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Network Diversity, Distance and Economic Impact in a Cluster: Visualizing Linkages and Assessing Network Capital

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1. Introduction

A range of research focuses on the role of inter-organizational collaboration with explicit focus on knowledge exchange given its role in economic growth (Antonelli et al., 2011; Grossman and Helpman, 1994). Both organizational and geographic processes have been identified as playing roles in the various creation, accumulation and transmission phases of knowledge development. Agglomeration and clustering processes suggest potential economies from firms' spatial locations (Marshall, 1921; Porter 1990; Brosnan et al, 2016), while differential capacities of firms in absorbing external knowledge points to the role of firm-level willingness and ability to develop knowledge networks as also important (Cohen and Levinthal, 1990; Zahra and George, 2002). As Huggins and Thompson (2014) indicate, the geographic and spatial elements are related since absorptive capacity depends on locational and historical context – regions with high absorptive capacity exhibiting above average proportions of organizations with advanced capacities.

The study of the impact of organisations' external ties within collaborative networks is central to this study. The focus on organisations includes firms and other relevant actors focusing on supporting flows of knowledge within and across regions, via networking, such as universities, chambers of commerce and support agencies targeted with business development.

Network research may be underpinned by network visualisations, where actors and ties or linkages are mapped a-spatially (Purchase et al., 1997). However, social network analysis maps do not account for important features impinging on relational space such as physical distance between linkage nodes or the capacities of networks to translate networking activity into economically beneficial knowledge (Huggins et al., 2012). Here we demonstrate that network visualisations contribute to cluster analysis by improving how distinct elements of network linkages and their impacts may be both understood *and* estimated. Explaining variations in not only the quantity but also the quality (i.e. absorptive capacity) of network relations between participants aids explanation of how networks operate, also contributing evidence bases appropriate for business and public policy (Gatto, 2015).

We proceed by extending the concept of *network capital* to the cluster context. Network capital consists of investments in strategic and calculative relations to access knowledge to enhance expected economic returns (e.g. Huggins and Weir (2007); Huggins and Thompson (2015)). We focus on sources of network capital that are developed across activities that serve a range of economic outcomes for organizations and regional development, revealed across a measured set of linkages. Aligning with Simonin (1999) our interests include not only technological or innovation networks but also those linkages involving market, industry and managerial knowledge, addressing an area that “has not yet received proper conceptual or empirical elaboration”. (Sammarra and Biggiero, 2008: 801) The first contribution of the study is development of a network-impact framework enabling assessment of both inputs into and outputs from a distinct set of functional networking activities, targeting a range of knowledge links.

The second contribution of the research is in applying network visualisation based on primary and qualitative data, a need highlighted in Bergman and Feser (1999). The selected research context is a knowledge-intensive cluster in Information and Communications Technologies

(ICT)[1] in which our visualisation approach (denoted *V-LINC* i.e. Visualisation of Linkages in Networks and Clusters) permits recording, visualisation and analysis of linkages to explore the nature and impact of inter-organizational relations. Thus, we illustrate the web of network capital configured by both its spatial and functional dimensions, permitting comparison of networking inputs and their economic returns. The methods followed are open to application in other cluster and networking contexts across different spatial scales, to consider configurations of network capital and the benefits, or costs, of network activities.

Our analysis also allows us shed light on the role of geography (local to international) on the extent of linkage activity and linkage impacts for a set of networks. Knowledge-based concepts of clusters emphasize that geographic proximity *may* generate positive impacts from collaborative interactions (Arikan, 2009; Malmberg and Power, 2005; Boschma, 2005). Relational as well as functional aspects of Porter's cluster concept (outlined in Brosnan et al, 2016) point to the contested role for geography on economic impacts of linkages. We contribute to this debate by assessing network impacts in the context of geographical scales.

The questions addressed in the paper are:

a) Which types of network-capital linkages do firms most frequently access and maintain?

b) How does the role of distance vary across different types of network linkage?

c) How are geographic and functional linkage characteristics of knowledge networks associated with performance outcomes of network-capital linkages?

In Section Two the conceptual underpinnings of our impact framework are set out in the context of challenges for estimating network impacts in economic terms. Our network-capital based framework for assessing network impact is presented. Section Three presents our data collection and empirical strategy. Results are presented in Section Four where visualisation

[1] The study was facilitated through an EU-funded project, *Be Wiser* (Building Enterprises – Wireless and Internet Security in European Regions) granted to authors Byrne and Hobbs: see http://be-wiser.eu/.

from the V-LINC method of network analysis are introduced, as well as tabulated analysis and findings. Section Five summarises and presents conclusions on implications for effective network-capital based development.

2. Theoretical Background and Conceptual Framework

Agglomeration, Clustering and Networking

From theory, the spatial agglomeration of firms results from different types of external benefits (Marshall, 1921): a more extensive pool of labour may emerge, specialised inputs may be developed, and local knowledge flows can be enabled, potentially generating benefits (Brosnan et al., 2016). In practice, substantial variation in the impacts of such externalities on firms has been estimated (Beaudry and Schiffauerova, 2009; de Groot et al., 2015). Prior research indicates the relative impact of inter-firm linkages seems largest for inputs (i.e. input-output or value-chain linkages), with labour linkages the next most important, and knowledge spillovers the weakest (Ellison et al., 2010). Notwithstanding the range of related research, Diodato et al. (2016:2) argue that agglomeration impacts remain "poorly understood".

Knowledge spillovers are problematic as a concept as knowledge itself is so broad (Sammarra and Biggiero, 2008). Ambiguity over the impact of knowledge spillovers, and their variation over the industry life cycle (Audretsch and Feldman, 1996) has the added complication that market imperfections also generate unintended spillovers (Scotchmer, 2004).

Attempting to separate out the variety of interacting factors affecting performance of agglomerations, and firms within them, is challenging. One means to this end is through investigation of the place-based collaborative networks in which firms are engaged. Specifying different types of collaboration is also an option, through distinct categorisation of technological, market, industry-specific and managerial knowledge (Simonin, 1999). Such inter-organizational knowledge exchanges are recognized as playing an important role in economic growth through endogenous effects (Antonelli et al., 2011; Grossman and Helpman, 1994). The growth of cities, for example, has been explained in endogenous terms "stemming from a city's capability to invest in a range of intangible assets, in particular human capital" (Huggins, 2016).

Endogenous growth and increasing returns are evident in the agglomeration concept developed by Porter (1990) i.e 'cluster'. In fact, in Porter's (1990: 131) initial formulation of the concept while geographic proximity was identified as important, the focus was rather on the system of evolved linkages, relationships and processes connecting businesses i.e. "industries related by various links of various kinds". The processes through which increasing returns might be generated include scale effects, network effects, learning effects and other interaction effects (Arthur, 1988). Within collaborative clusters all sources of increasing returns matter "with the potential for realising scale effects and learning effects magnified by the potential of interaction and networking effects" (Brosnan et al, 2016: 508). Research into network contexts, therefore, contributes to understanding the nature, structure and impacts of knowledge flows in a variety of networks.

Across cluster-focused research Speldekamp et al. (2019) note that while understanding of the contribution of clusters to economic performance has improved, significant contradiction remains across empirical results with respect to *how* clusters generate economic growth or innovation (Wolman and Hincapie, 2014). Positive benefits of regional clusters has been reported (e.g. Hospers and Beugelsdijk, 2002; Delgado et al., 2014), while ambiguity is evident with other findings of limited positive productivity effects and no strong innovation effects (Duranton, 2011).

In policy contexts, network-based policies that target regional development have been found to generate different results in different contexts (Martin et al., 2011; Falck et al., 2010). Acknowledging that poor networking sets limitations on knowledge flows (Breschi and

Lissoni, 2001), there is widespread agreement that developing co-operative relationships across firms and other agents is an important policy goal (Schott and Wickstrom-Jenson, 2016; Huggins, 2000). As argued by Graf and Broekel (2020: 12), it is necessary to consider "what type of network failures are actually present" to better understand how networks function, or exhibit dysfunction, and to target appropriate policies.

Over time market failure arguments in favour of traditional industrial policy have been supplemented by *network* failure rationales for regional cluster-type policies (McCann and Ortega-Argiles, 2013). Network failures have been studied alongside cluster life-cycles (Suire and Vicente 2009; Brenner and Schlump 2011) with such failures associated with economic decline. Where markets fail to produce sufficient productive knowledge, policy options target network expansion through innovation incentives, reducing risks in under-appropriation of knowledge, upgrading human capital, and improving general knowledge infrastructures (Scotchmer, 2004; Vicente, 2017). Solutions to network failures include increasing network density through, e.g., clustering supports. More detailed analysis of networking activities sheds light on where weaknesses lie.

Proximity and Network Capital

Geographic proximity has been found to offer no immutable guarantee of benefits from agglomeration or local interaction (Bathelt et al., 2004; Tallman and Phene, 2007). Rather, many useful flows of knowledge have been identified through distant rather than local networks (Ceci and Iubatti, 2012; Fitjar and Rodriguez-Pose, 2011). More distant knowledge sources tend to feature for innovation-based links (Davenport, 2005). When benefits from knowledge networks arise, they appear to depend on a range of institutional, cognitive, organizational and social proximities (Boschma, 2005; Tödtling et al., 2011; Fritsch and Kauffeld-Monz, 2008). Membership of knowledge-sharing networks, however spatially configured, rather than proximity, represents a distinct dimension of network impact.

As envisaged here, network capital includes scope for greater spatial reach than in, for example, the related ‘social capital’ concept, which tends to be built up and concentrated across communities in spatial terms and consists of assets such as goodwill, belonging, and social intercourse (OECD, 2001). Where social capital is developed it results in trust and keeps people connected in ways where they can live and work productively together. As Huggins clarifies (2010), social capital focuses on individual actors within inter-personal networks (following Putnam, 2000) and it may contribute to the creation of socially beneficial resources. However, it is essentially built up *without* expectation of the results generated from relational interactions. In contrast, network capital is a firm-centric concept, defined as investments in strategic and calculative relations to access knowledge to enhance expected economic returns (Huggins and Thompson, 2015). Investing deliberately or as Williamson (1993) terms it – calculatively - involves an expectation of economic return (Belussi and Sedita, 2012).

In addition to the economies associated with agglomeration that generate different impacts for firms, organisations also differ in their ability to convert collaborative interactions into profitable outcomes. Firms’ absorptive capacity – their ability to exploit external knowledge - is complementary to external knowledge acquisition (Laursen and Salter, 2006; Cohen and Levinthal, 1990; Hansen and Birkinshaw, 2007) and considered to be multi-dimensional given the separate processes it encompasses (Volberda et al., 2010; Ferreras-Mendez et al., 2015). This implies that the underlying relational dynamics of firms engaging in collaboration, irrespective of other benefits, generates benefits from interactions and is worthy of investigation (Smith et al., 2020). It also points to the potential in separating out resources used by firms in investing in the creation and maintenance of networks when assessing their benefits. In this way whether the expectation of economic return from investments in network capital has been fulfilled may be examined.

Visualising Networks: Framing Assessment of Network Capital

Visual representation of a network requires linkage types to be identified. Some research has acknowledged the important roles of input and output linkages (including e.g. Porter, 1990, 1998b; Sölvell and Protsiv, 2008; Sölvell et al., 2009). In examination of various "cooperative arrangements" for "knowledge and information sourcing" as the basis for network capital, Huggins and Weir (2007: 713) identify linkages to include those with other firms; suppliers; clients; competitors; consultants; R&D laboratories; and higher educational institutions. Porter (1998a: 78) highlights the importance of linkages for productivity improvement and identifies partners including "governmental and other institutions, such as universities, standard-setting agencies, think tanks, training providers, and trade associations, who provide specialised training, education, information, research and technical support." Value chain or transactional approaches can also be considered with linkage categories derived from related literature (Marshall, 1921; Porter, 1998a; Contractor and Lorange, 2002; Leydesdorff, 2012).

Within each linkage category lies potential interaction that may be organised around activities, actors and/or resources. In short, no standard mapping or visualization techniques have emerged with some scholars calling for mapping conventions to be used (e.g. Gardner and Cooper (2003) for supply-chain research). A functional approach to linkages gives rise to the set identified from the literature in Table 1 where firms may choose to engage in networks with a range of partners, in the business realm and beyond, into governmental and support institutions.

INSERT TABLE 1 ABOUT HERE

Establishing networks of linkages - whatever their classification or typology - requires effort and, therefore, investment and indeed maintaining linkages over time similarly has resource implications. It is useful to employ the concept of network capital, defined as investments in strategic and calculative relations to access knowledge to enhance expected economic returns

(Huggins and Thompson, 2015). In the context of a range of possible business-relevant linkages, they can be identified as a set of separate investments in network capital, or disparate types of network capital. This approach permits identification of such investments by linkage category offering a route to evaluate their business impact by linkage type, and a firm-specific perspective that may be applied in the context of networks and clusters. To date research on network capital has not adopted such disaggregated approaches focusing on a span of different linkages.

Assessing investment in network capital is complex and may be proxied using time (Burnham et.al, 2003) to account for the time-input required to create and maintain relations, as well as the frequency of such commitments. Active network management may be needed in some cases more than others and competence in managing external relationships has been identified as the basis for a dynamic capability with consequences for performance (Kale and Singh, 2007). Strong and weak linkages may be measured in terms of time input. Further insight is revealed via the dimension of linkage breadth that includes information on whether the linkage involves more than one contact, or by the organizational position/status of the contact. This is useful to establish how a consequential interest might be generated from effective network investment. Such measures of input arguably account for activity, however, rather than impact or outcome. Features that impact on the effect of external knowledge on performance outcomes have included the breadth of linkages established, and their depth, or intensity (Nieto and Santamaria, 2007; Chen et.al., 2013).

Further research is required to better understand those linkages that generate the highest returns, according to Love et al., (2014) who focus on the relationship between the number of firm's linkages in the context of decisions to innovate and without consideration of the impact of that innovation. On a related note, Lichtenthaler (2005) also argues that development of measures of success of external knowledge exploitation are needed that take into consideration the strategies, processes and structures through which firms translate it into commercial propositions.

We propose a network impact framework, in Table 2, as a comprehensive means for understanding the performance that organisations achieve from their networking and external knowledge exploitation efforts, that crucially serves to measure economic success or failure. Whereas social capital is associated with individuals' capacity to mobilize their individual networks, network capital features organization-centricity. Social capital can 'lubricate' flows of knowledge (Vorley et al., 2012) but it does not determine flows of *economically* useful knowledge (Huber, 2012). In contrast, network capital development is targeted at economic advantage as intentional effort in knowledge interactions is considered important for creating superior knowledge through collective processes (Antonelli, 2008). It is important that impact indicators differentiate between linkages generating benefits in terms of e.g. current mission criticality and future-oriented development. Identification of impact across linkage types (following Table 1) reveals the extent to which targeted investment generates differentiated economic returns, on the basis of linkage-type.

TABLE 2 ABOUT HERE

The business impact is separated into two elements of inputs by, and outcomes from deliberate networking. Organizational input (OI) encompasses investment and involvement indicators. Organisational investment is measured through both time commitment and the frequency of contacts required to maintain the linkage. Organizational involvement accounts for two additional indicators; the breadth of contacts in the target organisation and contacts' proximity to decision-making. In this way we expand on the basic elements relating to network investment outlined in e.g. Grabher and Ibert (2006), Huggins and Weir (2007) and Huggins and Thompson (2015), addressing the nature of the underpinning relationships.

To compare organisational inputs to outcomes, Importance and Intensity indicators are identified. Identifying separate dimensions of network outcomes is necessary to appreciate the network input-output (or investment-impact) relationship. Importance addresses the criticality of the linkage for the organisation's operations - capturing linkages which might not be mission critical but still generate benefit. Finally, Intensity measures linkage strength and the expectation of future continuity. If the commitment to current organisational activities is compromised by diverting resources into network investment, network impact may be diminished rather than augmented by over-investing in linkages (Lindner and Strulik, 2014).

3. Data and Empirical Strategy

Qualitative research on the nature and extent of organizational linkages was undertaken. Structured interviews with a set of focal firms followed a tailored design approach (Wolfe, 1999; Dillman et al,. 2014) based on eight linkage categories and four dimensions.[2] Firms in the cluster region were identified and a sample invited for interview. In selecting practitioners, a purposive, convenience sampling approach was used as interviewees with experience were required to glean the information requested (Lavrakas, 2008). Assistance in identifying firms was provided through engagement with IT@Cork, a not-for-profit, independent cluster organisation representing interests of local ICT businesses.[3] A range of personnel in each organisation with knowledge of linkages was targeted with interviews arranged at the firms' premises, or the cluster organisation.

[2] Access to companies was possible through a project insert post review

[3] IT@Cork is an industry led cluster initiative and achieved the Bronze label for cluster management excellence from the European Secretariat for Cluster Analysis. Established in 1997 the organisation has 200 ICT-related companies employing over 11,500 (INNO, 2014a). Its membership include firms providing services to the cluster, such as accounting, legal, financial, hospitality and recruitment. The majority (94%) of IT@Cork's income is achieved through private subscriptions, sponsorship and event ticket-sales, with the remainder from public funding.

A sample of sixteen firms was selected for interview, including twelve Small and Medium-sized enterprises (SMEs) and four large firms: ten of the sixteen were indigenous businesses. This sampling approach was necessary due to the resource-intensity of face-to-face interviews. Forty-seven face-to-face interviews took place across four months, and interviews typically took two hours.

For each linkage identified by interviewees, they were requested to provide a score along four dimensions of Investment, Involvement, Importance and Intensity (developing measures in Hobbs, 2010). In the absence of *a priori* reasoning we applied an equal weighting of input and outcome elements in measuring network capital impact. Each of the eight sub-indicators was organised with Likert scale responses from 1–10 (10 measuring maximum strength): a maximum possible score for each linkage type for each focal firm was 40. The value of each dimension includes two sub-indicators, weighted equally. Scores for each linkage were arranged into one four bands: High (>30 to 40); Medium (>20 to 29); Low (>10 to 19); and Tenuous (1 to 9).

Interviewees were requested to indicate the spatial reach of linkages across four potential geographies. Linkages outside the cluster region but within the country were denoted 'national'; linkages outside national boundaries but within Europe were denoted 'European' with remaining linkages 'international'. All remaining linkages were 'local'. Local geographic scope and cluster boundaries were defined as County Cork[4], within which there were 889 ICT enterprises employing 5,485 people (CSO, 2016).[5] The ICT sector includes a number of embedded multinational companies (among which, Apple and Dell-EMC).

[4] Cork county is part of the South-West, NUTS level 3, region (including counties Cork and Kerry) with a population of 542,868 (2017 data: CSO, Ireland). The GDP of the South-West region in 2015 was €32 billion, approximately 18% of Ireland's total – due to confidentiality concerns no regional data for the South-West was provided since (Eurostat, 2016).

[5] Employment and number of enterprises in each region relate to NACE section J, (divisions 58 – 63) encompassing ICT services, software publishing and programming, and telecommunications activities.

To address the research questions, we examined the data across linkage type and geography using a series of Wilcoxon signed-rank statistical tests. These are appropriate for small samples and make no assumptions regarding the underlying distribution of the data collected (Harris and Hardin, 2013). The nonparametric tests allow for examination of whether any statistically different patterns are evident for specific linkage measures, across different linkage types (Table 1) and by linkage-geography categories.

4. Results

From Linkage Type to Impacts: ICT Cluster Considerations

Results of V-LINC analysis are presented in tables and visualisations for 571 linkages identified. The observations yielded by the data generation approach and its ordinal nature was suited to non-parametric tests of differences (Wilcoxon rank sum tests) that permit measurement of differences between linkage types and across geographies. Across cluster firms we identify the nature of network capital across linkages and geographies considering impact in terms of both input and outcome.

Linkage Identification: Type and Geography

Figure 1 and Table 3 present network capital by linkage category across geographies. Figure 1 displays the geographic pattern of linkages with locational markers (highlighted pins) in each panel representing the respondent firm sample. Local linkages are focused on the Cork area with evidence of a linkage highway to Ireland's capital, Dublin. A range of linkages is evident across European and other international destinations.

INSERT FIGURE 1 ABOUT HERE

Table 3 indicates that across the 571 measured linkages, the most frequent were Output (157 linkages), over 50% higher than the next most frequent category, Specialist Services (97). Within the categories of Outputs, Specialist Services, Inputs and Industry Associations (ranked 1 to 4 in Table 3, col. 6), 70% of all linkages constituting this cluster's network capital are represented. Table 3 distinguishes the geographic patterns. Across the sample 33% of linkages are local (190/571) with 27% national. The remaining 40% are evenly dispersed between European and other international locations.

Local plus national linkages dominate several categories especially Government Agencies (98% of linkages), Industry Associations (80%), Industry Peers (63%), Specialist Services (70%), and Training (89%) and Research and Development (61%). The largest international shares, European plus international linkages, are observed for Outputs (70%), Inputs (45%), R&D (39%), and Industry Peers (37%). In one linkage category only did international linkages account for more than 50% i.e. in the highest-frequency category, Outputs. Local plus national linkages represent the majority in this sample with local linkages dominating national in categories of Industry Associations, Industry Peers, R&D, Specialist Services and Training.

A balance favouring local linkages may indicate potential to benefit from knowledge spill-overs, *if* (as often assumed) proximity reduces search and co-ordination costs (encompassed in investment and involvement (input) indicators). We examine the extent to which firms in the cluster generate strong outcomes from the most local linkages (Jaffe et al., 1993: Hasan and Koning, 2017). As widely acknowledged both local and global linkages simultaneously feature in international production and consumption webs, and especially for innovation-driven growth it is emphasized that international links and international knowledge sourcing are required (Davenport, 2005; Drejer and Vinding, 2007).

TABLE 3 ABOUT HERE

To consider the role of distance in explaining frequency/share of linkages, a series of Wilcoxon signed-rank tests was conducted between the shares of aggregate network linkages for each geography. A statistically significant difference is evident between the shares of *local-plus-national* compared to *European-plus-other international* network capital. Estimates (significant at the 1% level) indicate relative importance of the local-plus-national share, using network density or frequency data, suggesting potential for local spill-overs. This was supported by statistically significant differences estimated for each comparison of local-to-European (1% significance), local-to-other International (5% significance), national-to-European (5% significance) and national-to-European (5% significance) linkages, respectively. In contrast, the comparison of local to national linkages suggested that the local/national distance discrepancy does *not* explain the relative frequencies of these aspects of network capital. Evidence of the importance of local and national collaborations are also favoured in the North of England, Greece and Turkey, in related work on network capital (Huggins, Thompson and Johnston, 2012). Distance and linkage density appear inversely related for aggregate linkages.

Geographical Differences in Network Capital

Linkage impacts are presented in Table 4 for each category, for all geographies combined, and separately. Measures are organised into two impact bands: High plus Medium linkages (H+M), and Low plus Tenuous linkages (L+T).

Approximately 68% of linkages fall into the higher band (H+M) with a range of 41% for R&D to 92% for Outputs. The top three linkages of highest frequency (i.e. Outputs, Specialist Services and Inputs) also rank highest for impact. While less than one third (32%) of linkages are low or tenuous, substantial shares of are reported in this band for R&D (59%), Inputs (58%), Training (51%), and Industry Associations (51%).

For geography, more balance across bands is evident for Local and National linkages. For local linkages 58% are in the H+M band with 56% of national linkages. For both international measures, higher shares are evident of 84% and 86% respectively. Aggregate shares by geography provide no evidence that impact declines with distance.

Focusing on the 190 local linkages, 58% are in the higher impact band. The largest shares of linkages here are Outputs (89%), Input (86%) and Specialist Services (67%). Local shares are 39% of Specialist Service linkages, 27% of Inputs and 14% of Outputs. Industry Peer linkages are recorded with lowest impact in 90% of cases. High proportions of lower impact are observed for local R&D (62%) and Industry Association (52%) linkages.

Of the 155 national linkages, 56% are in the higher impact band, including shares of 85% for Output, 82% for Input, and 67% for Government Agency linkages. However, 80% or more of national Industry Association, Industry Peer and R&D linkages were lower impact.

The 119 European linkages reveal 86% in the higher band. Four linkage types exhibit over 80% of linkages in this band: Outputs (97%), Industry Association (88%), Input (86%) and Industry Peers (83%). Half of R&D and Training linkages fall into the low impact category. The one linkage of Government Agency was low impact.

Of the 107 international (non-European) linkages, 84% are high impact. All four linkage types featuring above 80% high-impact linkages for Europe demonstrate similar performance here – and all linkages for Industry Association and Industry Peers display higher impact (100%). Over two thirds of training linkages are lower impact for this geography.

If distance holds explanatory power for linkages of impact, an inverse relationship would be evident (and statistically significant) between density/frequency and distance for high and medium linkages (390 in Table 4). Wilcoxon signed-rank tests of differences in linkage frequency between geographies were conducted. Tests for comparisons with local linkage frequencies indicated significant differences in linkage frequency for the comparison of local-to-national linkages only (at 5% significance) and local collaborations revealed an average higher frequency of 8 percentage points. Neither local-to-European nor local-to-other international linkages exhibited significance. Therefore, impact was associated with local rather than national linkages.

Significant differences were also identified for comparisons of national-to-European (at 10% significance) and national-to-other international linkages (at 5% significance). However, results indicated that impact was associated with *higher* frequency of linkages with European and other-international locations. On average linkages with European collaborators were 16 percentage points higher, and for other international partners the figure was 19 points. Distance was no hindrance to impact generated in these linkages.

Network Capital: Composition and Value-Adding Impact

Our data allow for differentiating between bonding and bridging network capital (following Putnam (2000) for social capital). Bonding capital is typified by dense networks with many member ties evident, whereas sparser links characterize bridging capital where new knowledge may refresh available stocks (as with weak ties (Granovetter, 1973). The network structure in the ICT cluster reveals bonding network capital for those relatively higher densities evident across four of the eight linkage types examined (Outputs, Specialist Services, Input, and Industry Associations: see Table 3).

TABLE 4 ABOUT HERE

Density, as outlined by Vicente (2017) provides limited insight into impact. Density *may* indicate cohesion within a network but benefits from collaboration may also generate negative lock-in and hinder efforts to attract new members (Crespo et.al., 2014). If bridging network capital dominates (in the lower-density linkages e.g. Training, Industry Peers, R&D and

Government Agencies) such weaker associations may indicate potentially rich opportunities for *future* brokerage opportunities.

Drilling into linkage quality, we focus on High plus Medium linkages (consisting of 68% of all linkages: Table 4) and consider evidence of impact differences across geographies and linkage types. Where firms successfully engage in generating returns from network capital, outcome effects are greater than inputs so net returns are positive. Our measure of network capital allows us to discriminate between those linkages where outcome impact is greater than input, across both geography and by linkage type. Table 5 indicates outcome and input measures of impact for the eight linkage categories.

INSERT TABLE 5 AROUND HERE

In aggregate across the eight linkage categories, outcome dimensions of impact are generally greater than for input, as indicated by shares of impacts scored as higher and medium (73% > 62% from Table 5). This pattern is evident in six categories with only Industry Peer linkages demonstrating a greater share of high-and-medium linkages for inputs (58%) than outcome (51%): for Industry Association links the shares are similar at 55%. There is close alignment between the impacts of inputs into and outcomes from network capital in the case of the most frequent linkage observed, Outputs, with high shares of linkages at H+M levels (85% and 88%). Substantial misalignment is observed for linkages of Inputs, Training, Government Agencies, R&D, and Specialist Services (ranging from differences of 28% to 12%) indicating strong returns to network inputs. Misalignments for the four most frequent linkages (in italics in Table 5) indicate that returns to network capital inputs are among the weakest for the most frequent categories (Outputs, Specialist Services and Industry Associations). Hence, density or frequency of linkages, does not align simply with impact.

For a spatial perspective, a set of estimations of differences between outcome and input dimensions for each linkage, for each firm, was performed with comparisons across geographies (Wilcoxon signed rank tests were used). Table 6 presents the results.

Across the four linkage types with highest frequencies (italicised in Table 6: Output, Specialist Services, Input and Industry Associations) European linkages displayed a statistically significant positive difference between outcome and input dimensions. European linkages vary in their frequency (see Table 3) across Output (43%), Specialist Services (13%), Inputs (17%) and Industry Associations (12%). However, for these linkage types the impacts on outcome are *greater* than input impacts.

INSERT TABLE 6 AROUND HERE

Even where firms use these linkage types relatively infrequently, the impact of input investments on outcome remains positive. A positive impact is also evident for the Industry Associations linkage. Linkages of Outputs and Inputs also exhibit positive returns at national level. Local linkages with positive returns are identified for Specialist Services and Inputs. Other international linkages with positive returns are estimated for Industry Associations.

For the less frequent linkages listed in the lower rows of Table 6, more limited evidence is provided in support of positive returns. At both national and local levels, the returns to network capital inputs were positive for Training and Government Agencies. In addition, positive returns are observed for Industry Peers from non-European international linkages. The R&D linkage stands in the absence of positive returns to investment across all geographies.

5. Discussion

This paper examined differences in network capital linkages used by set of firms within an ICT cluster context. It focused on differences across eight types of linkage according to the spatial level of linkages and estimated economic inputs to and outputs from linkages. The study is limited in its findings given the number of observations considered, however, it is possible to identify general conclusions relevant to development of network capital as conceptualised, visualised and operationalised here. Limitations arise also given the specific cluster context, however, as an example of how the conceptualised framework may be applied, it is informative. We see connections with research focussed on absorptive capacity and its distinct organisational (Cohen and Levinthal, 1990) and regional (Miguelez and Moreno, 2015) manifestations, that offer explanations for differential knowledge-flow impacts.

To date, visualisations of clusters have consisted of maps of organisational links, such as for the Boston Biopharmaceutical Cluster Maps (US Cluster Mapping, 2015) or the Danish Food Cluster Ecosystem (Napier and Bjerregaard, 2013), or a-spatial network maps (Giuliani, 2013). V-LINC maps introduce a novel element, i.e. geography, incorporating network theory into understanding of knowledge relationships and networks within clusters. V-LINC maps reveal which types of intra-regional and extra-regional linkages generate greatest *impact*, given their frequency. The approach adds to available cluster visualisation and analysis approaches through identifying patterns of disaggregated knowledge flows and impacts.

The ability to visualise a cluster's spatial connections contributes to understanding clustering as a process of knowledge seeking and sharing, regionally and globally. Given the structure of the Irish economy and its international linkages, this element is important for considering the capacity to exploit specific knowledge-by-geography flows for economic impact. Greater understanding of types of linkage within particular geographic scopes offers foundations for the evaluation of linkages from both policy and strategic business perspectives beyond the cluster and location specified here.

For a policy perspective, development of cluster support programmes can benefit from inclusion of geographic scales and the finding that distance plays distinct roles across different network capital linkages. Our granular evidence on the role of distance for different linkage types supports arguments from network research that analysis should underpin programmes and efforts based on *assumed* network failures i.e. sub-optimal density of networks. The relative density of four linkage types (Training, Industry Peer, R&D and Government Agencies) appear low pointing to a role for targeted supports for further collaborations. Density may generate negative network impacts, such as lock-in, inertia, and status-quo preferences within clusters. Taken as a group, these four linkage types here generate impacts greater than their inputs, and so any programme of intervention must be more distinctive in its targets.

Input and outcome indicators assist understanding of network capital relevant for policy makers but also cluster members engaged in networking activies. Data on organisational input (investment and involvement indicators) provide measures of *business* choices, i.e. strategic organisational decisions and their corresponding operational plans including investments projected to generate positive outcomes. Data on outcomes provide direct measures of those projections and investments in terms of the extent to which organisational absorptive capacity plus acquired knowledge have jointly generated positive impact.

Impact measures support the view that superior knowledge originates from beyond the home region as 85% of linkages outside Ireland fall into the high and medium category. Supports for developing additional non-national linkages appear appropriate in this context. As an exception, however, linkages with Industry Peers generate positive returns *only* from international linkages: similar positive returns from this geography are evident in the denser category of Industry Association.

Proximity may reduce search and co-ordination costs and our data point to some nuanced considerations. Input impact indicators are highest for linkages with lowest shares of local linkages (e.g. Outputs, Input). Returns to network capital inputs are among the *weakest* for the most frequent linkages, where non-local and non-national links vary between 20% and 70%.

Hence, density or frequency of linkages does not align simply with proximity or impact and intensification of density is blunt if the goal is to increase impact.

The singular lack of positive impact across any geography for R&D stands out, a finding evident only from our differentiation of impact. A low-density linkage, R&D is among the lowest ranked (Table 5) in terms of *both* outcomes and input impacts. Our finding does not indicate that benefits are not generated from R&D linkages, only that outcomes align with (i.e. are not greater than) inputs. Perhaps the breadth of knowledge links is a less useful measure of impact than further insight into depth measures might indicate. For instance, exploitative learning has been associated with transferring deep, fine-grained knowledge in science-technology-innovation (STI) mode industries that may characterise ICT. As outlined in Ferreras-Mendez et. al (2015), deep relations with external partners is an appropriate means for sharing such knowledge (Yli-Renko et al. 2001). Alternative exploratory learning offers a flexible means to identify appropriable knowledge from collaborations. Explorative capabilities currently demonstrated in cluster firms indicate their commitment to engagement and may be sufficient for their performance, without necessarily generating R&D benefits. It is also possible that through more effective network management, the strategic and intentional investment in network capital could permit generation of greater outcomes or reduction in input resources, or both.

In terms of the specific policy context of the cluster examined, the Irish government devoted limited resources to cluster policies since the 1990s (e.g. Culliton Report, 1992; Cooke, 1996; NESC, 1997: 1998). Interest has been recently revived with programmes announced (e.g. Enterprise Ireland 2012 and 2016), however, its focus and investments are removed from what is internationally classified as ‘national cluster policy’ (van Egaraat and Doyle, 2018; O’Connor et al. 2017). Various cluster initiatives have been supported at regional level in adhoc fashion. Through analysis based on empirical V-LINC analysis there is scope to address how specific clusters, or clustering more generally, might be developed more strategically. Our refinement of linkage types (supported in Huggins et al., 2012) based on resource-intensive qualitative research points to the need for further research to inform policy development, to include not only improving connectedness or density but also, crucially, impact.

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Figure 1: Cork ICT Linkages by Geographic Scope

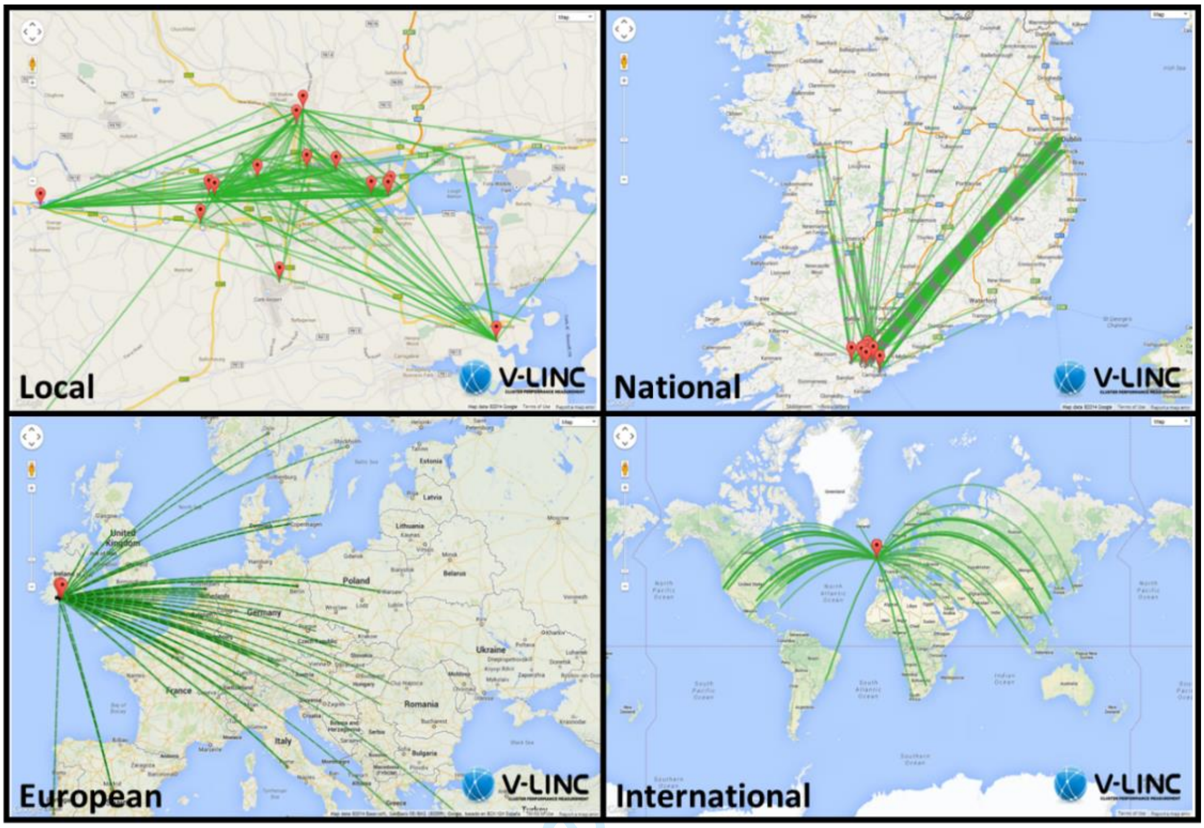

Table 1: Linkage Categories

1. **Government Agency linkages (GA):** all forms of linkages to government departments & agencies including state support for enterprise; e.g. regional authorities & local gov. agencies.
2. **Industry Association linkages (IA):** all memberships and relationships with organisations for collaboration; e.g. industry association groups, chambers of commerce, cluster organisations.
3. **Industry Peer linkages (IP):** formal and informal relationships with companies in similar or *related* industries, e.g. related via shared technologies or targeting complementary markets.
4. **Input linkages (IN):** links with suppliers of raw materials, goods and services with a critical impact on end product or service of the surveyed firm.
5. **Output linkages (OU):** customers & channel sellers - both goods and services. Outputs may be with individual customers or assigned to customer segments and regions.
6. **Research and Development linkages (RD):** include research and development relationships between companies and with academic and research institutes.
7. **Specialist Service linkages (SS):** relationships with vendors supplying essential services unavailable in-house to a surveyed firm (outside of inputs) e.g. services specific to an industry, distribution, IT, consultancy, marketing, financial and legal services.
8. **Training linkages (TN):** including third parties providing specific training /learning for employees, e.g. relationships with academic institutes addressing skills needs now/for future.

Table 2: Business Impact: Elements and Indicators

ELEMENTS	INDICATORS	
Organizational Input	***Investment*** • Frequency • Time commitment	***Involvement*** • Breadth of organizational contacts • Hierarchical position of contacts
Organizational Outcome	***Importance*** • Current Benefit • Mission Criticality	***Intensity*** • Linkage Strength for Firm • Prospective Durability

Table 3: Distribution of Network Capital Linkages by Category & Geographic Scope: Cork ICT Cluster

Geographic Scope → Linkage Category ↓	Local	National	European	Other International	Total Linkages & Rank [x]	Category as % of Total Linkages
Outputs	14%	16%	43%	27%	**157 [1]**	28%
Specialist Services	39%	31%	13%	17%	**97 [2]**	17%
Inputs	27%	27%	17%	28%	**81 [3]**	14%
Industry Associations	49%	31%	12%	8%	**65 [4]**	11%
Training	55%	34%	4%	6%	**47 [5]**	8%
Industry Peers	47%	16%	14%	23%	**43 [6]**	8%
Research & Development	37%	24%	20%	19%	**41 [7]**	7%
Government Agencies	38%	60%	3%	0%	**40 [8]**	7%
Avg Share | geo. scope	*38%*	*30%*	*16%*	*16%*		
Total (linkages)	**190**	**155**	**119**	**107**	**571**	
Share (%) of Total	**33%**	**27%**	**21%**	**19%**	**100%**	100%

Table 4: Network Capital Impact: Linkage Category and Geography

	Tot (n)	Tot%	NETWORK CAPITAL LINKAGE CATEGORY							
			GA	**IA**	**IP**	**IN**	**OU**	**RD**	**SS**	**TN**
ALL LINKAGES	**571**	100%	**40**	**65**	**43**	**81**	**157**	**41**	**97**	**47**
H + M	390	68%	63%	49%	42%	85%	92%	41%	63%	49%
L + T	181	32%	38%	51%	58%	15%	8%	59%	37%	51%
Linkage Share			**7%**	**11%**	**8%**	**14%**	**27%**	**7%**	**17%**	**8%**
Rank of Share			**7**	**4**	**5**	**3**	**1**	**7**	**2**	**5**
LOCAL	190		**15**	**32**	**20**	**22**	**22**	**15**	**38**	**26**
H + M	111	58%	60%	49%	10%	86%	89%	38%	67%	54%
L + T	79	42%	40%	52%	90%	14%	11%	63%	33%	46%
% Local Links			**8%**	**17%**	**11%**	**12%**	**12%**	**8%**	**20%**	**14%**
% Agg. Links			**4%**	**3%**	**6%**	**4%**	**4%**	**4%**	**3%**	**7%**
NATIONAL	155		**24**	**20**	**7**	**22**	**26**	**10**	**30**	**16**
H + M	87	56%	67%	20%	14%	82%	85%	20%	57%	44%
L + T	68	44%	33%	80%	86%	18%	15%	80%	43%	56%
% Nat. Links			**15%**	**13%**	**5%**	**14%**	**17%**	**6%**	**19%**	**10%**
% Agg. Links			**4%**	**4%**	**1%**	**4%**	**5%**	**2%**	**5%**	**3%**
INTERNATIONAL	226		**1**	**13**	**16**	**37**	**109**	**16**	**29**	**5**
H + M	192	85%	0%	92%	94%	87%	93%	56%	65%	40%
L + T	34	15%	100%	8%	6%	13%	7%	44%	35%	60%
% Int. Links			**0%**	**6%**	**7%**	**16%**	**48%**	**7%**	**13%**	**2%**
% Agg. Links			**0%**	**2%**	**3%**	**6%**	**19%**	**3%**	**5%**	**1%**
European	119		**1**	**8**	**6**	**14**	**67**	**8**	**13**	**2**
H + M	102	86%	0%	88%	83%	86%	97%	50%	62%	50%
L + T	17	14%	100%	12%	17%	14%	3%	50%	38%	50%
% Euro. Links			**1%**	**7%**	**5%**	**12%**	**56%**	**7%**	**11%**	**2%**
% Agg. Links			**0%**	**2%**	**3%**	**6%**	**19%**	**3%**	**5%**	**1%**
Other Int	107		**0**	**5**	**10**	**23**	**42**	**8**	**16**	**3**
H + M	90	84%	~	100%	100%	87%	90%	62%	69%	33%
L + T	17	16%	~	**0**	**0**	13%	10%	38%	31%	67%
% Oth. Links			~	**5%**	**9%**	**21%**	**39%**	**7%**	**15%**	**3%**
% Agg. Links			~	**1%**	**2%**	**4%**	**7%**	**1%**	**3%**	**<1%**

Table 5: Network Capital: Linkage Category with Outcome and Input Impact Dimensions

	Total Linkages	Tot%	NETWORK CAPITAL LINKAGE CATEGORY							
			GA	*IA*	IP	*IN*	*OU*	RD	*SS*	TN
OUTCOME										
H + M	417	73%	68%	*55%*	51%	*92%*	*88%*	54%	*70%*	60%
H+M RANK			4	*6*	8	*1*	*2*	7	*3*	5
L + T	154	27%	32%	*45%*	49%	*8%*	*12%*	46%	*30%*	40%
INPUTS										
H + M	355	62%	48%	*55%*	58%	*64%*	*85%*	39%	*58%*	36%
H+M RANK			*6*	5	3	*2*	*1*	7	*4*	8
L + T	216	38%	52%	*45%*	42%	*36%*	*15%*	61%	*42%*	64%
H+M Outcome-H+M Input	62	11%	20%	*0*	-8%	*28%*	*3%*	15%	*12%*	24%

Table 6: Network Capital Impacts: High and Moderate Linkages

Outcomes > Input?				
	Intern.	**Eur.**	**National**	**Local**
Outputs	***N***	***Y****	***Y****	***N***
Specialist Services	***N***	***Y****	***N***	***Y +***
Inputs	***N***	***Y****	***Y****	***Y****
Industry Associations	***Y^****	***Y^****	***N***	***N***
Training	na	na	**Y****	**Y****
Industry Peers	**Y***	na	**N**	**na**
R&D	**N^**	**N^**	**N^**	**N^**
Government Agencies	na	na	**Y****	**Y***

** Denotes statistical significance at 1%
* Denotes statistical significance at 5%
+ Denotes statistical significance at 10%
na denotes insufficient observations for statistical testing
^ Note: Separate geographies were summed (e.g. both National and Local or International and European) to generate sufficient observations for statistical testing.