Interlocking directorates; Resource dependency theory;
57 Network analysis
58
59
60

1. Introduction

How do director network ties impact firm performance? This is a question that has been increasingly debated in the last decades (Nicholson and Kiel, 2007). Do firms with directors with a large network, sitting on multiple boards represent a certification of their expertise, where these knowledgeable and experience directors add value to the firm (Fama and Jensen, 1983)? Or are these directors over-burdened and unable to fully commit to their governance roles on boards, resulting in a negative impact on firm performance (Cashman *et al.*, 2012; Sarabi and Smith, 2021)? Do directors provide linkages between firms, allowing for a flow of resources and information between them that would be otherwise unavailable (Martin *et al.*, 2015)? Do firms reap the benefits from access to these additional sources of knowledge provide by directors' network (O'Hagan and Green, 2004)? These are some of the questions that have been debated and discussed in recent years through the lens of interlocking directorates. Interlocking directorates are when a director sits on multiple boards, causing these firms to interlock (Mizruchi, 1996). Interlocking directorates can be viewed as a network of directors, and within the literature it is one of the most studied form of inter-organisational relationships (Haunschild and Beckman, 1998). The lack of consensus on whether directors sitting on multiple boards, creating inter firm linkages, has a positive or negative impact on firm performance has resulted in this debate becoming a somewhat controversial issue within the broader field of management and corporate governance (Connelly and Van Slyke, 2012; Smith and Sarabi, 2020).

The appointment of a director constitutes a strategic decision for a public company (Adams, 2017), often in their pursuit of improved performance or optimising the value of the firm. Strategies employed to optimise firm value can be viewed as a strategy to become dominant. Tang and Thomas (1994) define strategies for a firm to optimise firm performance or value (by some given criteria) as horizontally dominant strategies. Therefore, the appointment of directors

1
2
3 can be considered to be a horizontally dominant strategy, a strategy by a firm to achieve
4 increased value and a position of dominance in the market.
5
6

7
8 The issue of board members with multiple directorships has caught the attention of policy
9 makers, where in several countries there is legislation or governance codes advising against (or
10 event restricting) the number of directorships an individual can hold. In the UK, the Financial
11 Reporting Council (FRC) have noted that there should be careful consideration when deciding
12 to appoint a director with many existing directorships, and that the justification for any such
13 appointment should be included in the company's annual report (FRC, 2018). In the US, a
14 similar pattern to the UK can be observed, where the Institutional Shareholder Services (ISS)
15 (a key advisory body providing guidance on how institutional investors should vote at annual
16 meetings where directors are elected) recommends that when a director has more than six
17 existing appointments votes to appoint this director should be withheld (Institutional
18 Shareholder Services (ISS), 2017). In 2013, the Indian government passed a law limiting the
19 maximum number of board memberships to ten (Aggarwal *et al.*, 2020).
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35

36 Network analysis of the interlocking directorates has been frequently applied to address the
37 issue of whether board members with multiple directorships, creating ties or interlocks to other
38 firms, bring value to a firm (through increased performance) (Fennema and Schijf, 1978).
39 Network analysis of interlocking directorates often examine whether firms with a most central
40 position in these networks perform better, yet existing empirical work still provides mixed, and
41 even contradictory results. Whilst there is substantial research tackling the link between a firm's
42 position in these corporate networks and performance, what is often neglected is the impact of
43 the performance of network partners on firm performance. In the extant literature, studies that
44 do acknowledge the performance of network partners tend to focus on the preference of firms
45 to connect to prestigious actors (Ahuja *et al.*, 2009, 2012; Chandler *et al.*, 2013; Powell *et al.*,
46 2005), rather than performance implications. As noted by Brennecke and Rank (2017), there is
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 a tendency to treat all interlock ties equally in existing studies, and to not fully acknowledge tie
4
5 heterogeneity in interlock ties. This is especially important when considering performance;
6
7 would a link to a well performing firm have a different impact on firm performance, practices,
8
9 and strategy, compared to a firm in decline, with a poor performance?
10
11

12
13 This study aims to contribute to the literature examining the link between firm performance and
14
15 interlocking directorates ties, by examining a relatively understudied area: the impact of the
16
17 performance of network partners on a firm's performance. More specifically, we examine
18
19 whether market capitalisation is associated with boardroom interlocking amongst the UK FTSE
20
21 350. We use market capitalisation as a measure of rank, which we refer to as market
22
23 capitalisation rank, or MCR, from here on. Firms with a higher MCR have larger values of
24
25 market capitalisation. Market capitalisation is a forward-facing, market-based measure of firm
26
27 performance. Market capitalisation is a forward-facing, market-based measure of firm
28
29 performance. Additionally, market capitalisation represents a basic valuation technique that
30
31 reflects the market position and value of the firm, and is in a form that is understandable (and
32
33 readily available) to practitioners and users (Nazir and Malhotra, 2017).
34
35

36
37 In order to identify whether linking to firms with increased performance increases a firm own
38
39 performance, we employ a complex network model, the Temporal Network Autocorrelation
40
41 Model (TNAM). The application of the TNAM allows not only to test whether a firm's central
42
43 position in a network is associated with an increase in performance but can also test the specific
44
45 impact of the performance of direct network partners on performance. This can therefore
46
47 provide insights into how the performance of direct connections contributes to a firm's strategy
48
49 of (horizontal) dominance and optimise firm value (according to market capitalisation).
50
51

52
53 This paper is structured as follows: the next section provides an overview of the literature on
54
55 interlocking directorates, focusing on the link between a firm's position and its performance.
56
57 This section concludes with a more detailed presentation of the research questions that this
58
59
60

1
2
3 paper seeks to address. This is followed by a data and methods section, noting the data sources
4 and methodology (including the model specification) to address the research questions. A
5
6 results section follows, providing both the descriptive analysis and modelling results. In
7
8 addition, there is a section describing a set of robustness checks. The final section provides a
9
10 conclusion, an overview of the main results and limitations, along with directions for future
11
12 research.
13
14
15

16 17 18 **2. Literature review**

19
20 In this section, we discuss the central theoretical framework to explain director interlocks,
21
22 resource dependency theory. We then provide a discussion on a salient issue within interlocking
23
24 directorates studies, the relationship between firm centrality and performance. We unpack this
25
26 further, examining the impact of firm position on accounting-based measures of performance
27
28 and market-based measures of performance. Following this, we present an overview of firm
29
30 prestige and performance and conclude with the research questions that this study addresses.
31
32
33

34 35 2.1. Resource dependency theory and interlocking directorates

36
37 Several theoretical frameworks have been developed to understand the antecedents and
38
39 consequences of interlock ties at the organisational level. It has been argued that the
40
41 consequences of interlock ties are the dissemination of ideas and governance practices,
42
43 increasing the legitimacy of the firm, shaping strategy and ultimately impacting performance
44
45 (Caiazza *et al.*, 2019). A key theoretical framework to understand interlocking directorates is
46
47 resource dependency theory. This suggests that interlocking directorates create links to other
48
49 firms, which provide them with access to additional (often essential) sources of advice,
50
51 information, or market intelligence (Pfeffer and Salancik, 1978). Therefore, these interlocks
52
53 serve as a mechanism for firms to manage and reduce environmental uncertainty (Boyd, 1990).
54
55 Resource dependency theory would suggest that interlocking directorates allow firms to
56
57 establish effective relationships that can facilitate beneficial knowledge exchange between
58
59
60

1
2
3 firms (Hillman *et al.*, 2009). Resource dependency theory therefore argues that interlocking
4
5 directorates have a positive impact on firm-level outcomes and performance (Galvão *et al.*,
6
7 2019; Zona *et al.*, 2018). Resource dependency theory draws on insights from sociology and
8
9 management literature (Kiel and Nicholson, 2003; Pettigrew, 1992); sociologists indicate that
10
11 these director interlocks provide firms with access to the corporate elite, social (and in some
12
13 cases financial) capital, and (on rare occasions) competitors (Mizruchi and Stearns, 2006).
14
15

16
17 There has been growing interest in interlocking directorates (Caiazza, 2019; David and
18
19 Westerhuis, 2014), where empirical analysis of these networks is utilised to address research
20
21 questions on corporate governance (Kogut, 2012) and knowledge flow between firms (O'Hagan
22
23 and Green, 2002). The relationship between interlocking directorates and firm performance has
24
25 received particular attention (Sánchez *et al.*, 2017). Some scholars find, in line with the
26
27 expectation of resource dependency theory, that interlocks have a positive effect on firm
28
29 performance (Kiel and Nicholson, 2003). Others identify a negative effect (Santos *et al.*, 2012),
30
31 which points towards interlocking directorates spreading maladaptive practices in the network,
32
33 together with time constraints on directors with multiple appointments limiting their abilities as
34
35 effective monitors. This study proposes to contribute to this literature, by examining the link
36
37 between interlocking directorates and market capitalisation, complementing the existing
38
39 literature, by applying a forward-facing market-based measure of performance. Market
40
41 capitalisation has been utilised in a range of empirical studies to capture firm performance
42
43 (Nazir and Malhotra, 2017; Priyadharshini *et al.*, 2015).
44
45
46
47
48

50 2.2. Centrality and firm performance

51
52 When examining firm-level behaviour, it is important to acknowledge that firms do not act in
53
54 isolation from one another; rather, their behaviour is often highly interdependent, as they are
55
56 embedded in a networked environment (Granovetter, 1985). The notion of embeddedness has
57
58 often been used to explain how network ties influence firm-level outcomes. The concept, widely
59
60

1
2
3 discussed in Gulati and Gargiulo (1999), is based on the notion of centrality. Centrality captures
4 the importance or prominence of actors in a network and is one way of considering the “roles”
5 of actors in a network, without focusing on the specific individuals who play these roles
6 (Borgatti and Everett, 1992). This positional embeddedness approach allows for an
7 investigation into the benefits gained from information stemming from particular positions in
8 the network.
9

10
11
12 The interplay between centrality in an interlocking directorate system and firm performance
13 has been examined in detail (Drago *et al.*, 2015). Within this stream of literature, a wide range
14 of metrics and measures are used to capture firm performance; these are often categorised as
15 either market-based or accounting-based measures. Accounting-based measures tend to be
16 historical measures of performance, with a backward- and inward-looking focus, where they
17 reflect past firm successes and failures. They are, therefore, a staple reporting mechanism and
18 measure of corporate performance (Kiel and Nicholson, 2003). By contrast, market-based
19 measures reflect the overall value placed on the firm by the market and are forward-facing
20 measures of performance. Market-based measures place an emphasis on the future expected
21 earnings of the firm that capture current strategies. Examples of accounting-based measures
22 include Return on Assets (ROA), Return on Equity (ROE), and Return on Capital Employed
23 (ROCE). Examples of market-based measures include Tobin’s Q, market-to-book ratio, and
24 market capitalisation. Given the wide variety of measures to capture performance, the impact
25 of interlock ties can vary substantially.
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48

50 2.2.1. Accounting-based measures of performance

51
52 Several studies have examined the interplay between interlocks and firm performance, drawing
53 on accounting-based measures. Larcker *et al.* (2013), in an in-depth investigation of the
54 relationship between centrality and firm performance (measured by changes in ROA) in the
55 US, examine multiple measures of network centrality. Firstly, they examine degree centrality,
56
57
58
59
60

1
2
3 a count of the number of ties of each firm as determined by their interlocks. Firms with a higher
4
5 degree centrality are assumed to have more channels of interaction with others. Betweenness
6
7 centrality, the number of times an actor sits on the shortest path between two others, captures
8
9 the brokerage potential. Closeness centrality is a metric that captures how “close” an actor is to
10
11 all others in the network; information or resources may flow quicker to those with higher
12
13 closeness centrality. Eigenvector centrality captures the centrality of an actor’s alters, i.e. the
14
15 case when those well-connected actors are connected to other well-connected actors. Larcker
16
17 *et al.* (2013) note that there is a positive impact of firm centrality on performance (for all types
18
19 of centrality), yet the returns from holding a central position are not immediate. A further
20
21 analysis of ROA and interlocking directorates in the US is provided by Martin *et al.* (2015).
22
23 They identify a strong positive effect of interlock networks on firm performance, but only when
24
25 uncertainty is high.
26
27
28
29

30
31 Yu and Chiu (2013) analyse the impact of interlocks in Taiwan on another accounting-based
32
33 measure of performance, sales growth. Whilst there is often a lack of consensus on the impact
34
35 of centrality (or position in the interlock network) and firm performance, Yu and Chiu (2013)
36
37 state that this is due to a non-linear relationship between the two. They identify an inverted U-
38
39 shaped relationship between centrality and firm performance: centrality has a positive impact
40
41 on firm performance, until the centrality reaches a certain level, at which point it has a negative
42
43 impact on firm performance. They conclude that firms benefit from a moderate centrality,
44
45 where firms with higher levels of centrality experience higher costs in terms of absorbing and
46
47 integrating more diverse information extracted from interfirm network ties.
48
49
50

51 52 53 2.2.2. Market-based measures of performance

54
55 Market-based measures are also utilised in the extant literature considering the link between
56
57 firm performance and the corporate interlock system. Similar to studies utilising accounting-
58
59 based measures, studies using market-based measures have identified both positive (Baran,
60

1
2
3 2017; Baran and Wilson, 2018; Horton *et al.*, 2012) and negative (Nam and An, 2018)
4 relationships between market based performance measures and a firm's network position. Croci
5 and Grassi (2014) analyse the impact of a variety of centrality metrics on firm value as measured
6 by the Q-Ratio, a market-based metric, for a set of Italian firms. They identify a consistent
7 negative relationship between degree and eigenvector centralities and firm performance, while
8 betweenness centrality is not associated with a reduction in firm performance. This highlights
9 differences between centrality measures, and how they impact firm performance; while degree
10 and eigenvector centralities are likely to be associated with power and influence, betweenness
11 and closeness are associated with the flow and transfer of information between firms.
12
13
14
15
16
17
18
19
20
21
22

23
24 In this paper we make use of market capitalisation as a measure of firm performance. We
25 selected a market-based measure (rather than an accounting-based measure), as this study wants
26 to focus on how current strategies shape performance, to aid in the identification of the pathway
27 to dominance, and therefore, a forward-facing measure is more appropriate. This allows us to
28 look at how a firm's position within the network can impact future value, which is of particular
29 interest to practitioners and users.
30
31
32
33
34
35
36
37

38 2.3. Partner prestige and firm performance

39
40 In addition to the work examining the link between centrality and performance, there is a stream
41 of literature that examines the processes underpinning the formation of interlock ties, and the
42 preferences that firms have for certain types of firms when creating interfirm linkages. For
43 instance, Ahuja *et al.* (2009) argue that firms poorly embedded in corporate systems are less
44 likely to form interfirm ties as they lack the informational and reputational benefits; whereas
45 highly embedded firms are more likely to form ties with other highly embedded firms, to
46 mitigate uncertainty. Others note that many firms have a preference for creating ties with
47 prominent firms as they can enhance firm legitimacy (Knoben and Bakker, 2019), and that this
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 is of particular importance for younger firms (Gulati and Higgins, 2003; Higgins and Gulati,
4
5 2003).

6
7
8 This has resulted in another stream of literature examining how links to prominent and
9
10 prestigious firms impact performance. For instance, Jahan *et al.* (2020) find, in an examination
11
12 of firms from New Zealand, that prestigious board members have a positive impact on firm
13
14 performance (measured by both market- and accounting-based metrics). Gulati *et al.* (2011)
15
16 propose a set of key mechanisms to explain how network resources contribute to firm
17
18 performance: reach, richness, and receptivity. Reach refers to how wide-ranging and
19
20 heterogeneous the organisation's network connections are, where the greater the diversity, the
21
22 greater the reach. Richness is the value a firm can derive from the attributes of network partners,
23
24 i.e., the ability to orchestrate network ties and integrate them with the firm's own resources to
25
26 create greater value. Receptivity is the extent to which a firm is able to channel, leverage, and
27
28 utilise network resources. In this paper, we draw on the richness mechanisms to better
29
30 understand the impact of the interlock network on firm performance We focus on the concept
31
32 of richness (rather than reach and receptivity) as we are interested in how the MCR of network
33
34 partners can impact firm performance and contribute to the firm becoming (horizontally)
35
36 dominant.
37
38
39
40
41
42

43 2.4. Research questions

44
45 This paper aims to contribute to the ongoing debate on the relationship between networks and
46
47 firm performance. This paper asks several questions regarding the effect of network ties and a
48
49 firm's position in the network, on market capitalisation rank (MCR), using the UK FTSE 350
50
51 between 2014 and 2018 as the empirical setting. We ask questions regarding how a firm's
52
53 position in the network is associated with performance, drawing on measures of centrality, as
54
55 observed in the extant literature. More specifically, we follow the work of Larcker *et al.* (2013)
56
57 and utilise degree, betweenness, and eigenvector centralities. We then go beyond only looking
58
59
60

1
2
3 at centrality and examine the impact of the performance of network ties on firm performance,
4 not just the position of a firm in the network and the number of connections. This allows us to
5 empirically test the richness hypothesis outlined by Gulati *et al.* (2011), investigating whether
6 a firm draws value (in this case MCR) from the attributes of network partners.
7
8
9

10
11
12 We address the following focal research questions in our study, relating to the impact of the
13 firm's position in the network and effects on MCR amongst the FTSE 350.
14
15

- 16 1. Is centrality in the interlock network associated with higher MCR?
- 17 2. Are ties to firms with higher MCR associated with improving a firm's own MCR?

18
19
20 These research questions allow us to inform on whether network ties constitute an important
21 part of a firm's (horizontally) dominant strategy to optimise firm value (according to market
22 capitalisation).
23
24
25
26
27
28
29

30 **3. Data & methods**

31 3.1. Data

32
33 We examine a network of firms that are linked by 'shared' directors, which means directors
34 who sit simultaneously on the boards of these firms. We refer to this network as the interlock
35 network, where firms are linked by interlocking directorates.
36
37
38
39
40
41
42

43 We examine firms that are on the UK FTSE 350 index. Constituents of the UK FTSE 350
44 represent large and mid-sized firms listed on the London Stock Exchange (the top 350 firms
45 listed on the stock exchange). The UK FTSE 350 contains the constituents of the UK FTSE 100
46 and 250.
47
48
49
50
51

52 This data is extracted from a combination of Companies House (British government website)
53 and Bureau van Dijk's Orbis. Companies House provides data on the directors who sit on the
54 boards of UK firms, along with the start and end dates of their directorships, and details on the
55
56
57
58
59
60

1
2
3 sector the firm operates in (defined using the Standard Industrial Classification (SIC) codes).
4
5 Information from Companies House is used to construct the interlocking directorate network,
6
7 and to calculate the board size of each firm. Orbis provides additional firm-level data, more
8
9 specifically, firm financial data. We extract firm data on the number of employees and Return
10
11 on Capital Employed (ROCE) from Orbis. We examine UK FTSE 350 firms from 2014 to 2018.
12
13 We have selected this five-year period as it is a reasonably stable one in terms of market
14
15 changes, hence we can assume that market values during this period are more closely associated
16
17 with profit rather than risk. The market capitalisation data, the firm performance measure
18
19 utilised in this study, is extracted directly from the London Stock Exchange.
20
21
22

23
24 Table (1) provides descriptive information on the firm-level variables. We observe high levels
25
26 of variation in the ROCE amongst firms, suggesting a high level of variability in firm
27
28 profitability (in terms of how profit is generated from firm capital). Average firm size,
29
30 according to the number of employees (normalised), is constant across time. Board size appears
31
32 to be increasing, yet the variation in board size is decreasing (slightly).
33
34

35
36
37 -----
38
39 Insert Table 1 about here.
40
41 -----
42
43

44
45 In this study, we employ a number of network metrics and measures to study the interlock
46
47 networks of UK FTSE 350; these are discussed in further detail in the model specification
48
49 section.
50

51 3.2. Methods

52
53 An advanced network model is used to address the research questions presented in this paper:
54
55 the Temporal Network Autocorrelation Model (TNAM).
56
57
58
59
60

3.2.1. TNAM background

The autocorrelation model was first developed and applied to detect the presence of spatial autocorrelation, and its impact on a dependent variable ((Cliff and Ord, 1972). Autocorrelation models have been frequently applied in social network analysis (Leenders, 2002), mainly to model social influence and contagion patterns, as they allow researchers to empirically test for network effects on actor behaviour. In recent years increased attention has been given to the methodological development and extensions of network autocorrelation models, including temporal variants (Dittrich *et al.*, 2017; Leifeld *et al.*, 2017). The TNAM has been applied in a variety of contexts, such as to address research questions regarding networks and political actors (Metz and Ingold, 2017).

The model is applied by considering a weight matrix, W (the network), where w_{ij} reflects a tie between i and j , and the weight captures the extent to which actor j (the alter) influences the behaviour or performance of actor i (the ego). Leenders (2002) and Wang *et al.* (2014) provide a detailed description of the formulation of the network autocorrelation model. The TNAM is one of the most comprehensive models available to investigate the performance of an actor in a network. The performance of an actor i can be estimated conditional to a wide range of variables, including actor covariates, the performance of network partners, and the previous performance of actor i (see Silk *et al.*, 2017 for an in-depth discussion of the model). Following the approach outlined by Leenders (2002), a normalisation process is applied to the weight matrix. Utilising the established approach observed in the literature, and recommended by Leenders (2002), a row normalisation is applied to the weight matrix. With row normalisation, the same weight is assigned to every outgoing tie of actor i , proportional to the total number of connections actor i sends. Under this normalisation process, every actor is influenced to the same extent from all their connections, however, as their total number of connections increases, the less influence each individual actor j has on actor i .

3.2.2. Application of the TNAM to the interlock network

In this context the TNAM allows us to examine how the interlock network influences firm performance. However, when examining the link between the director interlock network and firm performance, the issue of endogeneity arises. Whilst a firm may intend to improve firm performance when appointing a director with multiple directorships, an alternative explanation is that prominent directors are matched to high-performing firms (Kim and Higgins, 2007; Omer *et al.*, 2014). That is, well-connected directors accept positions at highly performing firms. Given the potential endogeneity issues, a robustness check is implemented, following the main TNAM estimation.

We draw on the approach presented by Larcker *et al.* (2013), where they restrict the analysis in their robustness checks to subsets of firms. Following this approach in the robustness check analysis, the interfirm network (W) is split into two parts. The first is a network of interfirm ties that remained the same from the previous year ($t-1$) to the current year (t), and the other is an interfirm network of ties between firms that have changed from the previous and current year. The TNAM is then implemented separately for each of these networks. The results from the TNAM for the network that has remained unchanged from one year to the next are less likely to be a result of endogenous choices by firms (Barzuya and Curtis, 2014). Therefore, there will be three sets of TNAM applications: firstly, on the original data (we refer to this as the main TNAM), secondly to the interlock network where ties have remained constant, and finally to the interlock network where ties have changed from year to year (the final two model sets are referred to as the robustness check TNAMs).

3.3. Model specification

The outcome variable used in this study to reflect market rank is market capitalisation. We include a number of firm-level variables and network effects in the TNAM specification to

1
2
3 examine what influences the MCR over time. We include a lagged market capitalisation term
4
5 to assess the impact of previous MCR on current MCR levels.
6
7

8 3.3.1. Firm-level covariates 9

10 We include two firm-level covariates to control for company size and financials in the analysis:
11
12 number of employees and ROCE respectively. Number of employees is an established measure
13
14 to capture the size of the firm, and ROCE is an accounting-based firm metric (Kalsie and
15
16 Shrivastav, 2016). This allows us to better assess the impact of network effects on MCR – above
17
18 and beyond the effect of firm size and financials, and how network ties shape a firm's MCR.
19
20
21

22
23 A further firm covariate that is included is board size; the impact of board size on firm
24
25 performance has long been a matter of debate. Several studies have found that a larger board
26
27 has a negative impact on firm performance (Cheng, 2008; Nguyen *et al.*, 2016; Yermack, 1996),
28
29 where they argue that a larger board leads to poor communication and ineffective decision
30
31 making, which undermines effectiveness (Guest, 2009). However, others argue that a larger
32
33 board results in better monitoring, as larger groups naturally give rise to more diversified
34
35 opinions. These larger boards offer the opportunity for greater scrutiny, and an increased
36
37 likelihood of rejecting risky decisions, which can have a positive impact on performance. A
38
39 resource dependency theory perspective would argue that larger boards bring more
40
41 opportunities to access external resources, therefore should have a positive impact on firm
42
43 performance. Belkhir (2009) examines the impact of board size on performance in the banking
44
45 sector and does not find evidence of firms with smaller boards outperforming those with larger
46
47 boards, rather the results point towards an increase in performance of firms with a larger board
48
49 size.
50
51
52
53

54
55 The inclusion of board size in the model specification allows for an investigation of the impact
56
57 of board size on MCR, indicating whether it is an efficient board that is able to make decisions
58
59
60

1
2
3 quickly (a smaller board), or effective board governance and monitoring (a larger board), that
4
5 is associated with MCR.
6
7

8 We also create a sector similarity term to test whether firms operating in the same sector
9
10 (according to their one-digit SIC code) hold similar MCR. This term captures whether two firms
11
12 similar in one dimension (sector) are more or less likely to be similar in another (MCR).
13
14

15 16 3.3.2. Network effects

17
18 In addition to the firm-level covariates, we include several network effects. These are structural
19
20 effects that are based on the interlock network.
21
22

23 Firstly, a structural similarity term is specified (similar to the sector similarity term). This
24
25 measure allows for an examination of whether firms that hold equivalent (or structurally
26
27 similar) positions in the network, also have an equivalent MCR (Westphal *et al.*, 2001).
28
29

30 A further structural variable is also included in the model: clustering. This captures the extent
31
32 to which high levels of local connectivity and cohesion can have positive coordination effects.
33
34 Large levels of cohesion may lead to increased levels of redundant information exchanges,
35
36 which may have a negative impact on performance (Crocchi and Grassi, 2014).
37
38

39 Following the approach applied in the extant literature, we include centrality measures to
40
41 capture whether holding a more central position in the interlock network is associated with
42
43 higher MCR.
44
45

46 Firstly, we consider degree centrality, which we view as a measure of activity. In this context,
47
48 the degree centrality of a firm is the number of firms it is connected to via interlocking
49
50 directorate ties (Freeman, 1978). This allows us to test whether being connected to a high level
51
52 of firms is beneficial – by giving access to more resources.
53
54
55
56
57
58
59
60

1
2
3 Secondly, we consider betweenness centrality, which refers to the number of times a firm sits
4 on the shortest path between two other firms in the network (Freeman, 1977). Betweenness
5 centrality captures a firm's brokerage in the network, and we view this as a measure of flow.
6
7 This allows us to test whether acting as a broker in this firm interlock network is associated
8 with MCR.
9

10
11
12 Finally, we look at eigenvector centrality, which not only captures the number of ties a firm has
13 in the network, but also the number of ties of its network partners. Eigenvector centrality is a
14 measure of global connectivity. Firms with a high eigenvector centrality are connected to other
15 well-connected firms in the network (Bonacich, 1987).
16
17

18
19 Given the correlation between centrality measures (Valente *et al.*, 2008), these three terms are
20 included in different models. The inclusion of these centrality measures in the model
21 specification addresses the first research question posed by this paper.
22
23

24
25 In order to address the second research question, we include a network lag variable that we refer
26 to as the netlag term. The terminology originates from the spatial autoregressive modelling
27 literature, where the term spatial lag is used to capture the effect of spatial autocorrelation. The
28 netlag parameter captures how much direct network partners influence the MCR of firms. A
29 positive and significant parameter would indicate that, if a firm is connected to firms with a
30 high MCR, it is more likely to improve its own MCR. A negative and significant parameter
31 would indicate firms with prominent MCR potentially gaining more from interlock ties with
32 partners with less favourable MCR and hence having more bargaining power (Clark and
33 Mahutga, 2013). Additionally, the use of the netlag term allows us to test the mechanisms
34 proposed by Gulati *et al.* (2011) and, in particular, the richness process, where a positive and
35 significant term would indicate a firm's tendency to utilise high-performing (or rich) network
36 partners to increase their own value.
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

3.4. TNAM formulation

For all the structural and network effects (structural similarity, netlag term and various centrality measures), the lag is taken that is, the effect is for the position in the network of the company at the previous timepoint on current MCR. The lag is used, as it takes time for a firm to reap the benefits from an interlock tie (Larcker *et al.*, 2013), where beneficial knowledge exchange is unlikely to be instantaneous. Additionally, the use of lagged variables also aids in alleviating potential endogeneity effects (Li *et al.*, 2019).

Therefore, in this case the TNAM is defined as follows:

$$y_{it} = \rho W_{t-1} + \beta_1 x_{it-1} + \beta_2 z_{it} + \varepsilon$$

Where:

- y_{it} refers to the dependent variable, market capitalisation of actor i at time t
- W_{t-1} refers to the effect of the weight matrix – the firm interlock network
- x_{it-1} refers to the vector of lagged structural network effects of actor i (structural similarity, netlag term and various centrality measures)
- z_{it} refers to the vector of firm covariates (number of employees, ROCE, board size, sector similarity)

4. Results

4.1. Descriptive network analysis

Before proceeding to model implementation, several descriptive statistics are calculated to provide an overview of the network data under examination. Networks are often characterised by an area where most actors are connected, with only a limited number of actors disconnected from this area or section. This is referred to as the giant connected component (or main component), and has long been recognised as a feature of interlocking directorate networks

1
2
3 (Chu and Davis, 2016). In this paper, the network is also characterised by a giant connected
4 component. Given that we are focused on the impact of network ties on MCR, the analysis will
5 be restricted to firms that are part of the largest connected component during the timeframe.
6
7 Therefore 229 firms are included in this study and all subsequent analysis, both descriptive and
8
9 modelling, is limited to these 229 firms. Firms outside the connected component tend to be
10
11 isolates, or small sets of firms connected with a limited number of ties.
12
13
14
15

16
17 The descriptive statistics for the additional firm covariates specified in the model, ROCE,
18
19 number of employees, and board size are presented in Table (1). The mean ROCE appears to
20
21 have remained constant over time; however, the spread of ROCE has reduced substantially
22
23 since 2014. The mean and spread of number of employees has remained constant from 2014 to
24
25 2018. The average board size appears to have increased slightly since 2014. In Spain, policy
26
27 recommendations have been made outlining that the ideal board size is between 5 and 15
28
29 individuals (Campbell and Mínguez-Vera, 2008; Fernández-Fernández, 1999). Table (1)
30
31 indicates that the board size of UK FTSE 350 firms is within these guidelines.
32
33
34
35

36
37 Table (2) presents a set of descriptive network statistics for the giant connected component over
38
39 the five-year time period. To better understand the overall structure of the interlock networks,
40
41 we use various network measures, namely density, diameter, degree centralisation, and
42
43 clustering coefficient. These represent established measures within social network analysis to
44
45 explain the salient features of a network structure. We provide a short description for each of
46
47 these measures, and brief interpretations for the interlock network.
48
49
50

51
52 Density is defined by calculating the ratio of observed ties to all possible ties in a network
53
54 (Wasserman and Faust, 1994), and acts as a measure of network connectivity. Table (2)
55
56 indicates that network density is relatively low across the time period yet has increased very
57
58 slightly since 2016.
59
60

1
2
3 Network diameter is the longest geodesic distance in the network; where the geodesic distance
4 refers to the number of relationships in the shortest possible path from one actor to another
5 (Knoke and Yang, 2008). From Table (2), we can see that the actors in the network have become
6 “closer” to each other between 2017 and 2018, with a reduction in the diameter value. Chu and
7 Davis (2016) examine the average geodesic distances for the US case, from 1997 to 2010, in
8 their analysis of the US corporate elite. In their study, they note a contrasting result where, in
9 the main connected component, they observed an increase in the average geodesic distance.
10 This highlights a key difference between the US and the UK in terms of the structure of the
11 interlock network, indicating a fracturing and reduced connectedness amongst the corporate
12 elite in the US, a fracturing that is not widely observed in the UK where, instead, firms move
13 closer to each other.
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28

29 Degree centralisation captures distribution of degree centrality in the network. In a network
30 with a high degree centralisation score (closer to 1), the degree centrality is concentrated in a
31 handful of actors in the network, whereas a lower score (closer to 0) would indicate that it is
32 evenly distributed throughout the network (Borgatti *et al.*, 2018). Table (2) indicates that degree
33 centralisation remains relatively low across the time period, with a slight increase in 2018.
34
35
36
37
38
39
40

41 The clustering coefficient is a measure of network cohesion and represents the average of the
42 densities of the neighbourhoods of all of the actors (Watts and Strogatz, 1998), therefore it
43 captures the extent to which the network is characterised by areas of high density. As observed
44 in Table (2) the clustering coefficient remained relatively constant over the time period, yet it
45 dipped slightly in 2017 and 2018. This suggests that in later years the network is not
46 characterised by densely connected areas.
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Insert Table 2 about here.

4.2. TNAM results

4.2.1. Firm-level covariate results

Table (3) presents the results for the main TNAMs (the first set of TNAMs applied to the original data). There are three models, one model for each centrality measure. In terms of the firm covariate results, number of employees is positive and significant. This indicates that larger firms are much more likely to have higher MCR. However, the ROCE effect is not significant, suggesting that a higher level of financial resources is not associated with MCR amongst the UK FTSE 350. Board size is a positive and significant effect, indicating that firms with larger boards are more likely to have higher MCR. This is in line with the findings of Belkhir (2009), suggesting that these larger boards offer greater scrutiny, leading to less risky, performance-enhancing decision making. In regard to the ideal board size, as recommended by Spanish policy makers, this suggests a board size closer to 15 directors (the upper limit) may be more beneficial (in terms of firm performance).

Insert Table 3 about here.

Lagged market capitalisation is positive and significant, indicating that previous MCR has a significant impact on current MCR. This points towards some consistency in the dominant players in the FTSE 350 during the time period. Sector similarity is a negative, small, and weakly significant term in the model, indicating that firms belonging to the same sector do not significantly share MCR, rather they have diverging MCR. This potentially points towards an

1
2
3 uneven distribution of MCR in sectors, suggesting there are a few highly ranked actors in each
4 sector. An examination of sector leaders in the network represents an avenue for future research.
5
6
7

8 4.2.2. Network effect results 9

10 The network effects specified in the model include netlag, clustering, structural similarity, and
11 the various centrality measures. The netlag result is consistently positive and significant,
12 although this significance is reduced in the flow (betweenness centrality) and global
13 connectivity (eigenvector centrality) model results. This provides evidence that a firm enhances
14 its MCR by connecting to firms with high MCR. It also indicates that firms do not gain from
15 connecting to firms with low MCR, suggesting there is no benefit in having network partners
16 dependent on them for knowledge and advice. This also provides support for the richness
17 mechanism proposed by Gulati *et al.* (2011), that the richness of network resources is a key
18 component to enhance firm value.
19
20
21
22
23
24
25
26
27
28
29
30
31

32 The structural similarity effect is positive and weakly significant in the activity (degree
33 centrality) model (and non-significant elsewhere). This suggests that, in some cases, firms with
34 a similar position in the interlock network do share some aspects of their MCR. The clustering
35 parameter is non-significant, indicating that clustering does not accrue positive coordination
36 effects, nor does it lead to high levels of redundant information. It does not impact MCR
37 amongst the UK FTSE 350.
38
39
40
41
42
43
44
45

46 Overall, we do not observe consistent effects for the link between performance and centrality
47 across the different types of centrality, as seen in the main TNAM results presented in Table
48 (3) (a phenomenon observed elsewhere in the literature). For degree centrality, there is a
49 positive and weakly significant result, suggesting that having a higher number of ties accrues
50 positive performance effects. For both betweenness centrality and eigenvector centrality, the
51 parameters are non-significant. Weak and non-significant centrality terms may be a result of
52 the ambiguous link between firm performance and interlocking directorates, as noted in the
53
54
55
56
57
58
59
60

1
2
3 existing literature. However, Larcker et al. (2013) note that director networks provide economic
4 benefits that are not immediately realised in the stock market, and therefore may not have an
5 immediate impact on the market capitalisation of firms at the one-year lag we employ here.
6
7 This suggests future work should look to expand the timeframe of our study and focus on the
8 long-term impact of interlocks on market capitalisation rank.
9
10
11
12
13

14 4.3. Robustness checks

15
16 As noted in the methods section, when investigating the link between a firm's position in the
17 interlock network and firm performance, the issue of endogeneity arises. For instance, in the
18 results presented in Table (3), the positive and (weakly) significant degree centrality effect and
19 the positive and significant netlag effect may reflect a preference for well-connected directors
20 to sit on the boards of high-performing firms. However, in a slight contrast to this argument,
21 Jiang *et al.* (2020) note that declining firms will often appoint prominent directors, indicating
22 that director appointments are not only a result of matching, rather the appointment of these
23 directors is to increase the perceived performance of the declining firm, especially to outside
24 parties.
25
26
27
28
29
30
31
32
33
34
35
36
37
38

39 Therefore, to overcome these potential robustness issues, we implement the checks outlined in
40 the methods section, which follows the approach outlined by Larcker *et al.* (2013). Tables (4)
41 and (5) present the results of the robustness checks. Table (4) presents the TNAM results for
42 the interfirm interlock ties that have remained constant from one year to the next. Table (5)
43 reflects the TNAM results for interfirm network ties that have changed from one year to the
44 next. These results indicate that the netlag parameter is only significant for network ties that
45 remain unchanged from one year to the next, rather than new ties. This result is in line with the
46 work of Larcker *et al.* (2013), suggesting the return on performance from connecting with high-
47 performing firms is not immediate, rather performance benefits are accrued over time.
48
49
50
51
52
53
54
55
56
57
58
59
60

Insert Table 4 about here.

Insert Table 5 about here.

When examining the network effects in the robustness checks presented in Tables (4) and (5), we observe, for the structural similarity term, that the significance drops off slightly; however, the result was only significant for the degree centrality model in the main TNAM (the set of TNAMs applied to the original data). A similar pattern is observed for centrality in the degree centrality robustness models. This adds to the mixed results in the literature examining the link between firm performance and measures of firm centrality.

The netlag result in Table (4) follows the same pattern as the main TNAM given in Table (3), but in Table (5) the netlag result is non-significant (and negative). This indicates that the performance of network partners has a positive effect when these are long-term interfirm linkages, rather than newly formed. These findings are in line with Larcker *et al.* (2013), that the market value benefits from interlock ties are not instant. This result also suggests that the netlag result is less likely to be an outcome of endogenous firm choices and appointments. A further robustness check is presented in the appendix to further support the results presented in this paper.

Table (6) provides a summary of the key findings and differences between the main TNAM (those applied to the original data) and the robustness checks (the two sets of TNAMs applied to the network constant ties and changing ties). In particular, this highlights the differences in the netlag results.

Insert Table 6 about here.

5. Conclusion

This paper posed two research questions examining the role of network ties on market capitalisation rank (MCR) amongst the giant connected component of the UK FTSE 350, which consists of 229 companies. The paper seeks to contribute to the extant literature by applying a resource dependency perspective and to examine the richness element of the model proposed by Gulati *et al.* (2011). We asked whether firms occupying more central positions are more likely to improve their MCR and whether firms are more likely to improve their MCR by establishing ties to other firms with high MCR. To address these research questions an advanced network model, the Temporal Network Autocorrelation Model (TNAM), was applied to a network of interfirm connections amongst the UK FTSE 350 from 2014 to 2018.

In order to address the first research question, a set of centrality measures were included in the model specification. In line with extant studies on the impact of interlocking directorates and firm performance, the impact of centrality effects on MCR is mixed. There was some evidence that direct ties (degree centrality), more specifically the number of direct ties to other firms, are positively associated with MCR. By contrast indirect measures of network prominence, such as betweenness and eigenvector centrality, do not have a significant relationship with MCR. These results are in line with those of Yu and Chiu (2013), which suggest that moderate centrality is more likely to have a positive impact on firm performance than very high centrality levels. Future work could unpack the relationship between market capitalisation rank and a wider range of centrality measures to explore further the relationship between network centrality and firm performance. Additionally, there is scope to further test whether there is an inverted U-shaped relationship between centrality and market capitalisation performance.

1
2
3 To address the second research question, a netlag parameter was included in the model
4 specification. The results indicate that the MCR of network partners significantly affects a
5 firm's own MCR, providing some support for the richness mechanism proposed by Gulati *et*
6 *al.* (2011).
7
8
9
10
11

12
13 Overall, our analysis suggests that beyond firm size, the network effect that matters for a firm
14 to increase its MCR is not necessarily centrality in the interlock system (as reflected by the
15 weakly significant centrality results) but creating ties to other firms with high MCR. This has
16 an implication for strategic decisions about director appointments. Rather than appointing a
17 director with many other appointments, using multiple appointments as a certification of the
18 director's abilities (Cashman *et al.*, 2012), firms should examine the market capitalisation rank
19 and performance of the firms where the directors already hold an appointment. The results
20 presented in this paper indicate that MCR matters, and that when a firm is looking for network
21 partners for strategic knowledge exchange, the MCR of potential partners should not be
22 neglected. When firms appoint directors to create these strategic partnerships, they should look
23 to appoint directors from firms with higher MCR. Therefore, the practical contribution of this
24 research is that firms should not disregard the connectedness of directors when making
25 appointments, as the network partners have an impact on performance; however, they should
26 not focus only on the number of appointments a director holds but should also look at the quality
27 (or prominence) of these appointments. These results also indicate that network ties have the
28 potential to act as important elements of a firm's (horizontally) dominant strategies to optimise
29 firm value. Furthermore, we observe that a larger board size is also associated with increased
30 MCR; firms can practically implement this to potentially increase market capitalisation. This
31 paper also contributes to empirical work drawing on theories of resource dependency, and the
32 related work of Gulati *et al.* (2011) on the performance of network connections and related
33 consequences.
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

1
2
3 When comparing these results to previous studies, a number of similarities and differences
4 between the UK and US case (a prominent empirical setting for many interlock studies) emerge.
5
6 In particular, we observe that many of the findings here, both for the main results and the
7
8 robustness tests, are in line with the work of Larcker *et al.* (2013). For the case of the FTSE
9
10 350, the position and network ties emerging from the interlocking directorate system have a
11
12 positive impact on firm performance, yet the benefits are not instantaneous. In terms of the
13
14 structure of the network, differences emerge between the UK case and existing work examining
15
16 the US. Whilst many have noted that the interlocking directorate network is fracturing and
17
18 becoming less connected in the US in the past decade (Chu and Davis, 2016; Mizruchi, 2013),
19
20 this is not observed in the UK, for the case of the FTSE 350, where there still exists a main
21
22 connected component, with a short distance between firms.
23
24
25
26
27
28

29 5.1. Limitations of the study & future research

30
31 A salient point to note from the robustness checks presented in this paper, more specifically the
32
33 change in significance of the netlag parameter for the newly formed interlock ties network, is
34
35 that there is a need to interpret these results, along with practical recommendations, with
36
37 caution. There is also a need to further unpack the link between the performance of connections
38
39 and a firm's performance in future research.
40
41
42

43
44 There are limitations to the analysis of a market-based measure of firm performance presented
45
46 in this study. We only concentrate on the main connected component, and disregard other
47
48 isolated, or small components. The results indicate that it is not necessarily centrality that has a
49
50 positive impact on firm performance, rather it is the performance of partners, therefore this
51
52 suggests that further research would be required.
53
54

55
56 An additional avenue for future research would be to explore different market performance
57
58 measures, such as those that would capture the market dominance of firms in the interlock
59
60 system. This would allow for an investigation into whether the impact of the interlocking

1
2
3 directorate network remains consistent across market measures. Examples of potential
4 measures are presented by Hellmer and Wårell (2009) and Melnik *et al.* (2008) in their
5 examination of the Nordic electricity market. A further area to examine in more detail is the
6 dynamics of market capitalisation rank at the sector level, given that our results indicate
7 potentially uneven distribution of market performance at the sector level. In addition, further
8 research could also examine how the performance of network ties, and not only centrality
9 measures, shapes performance for accounting-based measures.
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

6. References

- Adams, R.B. (2017), “Boards, and the directors who sit on them”, *The Handbook of the Economics of Corporate Governance*, Vol. 1, Elsevier, pp. 291–382.
- Aggarwal, M., Chakrabarti, A.S. and Dev, P. (2020), “Breaking ‘bad’ links: Impact of Companies Act 2013 on the Indian Corporate Network”, *Social Networks*, Vol. 62, pp. 12–23.
- Ahuja, G., Polidoro, F. and Mitchell, W. (2009), “Structural homophily or social asymmetry? The formation of alliances by poorly embedded firms”, *Strategic Management Journal*, Vol. 30 No. 9, pp. 941–958.
- Ahuja, G., Soda, G. and Zaheer, A. (2012), “The genesis and dynamics of organizational networks”, *Organization Science*, INFORMS, Vol. 23 No. 2, pp. 434–448.
- Baran, L. (2017), “Director connectedness and firm value in S&P 500 Index reconstitutions”, *Journal of Economics and Business*, Vol. 92, pp. 63–79.
- Baran, L. and Wilson, R. (2018), “Whom You Connect with Matters: Director Networks and Firm Location”, *Journal of Financial Research*, Vol. 41 No. 1, pp. 113–147.
- Barzuza, M. and Curtis, Q. (2014), “Board interlocks and corporate governance”, *Del. J. Corp. L.*, HeinOnline, Vol. 39, p. 669.
- Belkhir, M. (2009), “Board of directors’ size and performance in the banking industry”, *International Journal of Managerial Finance*, Vol. 5 No. 2, pp. 201–221.
- Boehmke, F.J., Chyzh, O. and Thies, C.G. (2016), “Addressing Endogeneity in Actor-Specific Network Measures”, *Political Science Research and Methods*, Vol. 4 No. 01, pp. 123–149.
- Bonacich, P. (1987), “Power and centrality: A family of measures”, *American Journal of Sociology*, Vol. 92 No. 5, pp. 1170–1182.

- 1
2
3 Borgatti, S.P. and Everett, M.G. (1992), “Notions of position in social network analysis”,
4
5 *Sociological Methodology*, pp. 1–35.
6
7 Borgatti, S.P., Everett, M.G. and Johnson, J.C. (2018), *Analyzing Social Networks*, Sage.
8
9
10 Boyd, B. (1990), “Corporate linkages and organizational environment: A test of the resource
11
12 dependence model”, *Strategic Management Journal*, Vol. 11 No. 6, pp. 419–430.
13
14 Brennecke, J. and Rank, O.N. (2017), “Tie heterogeneity in networks of interlocking
15
16 directorates: a cost–benefit approach to firms’ tie choice”, *Business Research*, Vol. 10
17
18 No. 1, pp. 97–122.
19
20
21 Caiazza, R. (2019), “Governance and network: cross-national differences”, *Management*
22
23 *Decision*, Emerald Publishing Limited, Vol. 57 No. 10, pp. 2621–2629.
24
25
26 Caiazza, R., Cannella Jr, A.A., Phan, P.H. and Simoni, M. (2019), “An institutional
27
28 contingency perspective of interlocking directorates”, *International Journal of*
29
30 *Management Reviews*, Wiley Online Library, Vol. 21 No. 3, pp. 277–293.
31
32
33 Campbell, K. and Mínguez-Vera, A. (2008), “Gender Diversity in the Boardroom and Firm
34
35 Financial Performance”, *Journal of Business Ethics*, Vol. 83 No. 3, pp. 435–451.
36
37
38 Cashman, G.D., Gillan, S.L. and Jun, C. (2012), “Going overboard? On busy directors and
39
40 firm value”, *Journal of Banking & Finance*, Vol. 36 No. 12, pp. 3248–3259.
41
42
43 Chandler, D., Haunschild, P.R., Rhee, M. and Beckman, C.M. (2013), “The effects of firm
44
45 reputation and status on interorganizational network structure”, *Strategic*
46
47 *Organization*, SAGE Publications, Vol. 11 No. 3, pp. 217–244.
48
49
50 Cheng, S. (2008), “Board size and the variability of corporate performance”, *Journal of*
51
52 *Financial Economics*, Vol. 87 No. 1, pp. 157–176.
53
54
55 Chu, J.S. and Davis, G.F. (2016), “Who killed the inner circle? The decline of the American
56
57 corporate interlock network”, *American Journal of Sociology*, University of Chicago
58
59 Press Chicago, IL, Vol. 122 No. 3, pp. 714–754.
60

- 1
2
3 Clark, R. and Mahutga, M.C. (2013), “Explaining the trade-growth link: Assessing diffusion-
4 based and structure-based models of exchange”, *Social Science Research*, Elsevier,
5
6 Vol. 42 No. 2, pp. 401–417.
7
8
9
10 Cliff, A. and Ord, K. (1972), “Testing for spatial autocorrelation among regression residuals”,
11
12 *Geographical Analysis*, Vol. 4 No. 3, pp. 267–284.
13
14
15 Connelly, B.L. and Van Slyke, E.J. (2012), “The power and peril of board interlocks”,
16
17 *Business Horizons*, Vol. 55 No. 5, pp. 403–408.
18
19
20 Croci, E. and Grassi, R. (2014), “The economic effect of interlocking directorates in Italy:
21
22 new evidence using centrality measures”, *Computational and Mathematical*
23
24 *Organization Theory*, Vol. 20 No. 1, pp. 89–112.
25
26
27 David, T. and Westerhuis, G. (2014), *The Power of Corporate Networks: A Comparative and*
28
29 *Historical Perspective*, Routledge.
30
31
32 Dittrich, D., Leenders, R.Th.A.J. and Mulder, J. (2017), “Bayesian estimation of the network
33
34 autocorrelation model”, *Social Networks*, Vol. 48, pp. 213–236.
35
36
37 Drago, C., Millo, F., Ricciuti, R. and Santella, P. (2015), “Corporate governance reforms,
38
39 interlocking directorship and company performance in Italy”, *International Review of*
40
41 *Law and Economics*, Vol. 41, pp. 38–49.
42
43
44 Fama, E.F. and Jensen, M.C. (1983), “Separation of ownership and control”, *The Journal of*
45
46 *Law and Economics*, The University of Chicago Press, Vol. 26 No. 2, pp. 301–325.
47
48
49 Fennema, M. and Schijf, H. (1978), “Analysing interlocking directorates: Theory and
50
51 methods”, *Social Networks*, Vol. 1 No. 4, pp. 297–332.
52
53
54 Fernández- Fernández, J.-L. (1999), “Ethics and the Board of Directors in Spain: The
55
56 Olivencia Code of Good Governance”, *Journal of Business Ethics*, Vol. 22 No. 3, pp.
57
58
59
60 233–247.

- 1
2
3 FRC. (2018), “The UK corporate governance code”, Financial Reporting Council, available
4
5 at: www.frc.org.uk/getattachment/88bd8c45-50ea-4841-95b0-d2f4f48069a2/2018-
6
7 UK-Corpoate-Governance- Code-FINAL.pdf.
8
9
10 Freeman, L.C. (1977), “A set of measures of centrality based on betweenness”, *Sociometry*,
11
12 pp. 35–41.
13
14 Freeman, L.C. (1978), “Centrality in social networks conceptual clarification”, *Social*
15
16 *Networks*, Vol. 1 No. 3, pp. 215–239.
17
18 Galvão, A., Marques, C., Franco, M. and Mascarenhas, C. (2019), “The role of start-up
19
20 incubators in cooperation networks from the perspective of resource dependence and
21
22 interlocking directorates”, *Management Decision*, Emerald Publishing Limited.
23
24
25 Granovetter, M. (1985), “Economic action and social structure: the problem of
26
27 embeddedness”, *American Journal of Sociology*, pp. 481–510.
28
29
30 Guest, P.M. (2009), “The impact of board size on firm performance: evidence from the UK”,
31
32 *The European Journal of Finance*, Vol. 15 No. 4, pp. 385–404.
33
34
35 Gulati, R. and Gargiulo, M. (1999), “Where do interorganizational networks come from?”,
36
37 *American Journal of Sociology*, Vol. 104 No. 5, pp. 1439–1493.
38
39
40 Gulati, R. and Higgins, M.C. (2003), “Which ties matter when? the contingent effects of
41
42 interorganizational partnerships on IPO success”, *Strategic Management Journal*, Vol.
43
44 24 No. 2, pp. 127–144.
45
46
47 Gulati, R., Lavie, D. and Madhavan, R. (Ravi). (2011), “How do networks matter? The
48
49 performance effects of interorganizational networks”, *Research in Organizational*
50
51 *Behavior*, Vol. 31, pp. 207–224.
52
53
54 Haunschild, P.R. and Beckman, C.M. (1998), “When do interlocks matter?: Alternate sources
55
56 of information and interlock influence”, *Administrative Science Quarterly*, JSTOR,
57
58 pp. 815–844.
59
60

- 1
2
3 Hellmer, S. and Wårell, L. (2009), “On the evaluation of market power and market
4
5 dominance—The Nordic electricity market”, *Energy Policy*, Vol. 37 No. 8, pp. 3235–
6
7 3241.
8
9
- 10 Higgins, M.C. and Gulati, R. (2003), “Getting Off to a Good Start: The Effects of Upper
11
12 Echelon Affiliations on Underwriter Prestige”, *Organization Science*, INFORMS, Vol.
13
14 14 No. 3, pp. 244–263.
15
16
- 17 Hillman, A.J., Withers, M.C. and Collins, B.J. (2009), “Resource dependence theory: A
18
19 review”, *Journal of Management*, SAGE Publications Sage CA: Los Angeles, CA,
20
21 Vol. 35 No. 6, pp. 1404–1427.
22
23
- 24 Horton, J., Millo, Y. and Serafeim, G. (2012), “Resources or Power? Implications of Social
25
26 Networks on Compensation and Firm Performance”, *Journal of Business Finance &*
27
28 *Accounting*, Vol. 39 No. 3–4, pp. 399–426.
29
30
- 31 Institutional Shareholder Services (ISS). (2017), “United States summary proxy voting
32
33 guidelines – 2017 benchmark policy recommendations”, available at:
34
35 www.issgovernance.com/file/policy/2017-ussummary-voting-guidelines.pdf.
36
37
- 38 Jahan, M.A., Lubberink, M. and Peurseem, K.V. (2020), “Does prestigious board membership
39
40 matter? Evidence from New Zealand”, *Accounting & Finance*, available
41
42 at:<https://doi.org/10.1111/acfi.12601>.
43
44
- 45 Jiang, H., Xia, J., Devers, C.E. and Shen, W. (2020), “Who Will Board a Sinking Ship? A
46
47 Firm-Director Interdependence Perspective of Mutual Selection between Declining
48
49 Firms and Director Candidates”, *Academy of Management Journal*, No. ja.
50
51
- 52 Kalsie, A. and Shrivastav, S.M. (2016), “Analysis of Board Size and Firm Performance:
53
54 Evidence from NSE Companies Using Panel Data Approach”, *Indian Journal of*
55
56 *Corporate Governance*, SAGE Publications India, Vol. 9 No. 2, pp. 148–172.
57
58
59
60

- 1
2
3 Kiel, G.C. and Nicholson, G.J. (2003), “Board Composition and Corporate Performance: how
4 the Australian experience informs contrasting theories of corporate governance”,
5
6 *Corporate Governance: An International Review*, Vol. 11 No. 3, pp. 189–205.
7
8
9
- 10 Kim, J.W. and Higgins, M.C. (2007), “Where do alliances come from?: The effects of upper
11 echelons on alliance formation”, *Research Policy*, Elsevier, Vol. 36 No. 4, pp. 499–
12
13
14
15 514.
16
- 17 Knoblen, J. and Bakker, R.M. (2019), “The guppy and the whale: Relational pluralism and
18 start-ups’ expropriation dilemma in partnership formation”, *Journal of Business*
19
20
21
22 *Venturing*, Vol. 34 No. 1, pp. 103–121.
23
- 24 Knoke, D. and Yang, S. (2008), *Social Network Analysis*, Vol. 154, Sage.
25
- 26 Kogut, B.M. (2012), *The Small Worlds of Corporate Governance*, MIT Press.
27
- 28 Larcker, D.F., So, E.C. and Wang, C.C. (2013), “Boardroom centrality and firm
29 performance”, *Journal of Accounting and Economics*, Vol. 55 No. 2–3, pp. 225–250.
30
31
32
- 33 Leenders, R.T.A. (2002), “Modeling social influence through network autocorrelation:
34 constructing the weight matrix”, *Social Networks*, Vol. 24 No. 1, pp. 21–47.
35
36
- 37 Leifeld, P., Cranmer, S.J. and Desmarais, B.A. (2017), *Tnam: Temporal Network*
38
39
40 *Autocorrelation Models*, available at: <https://cran.r-project.org/package=tnam>.
41
- 42 Leifeld, P., Cranmer, S.J. and Desmarais, B.A. (2018), “Temporal exponential random graph
43 models with btergm: Estimation and bootstrap confidence intervals”, *Journal of*
44
45
46
47 *Statistical Software*, University of California, Los Angeles, Vol. 83 No. 6.
48
- 49 Li, D., Jiang, Q. and Mai, Y. (2019), “Board interlocks and capital structure dynamics:
50 evidence from China”, *Accounting & Finance*, Wiley Online Library, Vol. 59, pp.
51
52
53
54 1893–1922.
55
- 56 Liu, Y. (2014), “Outside options and CEO turnover: The network effect”, *Journal of*
57
58
59
60 *Corporate Finance*, Vol. 28, pp. 201–217.

- 1
2
3 Martin, G., Gözübüyük, R. and Becerra, M. (2015), “Interlocks and firm performance: The
4 role of uncertainty in the directorate interlock-performance relationship”, *Strategic*
5
6 *Management Journal*, Vol. 36 No. 2, pp. 235–253.
7
8
9
- 10 Melnik, A., Shy, O. and Stenbacka, R. (2008), “Assessing market dominance”, *Journal of*
11
12 *Economic Behavior & Organization*, Vol. 68 No. 1, pp. 63–72.
13
14
- 15 Metz, F. and Ingold, K. (2017), “Politics of the precautionary principle: assessing actors’
16 preferences in water protection policy”, *Policy Sciences*, Vol. 50 No. 4, pp. 721–743.
17
18
- 19 Mizruchi, M.S. (1996), “What do interlocks do? An analysis, critique, and assessment of
20 research on interlocking directorates”, *Annual Review of Sociology*, Annual Reviews
21
22 4139 El Camino Way, PO Box 10139, Palo Alto, CA 94303-0139, USA, Vol. 22 No.
23
24 1, pp. 271–298.
25
26
27
- 28 Mizruchi, M.S. (2013), *The Fracturing of the American Corporate Elite*, Harvard University
29 Press.
30
31
- 32 Mizruchi, M.S. and Stearns, L.B. (2006), “The conditional nature of embeddedness: a study
33 of borrowing by large US firms, 1973–1994”, *American Sociological Review*, Sage
34 Publications Sage CA: Los Angeles, CA, Vol. 71 No. 2, pp. 310–333.
35
36
37
38
39
- 40 Nam, H.-J. and An, Y. (2018), “The Effect of Interlocking Directors Network on Firm Value
41 and Performance: Evidence from Korean-Listed Firms”, *Global Economic Review*,
42 Routledge, Vol. 47 No. 2, pp. 151–173.
43
44
45
46
- 47 Nazir, N. and Malhotra, A.K. (2017), “The Effect of Ownership Structure on Market
48 Valuation of Firms in India: Evidence from BSE-100 Index Companies”, *Academy of*
49 *Accounting and Financial Studies Journal*, Vol. 21 No. 1.
50
51
52
53
- 54 Nguyen, P., Rahman, N., Tong, A. and Zhao, R. (2016), “Board size and firm value: evidence
55 from Australia”, *Journal of Management & Governance*, Vol. 20 No. 4, pp. 851–873.
56
57
58
59
60

- 1
2
3 Nicholson, G.J. and Kiel, G.C. (2007), “Can Directors Impact Performance? A case-based test
4
5 of three theories of corporate governance”, *Corporate Governance: An International*
6
7 *Review*, Vol. 15 No. 4, pp. 585–608.
- 8
9
10 O’Hagan, S. and Green, M.B. (2002), “Interlocking directorates: An example of tacit
11
12 knowledge transfer”, *Urban Geography*, Taylor & Francis, Vol. 23 No. 2, pp. 154–
13
14 179.
- 15
16
17 O’Hagan, S.B. and Green, M.B. (2004), “Corporate knowledge transfer via interlocking
18
19 directorates: a network analysis approach”, *Geoforum*, Vol. 35 No. 1, pp. 127–139.
- 20
21
22 Omer, T.C., Shelley, M.K. and Tice, F.M. (2014), “Do well-connected directors affect firm
23
24 value?”, *Journal of Applied Finance (Formerly Financial Practice and Education)*,
25
26 Vol. 24 No. 2, pp. 17–32.
- 27
28
29 Pettigrew, A.M. (1992), “On studying managerial elites”, *Strategic Management Journal*,
30
31 Wiley Online Library, Vol. 13 No. S2, pp. 163–182.
- 32
33
34 Pfeffer, J. and Salancik, G.R. (1978), “The external control of organizations: A resource
35
36 dependence approach”, *NY: Harper and Row Publishers*.
- 37
38
39 Powell, W.W., White, D.R., Koput, K.W. and Owen-Smith, J. (2005), “Network Dynamics
40
41 and Field Evolution: The Growth of Interorganizational Collaboration in the Life
42
43 Sciences”, *American Journal of Sociology*, The University of Chicago Press, Vol. 110
44
45 No. 4, pp. 1132–1205.
- 46
47
48 Priyadharshini, S. k., Kamalanabhan, T. j. and Madhumathi, R. (2015), “Human resource
49
50 management and firm performance”, *International Journal of Business Innovation and*
51
52 *Research*, Inderscience Publishers, Vol. 9 No. 2, pp. 229–251.
- 53
54
55 Sánchez, L.P.-C., Guerrero-Villegas, J. and González, J.M.H. (2017), “The influence of
56
57 organizational factors on board roles”, *Management Decision*, Emerald Publishing
58
59 Limited.
60

- 1
2
3 Santos, R.L., Silveira, A. di M. da and Barros, L.A. (2012), “Board Interlocking in Brazil:
4
5 Directors’ Participation in Multiple Companies and Its Effect on Firm Value and
6
7 Profitability”, *Latin American Business Review*, Vol. 13 No. 1, pp. 1–28.
8
9
- 10 Sarabi, Y. and Smith, M. (2021), “Busy female directors: an exploratory analysis of the
11
12 impact of quotas and interest groups”, *Gender in Management: An International*
13
14 *Journal*, Vol. ahead-of-print No. ahead-of-print, available at:
15
16 <https://doi.org/10.1108/GM-07-2019-0129>.
17
18
- 19 Silk, M.J., Croft, D.P., Delahay, R.J., Hodgson, D.J., Weber, N., Boots, M. and McDonald,
20
21 R.A. (2017), “The application of statistical network models in disease research”,
22
23 *Methods in Ecology and Evolution*, Vol. 8 No. 9, pp. 1026–1041.
24
25
- 26 Smith, M., Gorgoni, S. and Cronin, B. (2016), “The fragmentation of production and the
27
28 competitiveness of nations in the automotive sector—A network approach”.
29
- 30 Smith, M. and Sarabi, Y. (2020), ““What do interlocks do’ revisited – a bibliometric
31
32 analysis”, *Management Research Review*, Vol. ahead-of-print No. ahead-of-print,
33
34 available at:<https://doi.org/10.1108/MRR-05-2020-0258>.
35
36
- 37 Tang, M.-J. and Thomas, H. (1994), “Developing theories of strategy using dominance
38
39 criteria”, *Journal of Management Studies*, Wiley Online Library, Vol. 31 No. 2, pp.
40
41 209–224.
42
43
- 44 Valente, T.W., Coronges, K., Lakon, C. and Costenbader, E. (2008), “How correlated are
45
46 network centrality measures?”, *Connections (Toronto, Ont.)*, Vol. 28 No. 1, p. 16.
47
48
- 49 Wang, W., Neuman, E.J. and Newman, D.A. (2014), “Statistical power of the social network
50
51 autocorrelation model”, *Social Networks*, Vol. 38, pp. 88–99.
52
53
- 54 Wasserman, S. and Faust, K. (1994), *Social Network Analysis: Methods and Applications*,
55
56 Cambridge University Press, Cambridge; New York.
57
58
59
60

1
2
3 Watts, D.J. and Strogatz, S.H. (1998), “Collective dynamics of ‘small-world’ networks”,
4
5 *Nature*, Vol. 393 No. 6684, p. 440.
6

7 Westphal, J.D., Seidel, M.-D.L. and Stewart, K.J. (2001), “Second-Order Imitation:
8
9 Uncovering Latent Effects of Board Network Ties”, *Administrative Science Quarterly*,
10
11 SAGE Publications Inc, Vol. 46 No. 4, pp. 717–747.
12
13

14 Yermack, D. (1996), “Higher market valuation of companies with a small board of directors”,
15
16 *Journal of Financial Economics*, Vol. 40 No. 2, pp. 185–211.
17
18

19 Yu, S.-H. and Chiu, W.-T. (2013), “Social networks and corporate performance: the
20
21 moderating role of technical uncertainty”, *Journal of Managerial Issues*, JSTOR, pp.
22
23 26–45.
24
25

26 Zona, F., Gomez-Mejia, L.R. and Withers, M.C. (2018), “Board Interlocks and Firm
27
28 Performance: Toward a Combined Agency–Resource Dependence Perspective”,
29
30 *Journal of Management*, Vol. 44 No. 2, pp. 589–618.
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

7. Appendix

The paper highlights the issue of endogeneity when examining firm performance and the interlock network. It may not be the case that ties created by the interlock network result in increased performance, rather that prominent directors are matched to high-performing firms. The robustness checks presented in the main text follow the approach of Larcker *et al.* (2013). In this appendix, further supporting robustness checks are implemented to provide additional checks on the main results.

The robustness check that is implemented in this appendix to alleviate the endogeneity issue in this study follows the approach outlined by Boehmke *et al.* (2016). This robustness check uses an Instrumental Variable (IV) two-stage estimator; IV approaches are an established technique to address endogeneity concerns (Liu, 2014). The underlying concept associated with this technique is that endogeneity is stripped from the variables in question by substituting them with a set of suitable instruments; as noted by Ahuja *et al.* (2012), it is often difficult to identify appropriate instruments for robustness tests. This paper follows the strategy outlined by Boehmke *et al.* (2016), utilising an *Instrumented Network* in our estimation. In the two-step estimator procedure, an instrumented network is utilised instead of a direct IV. This approach involves, firstly, simulating the firm interlock network to construct the instrumented network. This Instrumented Network is then used to construct the relational effects specified in the model, acting as IVs in the estimation process.

When simulating the firm interlock network to create the Instrumented Network, a complex network model, a Temporal Exponential Random Graph Model (TERGM), as developed by Leifeld *et al.* (2018) is used. This approach has been utilised in empirical network studies to deal with endogeneity concerns (Smith *et al.*, 2016). The TERGM approach allows us to specify a model of network tie formation, which is then used to simulate the network based on this model.

1
2
3 Table (7) presents the results for the robustness check, utilising the second approach, the
4
5 Instrumental Variable (IV) approach. This is the result for the TNAM model utilising the
6
7 simulated networks to construct the network metrics, along with weight matrix – the firm
8
9 interlock network. There are some noticeable differences when comparing the results from the
10
11 robustness check presented in Table (7) with the main results given in Table (3). In particular,
12
13 we observe on the robustness check that the significance levels have dropped for the netlag
14
15 terms, and centrality (in the case of the degree centrality model). This indicates some caution
16
17 must be used when making firm recommendations on the basis of the netlag parameter. The
18
19 findings from the robustness checks in the main text may act as a potential explanation for the
20
21 drop in significance level of the netlag parameter in this IV TNAM.
22
23
24
25
26
27

28 -----
29 Insert Table 7 about here.
30 -----
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Table 1: Descriptive statistics for firm covariates for in the main component of UK FTSE 350, 2014 – 2018

| Variable | 2014 | 2015 | 2016 | 2017 | 2018 |
|--------------------------------|-------------|-------------|-------------|-------------|-------------|
| ROCE (log) Mean | 15.44 | 10.54 | 12.76 | 13.19 | 13.78 |
| ROCE (log) SD | 35.23 | 41.84 | 18.61 | 17.32 | 12.96 |
| Number of Employees (log) mean | 8.54 | 8.54 | 8.57 | 8.66 | 8.66 |
| Number of Employees (log) SD | 2.07 | 2.01 | 2.00 | 1.98 | 1.97 |
| Board Size Mean | 8.72 | 9.27 | 9.27 | 9.86 | 10.24 |
| Board Size SD | 3.24 | 2.74 | 2.74 | 2.49 | 2.46 |

Table 2: Descriptive network statistics for main component of the interlock networks of UK FTSE 350, 2014 – 2018

| Network Statistics | 2014 | 2015 | 2016 | 2017 | 2018 |
|---------------------------|-------------|-------------|-------------|-------------|-------------|
| Density | 0.0063 | 0.0069 | 0.0069 | 0.0081 | 0.0094 |
| Diameter | 22 | 22 | 22 | 22 | 20 |
| Degree centralisation | 0.0245 | 0.0195 | 0.0195 | 0.0227 | 0.0302 |
| Clustering coefficient | 0.2479 | 0.2992 | 0.2992 | 0.2075 | 0.1794 |

Management Decision

Table 3: TNAM Results

| | Activity (Degree Centrality) | Flow (Betweenness Centrality) | Global Connectivity (Eigenvector Centrality) |
|-------------------------------|---|--|---|
| (Intercept) | 2.6118*** (0.2362) | 2.5718*** (0.2366) | 2.5687*** (0.2396) |
| time | 0.0631** (0.0195) | 0.0624** (0.0196) | 0.0625** (0.0196) |
| ROCE | 0.0010 (0.0009) | 0.0010 (0.0009) | 0.0010 (0.0009) |
| Number of Employees | 0.0605*** (0.0132) | 0.0605*** (0.0133) | 0.0619*** (0.0133) |
| Board Size | 0.0446*** (0.0089) | 0.0464*** (0.0089) | 0.0468*** (0.0090) |
| Lagged Market Capitalisation | 0.7066*** (0.0158) | 0.7058*** (0.0159) | 0.7074*** (0.0159) |
| Sector Similarity | -0.0003** (0.0001) | -0.0003* (0.0001) | -0.0003* (0.0001) |
| Structural Similarity (Lag 1) | 0.0022** (0.0007) | 0.0004 (0.0002) | 0.0002 (0.0002) |
| Netlag (Lag1) | 0.0610*** (0.0169) | 0.0292* (0.0116) | 0.0238* (0.0110) |
| Clustering (Lag 1) | -0.2059 (0.4901) | 0.0127 (0.5279) | -0.2458 (0.5279) |
| Degree (Lag 1) | 0.2749** (0.0963) | | |
| Betweenness (Lag 1) | | 0.0000 (0.0000) | |
| Eigenvector (Lag 1) | | | 0.0245 (0.3973) |
| AIC | 1910.1045 | 1933.4348 | 1915.3846 |
| BIC | 1972.7647 | 1996.0950 | 1978.0448 |
| Log Likelihood | -942.0522 | -953.7174 | -944.6923 |

***p < 0.001, **p < 0.01, *p < 0.05

Table 4: Robustness test results – ties that remain constant from one year to the next

| | Activity (Degree Centrality) | Flow (Betweenness Centrality) | Global Connectivity (Eigenvector Centrality) |
|---------------------------------|---|--|---|
| (Intercept) | 2.5677*** (0.2375) | 2.5543*** (0.2373) | 2.5542*** (0.2399) |
| time | 0.0624** (0.0196) | 0.0622** (0.0196) | 0.0622** (0.0196) |
| ROCE | 0.0010 (0.0009) | 0.0010 (0.0009) | 0.0010 (0.0009) |
| Number of Employees | 0.0633*** (0.0132) | 0.0623*** (0.0132) | 0.0625*** (0.0132) |
| Board Size | 0.0468*** (0.0089) | 0.0470*** (0.0089) | 0.0470*** (0.0090) |
| Lagged Market Capitalisation | 0.7055*** (0.0159) | 0.7055*** (0.0159) | 0.7064*** (0.0159) |
| Sector Similarity | -0.0003* (0.0001) | -0.0003* (0.0001) | -0.0003* (0.0001) |
| Structural Similarity (Lag 1) | 0.0006 (0.0005) | 0.0002 (0.0002) | 0.0001 (0.0001) |
| Netlag (Lag1) | 0.0250** (0.0093) | 0.0213* (0.0086) | 0.0205* (0.0087) |
| Clustering (Lag 1) | -0.3826 (0.4897) | -0.2356 (0.5135) | -0.3236 (0.5278) |
| Degree (Lag 1) | 0.0773 (0.0667) | | |
| Betweenness (Lag 1) | | 0.0000 (0.0000) | |
| Eigenvector (Lag 1) | | | -0.0295 (0.3915) |
| AIC | 1917.1119 | 1934.2998 | 1914.9109 |
| BIC | 1979.7721 | 1996.9600 | 1977.5711 |
| Log Likelihood | -945.5559 | -954.1499 | -944.4554 |

***p < 0.001, **p < 0.01, *p < 0.05

Table 5: Robustness test results – ties that change from one year to the next

| | Activity (Degree Centrality) | Flow (Betweenness Centrality) | Global Connectivity (Eigenvector Centrality) |
|---------------------------------|---|--|---|
| (Intercept) | 2.5879*** (0.2380) | 2.5931*** (0.2369) | 2.6100*** (0.2387) |
| time | 0.0627** (0.0196) | 0.0628** (0.0196) | 0.0631** (0.0196) |
| ROCE | 0.0011 (0.0009) | 0.0011 (0.0009) | 0.0011 (0.0009) |
| Number of Employees | 0.0673*** (0.0132) | 0.0675*** (0.0131) | 0.0673*** (0.0131) |
| Board Size | 0.0484*** (0.0090) | 0.0483*** (0.0090) | 0.0477*** (0.0090) |
| Lagged Market Capitalisation | 0.7059*** (0.0159) | 0.7055*** (0.0160) | 0.7053*** (0.0159) |
| Sector Similarity | -0.0003* (0.0001) | -0.0003* (0.0001) | -0.0003* (0.0001) |
| Structural Similarity (Lag 1) | -0.0003 (0.0004) | -0.0002 (0.0001) | -0.0002* (0.0001) |
| Netlag (Lag1) | -0.0121 (0.0076) | -0.0117 (0.0075) | -0.0123 (0.0075) |
| Clustering (Lag 1) | -0.4435 (0.4934) | -0.4249 (0.5196) | -0.3334 (0.5294) |
| Degree (Lag 1) | -0.0103 (0.0621) | | |
| Betweenness (Lag 1) | | 0.0000 (0.0000) | |
| Eigenvector (Lag 1) | | | -0.2307 (0.3900) |
| AIC | 1922.0899 | 1938.2137 | 1918.0939 |
| BIC | 1984.7501 | 2000.8740 | 1980.7542 |
| Log Likelihood | -948.0450 | -956.1069 | -946.0470 |

***p < 0.001, **p < 0.01, *p < 0.05

Table 6: Comparison of results from the model and robustness checks

| VARIABLE | MAIN TNAM | RC: TIES THAT REMAIN CONSTANT FROM ONE YEAR TO THE NEXT | RC: TIES THAT CHANGE FROM ONE YEAR TO THE NEXT |
|--------------------------------------|--|--|--|
| ROCE | No significant relationship between MCR and financial performance. | | |
| NUMBER OF EMPLOYEES | Larger firms associated with higher MCR. | | |
| BOARD SIZE | Larger boards are associated with higher MCR. | | |
| LAGGED MARKET CAPITALISATION | High MCR at time t-1 is associated with high MCR in time t. | | |
| SECTOR SIMILARITY | Firms in the same sector do not share MCR levels. | | |
| STRUCTURAL SIMILARITY (LAG 1) | Limited evidence that firms that hold equivalent positions in the network, hold equivalent MCR levels. | No evidence that firms that hold equivalent positions in this network, hold equivalent MCR levels. | Very limited evidence that in this network, firm's with equivalent positions, hold diverging MCR levels. |
| NETLAG (LAG1) | Ties to firms with high MCR increases a firm's own MCR. | Ties to firms with high MCR increases a firm's own MCR. | MCR of network partners has no significant impact on a firm's MCR. |
| CLUSTERING (LAG 1) | Clustering has no significant relationship with firm MCR. | | |
| DEGREE (LAG 1) | There is a positive and weakly significant association between degree centrality and MCR. | Degree centrality has no significant relationship with firm MCR. | |
| BETWEENNESS (LAG 1) | Betweenness centrality has no significant relationship with firm MCR. | | |
| EIGENVECTOR (LAG 1) | Eigenvector centrality has no significant relationship with firm MCR. | | |

Note: RC – Robustness Checks

Table 7: Robustness Test – Instrumented Network TNAM

| | Activity (Degree Centrality) | Flow (Betweenness Centrality) | Global Connectivity (Eigenvector Centrality) |
|---------------------------------|---|--|---|
| (Intercept) | 7.0533*** (0.4992) | 7.0597*** (0.4988) | 7.0818*** (0.4990) |
| time | 0.1257*** (0.0156) | 0.1258*** (0.0156) | 0.1261*** (0.0156) |
| ROCE | 0.0077 (0.0187) | 0.0074 (0.0188) | 0.0084 (0.0188) |
| Number of Employees | 0.1187*** (0.0187) | 0.1195*** (0.0188) | 0.1208*** (0.0188) |
| Board Size | 0.0135 (0.0083) | 0.0143 (0.0084) | 0.0142 (0.0084) |
| Lagged Market Capitalisation | 0.1010*** (0.0147) | 0.1008*** (0.0147) | 0.1001*** (0.0147) |
| Sector Similarity | -0.0003 (0.0003) | -0.0003 (0.0003) | -0.0003 (0.0003) |
| Structural Similarity (Lag 1) | 0.0014* (0.0006) | 0.0002 (0.0001) | 0.0001 (0.0001) |
| Netlag (Lag1) | 0.0272* (0.0122) | 0.0087 (0.0072) | 0.0047 (0.0067) |
| Clustering (Lag 1) | 0.7023* (0.3335) | 0.6720* (0.3424) | 0.5816 (0.3277) |
| Degree (Lag 1) | 0.1520* (0.0720) | | |
| Betweenness (Lag 1) | | 0.0000 (0.0000) | |
| Eigenvector (Lag 1) | | | -0.3520 (0.2349) |
| AIC | 1093.5168 | 1113.1545 | 1093.3602 |
| BIC | 1152.4372 | 1172.0748 | 1152.2805 |
| Log Likelihood | -533.7584 | -543.5772 | -533.6801 |

***p < 0.001, **p < 0.01, *p < 0.05