**Within-Seller and Buyer–Seller Network Structures and Key Account Profitability**

Web Appendices

August 2018

**Appendix A**

**Sample Characteristics**

|  |  |
| --- | --- |
| Category | Breakup of Seller Informants |
| **Industry Groups** | Seller Industry | Buyer Industry |
|  Business and transportation services  (administrative, consulting and  legal, commercial aviation, railroad and trucking) | 45 | 22 |
|  Manufacturing  (automotive, electronics, consumer goods,  industrial equipment and chemicals) | 63 | 67 |
|  Healthcare and pharmaceuticals | 24 | 40 |
|  Information technology and telecommunication (computer hardware, computer services, computer software, telecom equipment and services) | 61 | 26 |
|  Natural resources (oil and gas, and minerals and mining) | 7 | 13 |
|  Aerospace and defense | 7 | 13 |
|  Consumer finance, insurance and real estate | - | 15 |
|  Government | - | 6 |
|  Utilities | - | 5 |
|  |  |  |
| **Firm Size (Annual Sales in $)** | Seller Size | Buyer Size |
|  Less than 5 million | 17 | 21 |
|  5–50 million | 39 | 53 |
|  51–250 million | 48 | 32 |
|  251–1000 million | 37 | 45 |
|  More than 1 billion | 66 | 56 |
|  |  |  |
| **Number of Employees** | Seller | Buyer |
|  Less than 500 | - | 29 |
|  500–999  | 28 | 56 |
|  1000–4999  | 52 | 33 |
|  5000+ | 127 | 89 |
|  |  |  |
| **Duration Key Account (Years)** |  |  |
|  Less than 2 years | 16 |  |
|  2–6 years | 79 |  |
|  6–10 years | 29 |  |
|  More than 10 years | 83 |  |
|  |  |  |
| **Informant Level** |  |  |
|  Sales manager | 51 |  |
|  Key account manager | 90 |  |
|  Account manager (global/national/regional) | 66 |  |
|  |  |  |
| **Informant Experience in Current Role (Years)** |  |  |
|  2–5 years | 46 |  |
|  5–10 years | 54 |  |
|  More than 10 years | 107 |  |

Notes: Total responses = 207. All data were reported by the seller-side informant, pertaining to the seller firm and key account (buyer firm) selected by this informant. Thus, for industry groups in the second row, 63 (out of total 207) seller informants belonged to the manufacturing sector. Among the buyer firms on whom the sellers responded, 67 were in the manufacturing sector.

**Appendix B**

**Robustness Checks: Ordered Logit Model, Industry Fixed Effects, and Non-linear Interactions Models**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Predictors** |  |  |  |  |  |
|  | **Ordered Logit FINALLIV Model: Interactions + LIV + Non-linear Effects**Coeff.(SE)**I** | **Industry Fixed Effects Model**Coeff.(SE) | **Non-Linear Interactions SDEN**Coeff.(SE) | **Non-Linear Interactions SCENTRAL**Coeff.(SE) |
| **Controls** |  |  |  |  |
| **Seller Firm Annual Sales** | .031 | .005 | .031 | .028 |
|   | (.023) | (.020) | (.021) | (.021) |
| **Buyer Firm Annual Sales** | .065\*\* | .051\*\* | .073\*\*\* | .065\*\*\* |
|   | (.026) | (.021) | (.022) | (.021) |
| **Number of Accounts Handled** | .059\*\* | .045\* | .057 | .269 |
|  | (.027) | (.025) | (.048) | (.629) |
| **Duration Key Account (Years)** | -.002 | -.036 | -.006 | -.002 |
|  | (.027) | (.030) | (.027) | (.027) |
| **Buyer Team Size** | .052 | .060\* | .065 | .524 |
|   | (.041) | (.035) | (.037) | (.652) |
| **Buyer Function Count** | .076 | .076 | .074 | .081 |
|   | (.055) | (.054) | (.056) | (.055) |
| **Seller Team Size** | -.042 | -.086\*\*\* | -.107\*\*\* | -.131\*\*\* |
|   | (.030) | (.031) | (.034) | (.029) |
| **Seller Function Count** | .084 | -.066 | .019 | .028 |
|   | (.061) | (.063) | (.065) | (.060) |
| **Buyer–Seller Interfirm Network** |  |   |  |  |
| **Buyer–Seller Interfirm**  | .712†† | .676† | .501†† | .103††† |
| **Density (IFDEN) (H1)** | (.417) | (.442) | (.244) | (.037) |
| **Similar-Function Ties** | .399 | .483 | 1.162 | 1.807 |
|  **(IFFUNCSIM) (H2)** | (.583) | (.596) | (1.315) | (1.475) |
| **Within–Seller Firm Network** |  |  |  |  |
| **Network Density**  | -.885 | -1.311 | -2.011 | -.945 |
|  **(SDEN)** | (.762) | (1.274) | (2.615) | (.868) |
| **Centralization**  | 1.186\*\* | 1.412\*\* | .539\*\*\* | 1.235\* |
| **(SCENTRAL)** | (.563) | (.643) | (.196) | (.679) |
| **Cross-Function Ties**  | .835 | 1.442 | 1.527 | 1.217 |
|  **(SCROSSFUNC)**  | (.866) | (1.118) | (2.205) | (1.261) |
| **Non-Linear** |  |  |  |  |
| **IFDEN \* IFDEN** | -1.096 | -2.041 | -1.758 | -1.897 |
|  | (1.369) | (1.998) | (1.388) | (2.002) |
| **SDEN \* SDEN** | -2.499\* | -2.308\* | -.965 | -2.383\* |
|  | (1.321) | (1.303) | (.673) | (1.365) |
| **SCENTRAL \* SCENTRAL** | -.972\*\*\* | -2.457\*\*\* | -2.248\*\*\* | -1.631\* |
|  | (.271) | (.953) | (.897) | (.966) |
| **Interactions** |  |  |  |  |
| **IFDEN \* SDEN (H3)** | -4.549†† | -2.621†† | -1.171†† | -3.162††† |
|   | (2.045) | (1.141) | (0.593) | (1.164) |
| **IFFUNCSIM \* SDEN (H4a/b)** | 1.135 | 1.423 | -.397 | -.470 |
|  | (1.327) | (1.064) | (1.111) | (1.168) |
| **IFDEN \* SCENTRAL (H5)** | 1.349†† | .976† | .899††† | 1.103†† |
|  | (.743) | (.646) | (.378) | (.541) |
| **IFFUNCSIM \* SCENTRAL (H6)** | 2.375†† | 2.193†† | 1.421†† | .304 |
|   | (1.144) | (1.164) | (.694) | (.843) |
| **IFDEN \* SCROSSFUNC (H7)** | -1.868† | -.472 | .351 | .557 |
|  | (1.385) | (.812) | (.945) | (1.039) |
| **IFFUNCSIM \* SCROSSFUNC** | .801†† | .769†† | 1.418††† | 1.734††† |
|  **(H8)** | (.414) | (.462) | (.596) | (.568) |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Predictors** |  |  |  |  |
|  | **Ordered Logit FINALLIV Model: Interactions + LIV + Non-linear Effects**Coeff.(SE) | **Industry Fixed Effects**Coeff.(SE) | **Non-Linear Interactions SDEN**Coeff.(SE) | **Non-Linear Interactions SCENTRAL**Coeff.(SE) |
| **LIV Correction Terms** |  |  |  |  |
| **IFDEN\_Error** | .847\* | .372 | -.427\*\* | -.127 |
|   | (.433) | (.545) | (.175) | (.174) |
| **IFFUNCSIM\_Error** | 2.383 | -3.567\*\* | -.884 | -1.795 |
|   | (1.828) | (1.777) | (1.353) | (2.246) |
| **SDEN\_Error** | .956 | 3.068 | .529 | 1.711 |
|   | (1.654) | (2.374) | (1.526) | (1.476) |
| **SCENTRAL\_Error** | -1.696\* | 1.443 | 1.31 | -1.166 |
|   | (1.025) | (.974) | (1.019) | (.951) |
| **SCROSSFUNC\_Error** | -1.721\* | 1.082 | .845 | .461 |
|  | (.968) | (.708) | (.732) | (.693) |
| **Support Point Intercepts** |  |  |  |  |
| **Class 1** | .928\*\*\* |  | .183\*\*\* | .128 |
|  | (.118) |  | (.023) | (.097) |
| **Class 2** | -.001 |  | -.091 | -.044 |
|  | (.318) |  | (.176) | (.157) |
| **Class 3** | -.193 |  | -.041 | -.083 |
|  | (.344) |  | (.180) | (.154) |
| **Class 4** | -.733\*\*\* |  |  |  |
|  | (.184) |  |  |  |
| **Industry Dummies** |  |  |  |  |
| **Industry\_dummy1** |  | -1.174\*\*\* |  |  |
|  |  | (.251) |  |  |
| **Industry\_dummy2** |  | .378\*\* |  |  |
|  |  | (.175) |  |  |
| **Industry\_dummy3** |  | .091 |  |  |
|  |  | (.21) |  |  |
| **Industry\_dummy4** |  | -.201 |  |  |
|  |  | (.172) |  |  |
| **Industry\_dummy5** |  | .193 |  |  |
|  |  | (.231) |  |  |
| **Industry\_dummy6** |  | .133 |  |  |
|  |  | (.173) |  |  |
| **Industry\_dummy7** |  | .231 |  |  |
|  |  | (.195) |  |  |
| **Non-Linear Interactions** |  |  |  |  |
| **IFDEN \* SDEN \* SDEN** |  |  | -4.117\* |  |
|  |  |  | (2.332) |  |
| **IFFUNCSIM \* SDEN \* SDEN** |  |  | -3.476 |  |
|  |  |  | (2.443) |  |
| **IFDEN \* SCENTRAL \* SCENTRAL** |  |  |  | 1.896 |
|  |  |  |  | (2.316) |
| **IFFUNCSIM \* SCENTRAL \* SCENTRAL** |  |  |  | -1.046 |
|  |  |  |  | (.844) |
| **R2** | 0.919 | .941 | .929 | .934 |

Notes: The standard errors are in parentheses;

**†††** *p* < .01. **††** *p* < .05. **†** *p* < .10 (one-tailed test for hypothesized effects).

\*\*\* *p* < .01. \*\* *p* < .05. \* *p* < .10 (two-tailed test for non-hypothesized effects).

**Appendix C**

**Considerations in Network Analysis in Our Research Design**

**Egocentric Network Data vs. Full Sociometric Network Data**

The egocentric and the full sociometric method are the two primary approaches to collecting social network data. In the egocentric approach, network data is collected from a single actor (the 'ego') and the ‘ego’ reports about their ties with other actors (the 'alters') in the network. Perceptions of network ties are not collected from the alters. In contrast, in the sociometric approach, every member of a network (based on identified network boundaries) reports their ties with all the other actors. Thus, each tie is reported on by both actors of the dyad so ties identified by one actor can be verified against the reports from other actors. While such a full sociometric approach provides an opportunity to verify the accuracy of reported ties, there is still the possibility that the dyadic actors disagree; in such cases, the average of the two reports is computed (Ustuner and Iacobucci 2012).

The sociometric approach is suitable when individual actor perceptions are being linked to actor level performance outcomes. However, the sociometric approach is not inherently superior to the egocentric approach, especially if the actors are not well-informed about the substantive issues at hand. Further, when analysis is at the level of the individual actor, sociometric data can be useful although effort-intensive to collect. For team or firm level outcomes, prior research suggests reliance on egocentric data is a valid approach (Cross and Cummings 2004). Indeed, egocentric data have been utilized to compute network constructs such as density by several organizational scholars (Burt 1997; Ibarra 1995; Podolny and Baron 1997). Morrison (2002, p. 1153) asserts that egocentric data is "ideal [for studying relationships which]...represent only a small fraction of the social system in which they are embedded," as is the case with KAM teams.

 Hence, some key criteria in deciding between the egocentric and sociometric approaches are: i) whether the informant is knowledgeable about and possess accurate perception of the underlying social network; ii) whether the level of analysis is at the individual actor vs. the aggregate team (network) level; and iii) whether the researcher's substantive interest is in studying only a small part of a larger system (e.g., a KAM team within a firm) vs. studying the entire social system. Additionally, in organizational contexts where employees are time-constrained (e.g., travelling salespeople), requirements for complete sociometric data can substantially reduce response rates. In our study, all the above criteria are fulfilled: key account managers possess accurate perceptions of the network (see below); we study team level outcomes; our focus is on limited-size KAM teams rather than the entire firm per se; and response rates are threatened by demands on the informants' time and confidentiality issues. As such, we adopted the egocentric approach.

**Account manager as most knowledgeable informan**t **for KAM selling teams egocentric networks**

Kumbasar et. al. (1994) note that more central actors in a network tend to possess an accurate perception of the network structure. Krackhardt (1990) similarly notes a strong link between an actor's position and their knowledge of the network. In KAM, the key account manager is deeply engaged and influential in the KAM activities, a fact that also came out repeatedly in our field interviews. In our dataset, 65% of the time, the central actor was the key account manager, our key informant. Given their central position and ongoing involvement, network data collected from account managers about work-related ties is likely to be an accurate representation of “actual” network data (Casciaro 1998). While reporting of all ties from a single informant can be inaccurate for friendship ties, the key informant approach is recommended for work networks (Kilduff and Balkundi 2011). Krackhardt (2003. p. 353) asserts that central actors possess a "more accurate picture" of network especially in "small" teams– such as the KAM teams which we study– because such actors are more likely to be directly involved in the workings of small teams. Finally, we note that Romney and Weller (1984) show that qualified informants from the same firm offer very similar responses, which suggests that obtaining responses from multiple informants will not yield incremental advantages beyond that obtained from an individual but qualified key informant's response (Heide and John 1990).

In our study, which involves account management activities in the buyer-seller and within–seller networks, the key account manager is the central actor with the greatest involvement in KAM activities. Therefore, the account manager possesses the most accurate perception of these networks, which represent specific work-related ties. As such, we elicited the account manager's perspective of the KAM networks we study.

**Defining the network boundaries**

For egocentric data, boundary specification involves deciding which actors are to be included in a focal network (Marsden 1990). For this purpose, we identified the network boundaries by instructing informants to "think of all the team members who are involved on a regular basis in engaging with the customer account." Similarly, informants were instructed to identify "all the buyer team members who were engaged with the selling team on a regular basis." Our informants were key account managers who regularly interact with buyer-seller and seller KAM teams.

Further, research suggests that it is both more manageable and more realistic for managers to have an accurate idea of ties (i.e., network boundaries) in small than in large networks (Moreland 1990). In our sample, the average selling team size is 7, and the buyer team size is 5. Thus, free recall of names of actors involved should not be an issue for the account manager. Finally, the interactions we capture are regular work-related interaction patterns which are fairly stable. Hence, account managers (informants) are likely to have an accurate recall of these network ties and boundaries. Carley and Kaufer (1993) suggest that by offering chances for ongoing interactions, a work role makes a respondent’s perceptions more accurate, an assertion Casciarco (1998) documents. Similarly, Krackhardt (1990) notes that managers, by virtue of their authority, are in a position to both observe and question their subordinates; these information sources offer managers a solid basis for accurate perceptions of network boundaries.

Even if the account manager were to forget some selling team members, the difference to the network's structure is unlikely to be significant. Marsden (2005, p.14), observes that “Brewer and Webster (1999) reported relatively high correlations between measures of centrality, egocentric network size, and local density based on *recalled alter only* [without a list], and the same measures based on *recalled and recognized alters”* [emphases added], when the respondent was given a complete list of names. Thus, the measures of centralization, network size and density seem largely robust to incompleteness in informant recall.

**Differences between perceived vs. actual network structure**

Much social networks research (Freeman et. al. 1991; Brashears and Quitane 2015) notes that while informants' recall of specific network interactions might not be accurate, recollection of 'regular' patterns of interaction that comprise a formal social structure are strikingly accurate (i.e., similar to the actual network). Hence, while a respondent might not accurately recall a particular interaction, the overall network structure resulting from the pattern of interactions recalled is quite robust. Morgan Neal and Carder (1997) conducted a repeated network measure study and found that network properties are stable across measurement occasions, even if the reported alters are not reliably recalled across all occasions. In a similar vein, Marsden (1990) reports a high (.8) correlation between perceptual responses and actual observations. Thus, respondents’ perception of network structure is fairly accurate, although they might miss or interchange a few individual nodes, not materially changing the network structure. Thus, the network properties that are calculated from the network structure are fairly robust.

Separate from the issue of accuracy of an actor's perceptions is the importance of the role that these perceptions play in decision-making. Objective reality is filtered through the perceptual screens of the key account manager, who responds to the subjective understandings of the situation (Suddaby 2006). This importance of a perceived, subjective reality was noted early on by Burt (1997) who writes that network positions of actors’ trigger feelings, impressions and decisions. Kilduff and Krachkardt (2008) suggest that individual preference-based decisions are based on the 'perceived state' of the network rather than the actual state. Likewise, Tasselli, Kilduff and Menges (2015, p. 1361) acknowledge that "social network structuring...cannot be fully understood" without considering the perceptions and psychology of individuals. Hence, for key accounts teams, where the account manager is primarily responsible for performance outcomes, the account manager’s perspective of the state of the network drives that manager’s decision-making. Therefore, the state of the network, as viewed by the key account manager, is of key relevance in our study.

**Robustness of network measures**

Prior research identifies conditions under which network measures such as density and centrality are robust. Borgatti, Carley and Krackhardt (2006) suggest that centrality measures (like degree) and network density are easily sampled and fairly robust to errors as well as to missing data (see Costenbader and Valente 2003). Second, Simpson et. al. (2011) find that, even when positional advantages (e.g., power) of network actors are manipulated, the recall accuracy for 'novel' networks (i.e., networks created for a specific purpose) is fairly high, between 76%-84%. Finally, Marsden (2002, p. 409) indicates that degree-based centrality is in principle identical for both egocentric and complete sociometric network data.

In the current study, we capture constructs such as density, whose measures have been shown to be robust (Marsden 2005). Our measure of centralization is based on dispersion of degree centrality, for which egocentric and sociometric approaches yield similar results. Moreover, this measure is favored for use with missing data or sampling error, as can be the case for survey-based research (Marsden 2002). Moreover, the selling team networks that we study are 'novel networks' (Simpson et al. 2011) dedicated to a key account, as opposed to generic friendship networks, which can have vaguer recalls. Hence, the networks reported by account managers are likely to be an accurate representation of actual buyer-seller and within–seller network characteristics.

**Multi-informants in a single firm vs. Single informants across multiple firms**

Several studies in the sales domain that utilize multiple informants do so in a single firm setting (see our literature review in Table 1 for examples). Multi-informant studied across multiple firms are rare. The effort involved in locating multiple informants across firms, who are also willing to participate in the study, is usually quite "excessive” (Kumar, Stern and Anderson 1993, p. 1636). Another "serious practical difficulty" is that multiple qualified informants may simply not be available given their "specific...organizational roles" (Heide and John 1990, p. 13). In a network context, Üstüner and Iacobucci (2012) address the difficulty of collecting data from multiple locations of even a single firm, concluding that the practical difficulty of doing so across several firms is often overwhelming.

Beyond the difficulties of data collection, it is unclear if multi-informant data offer additional insights into the substantive question at hand, beyond what has been obtained by single informant reports. Even proponents of the sociometric approach acknowledge that incomplete networks often yield the same results as complete networks data do. Üstüner and Iacobucci (2012, p.194) observe that “in checking descriptive comparisons, the excluded offices [office locations with response rate of less than 80% for complete network were excluded from the data] did not differ statistically from those included in our sample...”.

For our study, we had to choose between multi-informants in a single firm vs. multiple firms with a single informant each. We chose the latter for the broader generalizability of data obtained from a larger sample of firms. As we highlight in Table 1, our study in the only one in the KAM context to use network data gathered from 200+ firms and to use performance measure at the account level.

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