The formation and dissolution of inter-firm linkages in lengthy and stable networks in clusters

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Abstract

Firms aspire to take advantage of technical and business networks through inter-organizational interactions to improve performance. Consequently, researchers are increasingly focusing on the dynamics and implications of network formation at both local and global levels. The recent research trend does not consider a monotonic effect and simplistic approach to proximity because proximity is a complex multidimensional concept. Using data from a foodstuffs cluster in the Valencian region (Spain) and advanced econometric methods such as Exponential Random Graph Models, this study aims to clarify the detrimental effects and complementarities that may arise among proximity dimensions. After controlling for network endogenous forces and firm characteristics, findings reveal the negative effect of cognitive and institutional proximity dimensions on the creation of linkages in advanced stages of the cluster life cycle. Furthermore, social and geographical proximities favor the formation of inter-firm relationships and reinforce the organizational dimension.

Keywords: Clusters; networks; ERGM; social capital; proximity

1. Introduction

Recent research focuses on identifying key factors to achieve successful collaborations between organizations. Such interest stems from these collaborative relationships' critical role in generating innovation, particularly through common learning and knowledge spillovers (Asheim & Gertler, 2007).

Despite research on inter-organizational relationships, the origins and dynamics of network structures still merits additional investigation (Ahuja et al., 2012). While several studies focus on endogenous mechanisms leading to network development (Rivera et al., 2010), studies accounting for network unit attributes are less common. In particular, little research exists on the development of relational architectures and changes over time in characteristics of inter-organizational linkages.

Several studies dating from last decade and focusing on industrial clusters adopt an evolutionary approach (Boschma & TerWal, 2007; Giuliani & Bell, 2005; Morrison & Rabellotti, 2009). Industrial clusters are networks that are social in nature (TerWal & Boschma, 2009) comprising different stakeholders who interact, evolve, and contribute to a specific geographical context performance. Thus, these networks are appropriate structures for an in-depth analysis of firms' interactions.

The evolutionary approach explains the prerequisites for successful collaborations, thereby overcoming the "localist trap" that traditionally emphasized the role played by co-location and territorialized dynamics (Gertler, 2003). This view derives from Boschma's (2005) seminal contribution and focuses on five types of proximity: cognitive, social, organizational, institutional, and geographical. A close relation exists among these proximities (Ben Lataifa & Rabeau, 2013; Boschma & Frenken, 2010; Mattes, 2012), and the proximities co-evolve over time (Broekel, 2012).

Recent research reconciles the effect of structural mechanisms with the relevance of node attributes in the evolution of relationships (Balland et al., 2013; TerWal, 2013). Nevertheless, many aspects regarding network formation dynamics require further study.

This study aims to fill the research gaps by exploring the contribution of networks' structural tendencies and proximity dimensions to knowledge sharing and linkages. The study uses data from a sample of companies from a mature foodstuff cluster in the Valencian region. A 2011 survey to 36 nougat manufacturers and their suppliers provides the data. The study uses these data to test and develop an exponential random graph model (ERGM).

Section 2 presents the theoretical framework and hypotheses, section 3 discusses the industrial cluster's characteristics, section 4 describes the method, econometrics, and results, and section 5 presents the conclusion, key findings, and implications.

2. Theoretical background

2.1. The proximity approach

Proximity is a fuzzy concept that demands a complex approach (Markussen, 1999). Particularly, exponents of the French School (Torre & Rallet, 2005) advocate a multidimensional perspective to accurately assess the effects of geographical proximity (Autant-Bernard et al., 2007).

2.1.1. Cognitive proximity

Proximity among firms does not guarantee knowledge spillovers (Boschma & Iammarino, 2009). Interaction among units is the starting point for learning and knowledge sharing. However, the existence of a common interpretative scheme determines these processes' effectiveness. Firms may reveal cognitive constraints that impede optimal performance. The cognitive dimension describes actors' ability to communicate meaningfully and generate knowledge before the learning process starts, which implies sharing common and complementary skills and knowledge.

2.1.2. Organizational proximity

Organizational proximity is the extent to which firms share relations in an organizational arrangement; autonomy and control are the basis of organizational proximity. Greater control and possibilities to regulate interactions means greater organizational proximity. Conversely, firms with links that induce autonomy have less organizational proximity. Organizational proximity usually appears through prior collaboration experiences (D'Este et al., 2012) between firms within the same group (Balland, 2012) or in long-term subcontracting relationships. Hierarchical interconnection fosters knowledge sharing and common learning because hierarchical interconnection reduces uncertainty and limits the risk of opportunism.

2.1.3. Social proximity

Social proximity refers to the degree of interconnection via social networks or the degree of human behavior occurring within a social network. Such behaviors include friendship, kinship, and experiences. Hence, social proximity represents strongly embedded social relations between actors at the microlevel involving trust (Boschma, 2005). The degree of social proximity is crucial to explain economic outcomes (Granovetter, 1985) because trust-based ties foster knowledge transfers and common learning practices.

In a dynamic process over time, social links generate different trust levels and moderate the risk of opportunistic behaviors and rent appropriation (Dettam & Brenner, 2010). In this vein, geographical proximity reinforces social ties through frequent meetings and trust building, but geographical proximity is only necessary in the initial stages (Dettman & Brenner, 2010). Thereafter, temporary geographical co-location maintains social ties (Ramirez-Pasillas, 2010; Torre, 2008).

2.1.4. Institutional proximity

Following Edquist and Johnson (1997), institutions comprise sets of common habits, routines, recognized practices, rules, and law that regulate human and inter-organizational interactions. Hard institutional factors (laws and rules) are equally as important as soft ones (norms, values, and routines). Institutional proximity is a complex combination of hard and soft macro-level factors (Xu & Shenkar, 2002) that provides a framework of stability and shapes cooperative behaviors. Boschma (2005) highlights the interconnection of both organizational and institutional forms of proximity because governing intra- and inter-organizational relations is inherent to institutional settings. Boschma also indicates the possibility of an inverse relationship between the importance of geographical proximity and institutional proximity for successful learning and collaboration.

2.1.5. Geographical proximity

The literature shows widespread consensus about the localized nature of knowledge production and spillovers (Audretsch &Feldman, 1996). Innovation activities seem an exception to the death of distance resulting from the widespread adoption of modern ICT (Morgan, 2004). Some authors question the theoretical importance of the spatial or physical distance between actors for collaboration and knowledge exchange (Boschma, 2005; Breschi & Lissoni, 2001; Gertler, 2003). However, evidence does not support the decline of the spatial proximity effect (Frenken et al., 2010).

Despite the positive effects of geographical proximity on learning, geographical proximity's role as a moderator strengthens other forms of proximity (Broekel & Boschma, 2011), probably through indirect effects. In fact, geographical proximity promotes, among other things, the formation/evolution of institutions, embeddedness and trust, and/or cognitive proximity. Under certain circumstances, these four proximity dimensions may also function as substitutes for physical proximity (Boschma, 2005). For instance, spatial proximity may help to overcome institutional (Ponds et al., 2007) or cognitive distance (Singh, 2005).

2.2. Dynamics of cluster

Like the industry life cycle, a cluster comprises only a few firms at the emergence stage. Then, the number of firms and employees grow, and finally, the number of firms and employees declines.

This study focuses on the process of decline, to discover what internal and external causes generate these processes. According to authors, excessive embeddedness of the institutional context or a lock-in into an ineffective systemic framework can damage learning or creativity and cause cluster decline. Another potential cause of cluster decline is cognitive lock-in, which means that local firms share a common view that restricts understandings and novel responses to situations (Belussi, 2006; Grabher, 1993).

Lagnevik et al. (2003) suggest that European food clusters were already in the advanced stages of the life cycle (mature/decline or renaissance) at the beginning of the

2000s. At this time, the industry faced a surge in new technologies, many products became obsolete, and new actors invaded the competitive landscape. This study posits that evolution of some proximity dimensions partially explains the cluster life cycle.

3. Hypotheses

Cognitive proximity entails both opportunities and threats in the process of learning. Firms need to share common and complementary skills and a knowledge base to interact with each other successfully. Therefore, cognitive proximity eases collaboration and leads to positive outcomes thanks to continuous communication and absorption. However, lengthy cooperation in stable networks in the maturity stage may reduce diversity of inter-firm knowledge exchanges and progressively diminish learning opportunities (Wuyts et al., 2005). Consequently, because networking takes time and effort, partners avoid or dissolve linkages unlikely to produce benefits. Cognitively close organizations feel discouraged to engage in new interactions.

H1: Cognitive proximity negatively affects the creation of linkages in advanced stages of the cluster life cycle.

Institutions consist of informal constraints, customs, traditions, conduct codes, formal rules, constitutions, laws, and rights (North, 1991). Institutions are stable designs for a repetitive activity, bearing the characteristic of path dependency and cumulative causation. As a cluster grows, a set of rules and norms that legitimate and standardize behaviors and govern transactions emerges endogenously. While institutions initially stimulate agglomeration development, they may foster inertia that obstructs awareness and stifles opportunities during the decline stage of long-established systems (Grabher, 1993).

Such institutional sclerosis owes to a competency trap, which refers to individual organizations' competence to make specific achievements as well as the competence of institutions to manipulate the relationships between actors to interact successfully. This term also includes the vested interests that emerge in the formation process of the institutional setup, which may oppose necessary changes that undermine local firms' positions (Boschma, 2005).

H2: Institutional proximity negatively affects the creation of linkages in advanced stages of the cluster life cycle.

Firms usually form or reactivate ties to solve problems of network redundancy. Local embedding that lasts too long leads to excessive cognitive proximity and redundancies. This local embedding, however, also generates familiarity and trust (Gulati, 1995). Trust raises cooperative behavior, facilitates knowledge exchange, and makes knowledge transfers more effective (Singh, 2005). For instance, relationships become more frequent and valued when the actors trust one another. This trusting atmosphere emerges from face-to-face interactions, inherent to geographical proximity, and leads to knowledge sharing and cooperative behavior (Asheim & Gertler, 2007). Recent research highlights how both social and geographical proximities follow a similar path as the network matures (TerWal, 2013).

H3: Both geographical and social proximity favor the creation of linkages in advanced stages of the cluster life cycle.

A relation exists between institutional and organizational proximities. A set of common representations, models, and rules at the macrolevel are the basis of institutional thickness. Following Talbot (2007), organizational proximity may be a form of institutional proximity. Organizations (like firms or even formal partnerships) create a common space with their operational rules and routines, and governance structure that all members can observe. Ben Lataifa and Rabeau (2013) study this relationship by focusing on close linkages between organizational and institutional forms of proximity.

Advanced stages of the cluster lifecycle may not only present an unsuitable institutional framework for network formation, but also an excess of cognitive proximity causing overlaps and unplanned spillovers when firms compete in the same market with similar products (Vicente et al., 2007). Under these circumstances, firms will avoid these knowledge losses and harmful behaviors through a self-designed governance framework favored by cognitive commonalities. When norms and rules do not work at the macro level, firms tend to create an institutional context at the micro level. When collaborators develop a similar business view or strategy, they can easily attain organizational proximity, thus avoiding the need to foster new ties in the network. Finally, an excess of institutional proximity and an excess of cognitive proximity favor organizational proximity, and consequently, boost relationship creation in the network.
H4: In advanced stages of the cluster lifecycle, high institutional and cognitive proximities favor organizational proximity, enhancing organizational proximity's role in network formation.

4. The empirical context

This research draws on a sample of the firms belonging to the Spanish chocolate and confectionery industry. Production of Spanish traditional nougats and other Christmas candies in Xixona (Spain) exemplifies clustering in the foodstuffs industry.

ISTAT methodology recently identified this geographical area as industrial. However, controversy exists about different systemic aspects; not only those aspects regarding cohesion and cooperation dynamics, but also the prevalence of heterogeneous behaviors in key strategic outlines, which suggests a fragmented business community in terms of strategic and competitive advantages (especially large corporations vs. SMEs). Consistently, nougat manufacturers seem to benefit from location, but some deficits hamper technical and commercial synergies.

5. The study setting

5.1. The questionnaire

Data collection took place in Xixona during the second half of 2011. In a preliminary stage, face-to-face interviews with key manufacturers and local supporting organizations provided primary data about multiple aspects of the industry and the cluster. Using insights from the interviews and the literature, this study used a thorough questionnaire dealing with firm characteristics, innovation practices, inter-organizational relationships, and performance. After the pre-test, the universe of manufacturers within the cluster received the questionnaire.

5.2. Data collection

All 36 local manufacturers and suppliers in the TDC (the local nougat trade association) and the Regulatory Council completed the questionnaire, providing information about their local relationships. Peer debriefing confirmed that just a few artisans (usually self-employed) did not participate; the study considers all relevant actors. Finally, 24 nougat and Christmas candy manufacturers and 12 suppliers cooperated, yielding an appropriate response rate for a whole-network approach (Wasserman & Faust, 1994).

To collect network data, respondents chose from a list of 36 the firms to which respondents regularly asked for technical information over the previous three years.

Answers rated from 0 to 3 according to the existence and relevance of the connections. This "roster-recall" method reduced selectivity bias in the answers due to memory effects.

Table 1 here.

Table 1 presents descriptive statistics on firm level characteristics, such as size, decade of creation, legal structure, and international operations. Table 1 reports membership and main business activities.

5.3. Variables

Dependent variable: Relational data allowed the creation of a directed square network matrix, which served as the dependent variable. Each column *i* and each row *j* represents a firm, and the cell entries are the value that firm *i* perceives about its relationship with firm *j*. Note that this matrix is not symmetric because the value firm *i* perceives may differ from the value firm *j* perceives.

The estimating procedure and software demands a binary dependent variable. The study collapses the perceived value into a dummy variable, coded 1 for values 2 and 3, and 0 otherwise. Thus, the study shows relevant interactions because the threshold by which a firm's interaction is relevant may vary greatly.

Explanatory variables: The proximity insights lead to expect that proximity between firms affects network dynamics. To measure this effect, the study includes five dyadic covariates. Each dyadic covariate is a (36x36) symmetric matrix that takes a value for each pair of firms. In the geographical proximity covariate, values in the matrix reflect the physical distance between the two firms. NACE codes allow the creation of the cognitive proximity covariate. The covariate takes the value 1 if the firms share the same four NACE digits and 0 otherwise. The third dyadic covariate captures institutional proximity according to the firms' legal status. Cells in this matrix take the value 1 when firms have the same legal status and 0 otherwise. A new matrix measures whether firms belong to the same group to account for organizational proximity. Cells in the matrix take the value 1 if firms belong to the same group and 0 otherwise. Information from TDC enables configuration of a social proximity covariate based on the existence of familiar relationships between firms' owners. Cells take the value 1 if familiar relationships exist and 0 otherwise.

Indicators test whether firm characteristics affect the creation of ties by adding the following individual covariates or attributes: size (square root of total sales), age (square root of years since creation), absorptive capacity (0 when the firm does not employ workers with university degrees, and 1 otherwise) and supplier (0 when the firm is a nougat or candy manufacturer, and 1 otherwise). For different values of each individual characteristic, the study classifies firms into advice seekers (ego) or counsel givers (alter) and tests the effect of the absolute difference on a particular attribute.

Finally, the study controls a number of variables that tap into the knowledge network structure. These parameters reflect endogenous forces and tell whether interactions occur more or less often than random interactions do. Following Hunter's (2007) specifications, the study selects the mutual parameter that evaluates reciprocity or the inclination to give back cooperatively (e.g., tendency to A->B given that B->A). The cyclic closure term (CTriple) that reflects a tendency toward general reciprocity among organizations (e.g., triangle A-> B, B-> C, and C-> A). Additionally, the study uses the geometrically weighted parameter for the distributions of indegree (GWIDegree) and another for outdegree (GWODegree). Indegree indicates the distribution of tie frequency firms in the network report, whereas the second reflects the distribution of the outgoing ties that respondents report. Finally, geometrically weighted edge-wise shared partnerships (GWESP) evaluates the transitivity in the network and indicates cohesion. Essentially, transitivity refers to the fulfillment of the “friend of my friend is my friend” paradigm. In other words, if two firms share a common network partner, those firms usually become partners (e.g., A-> C and B-> C, then A-> B or B-> A).

5.4. *Statistical analysis and results*

To test the hypotheses, the study applies an exponential random graph model (ERGM). ERGM probability models represent the generative process of tie formation and investigate the structure within a complete social network. This study looks at inter-organizational linkages within a technical network, where a link represents one firm asking technical advice to another firm. These network relations do not form randomly but have an underlying pattern. This study uses ERGM to examine and empirically test these structural patterns and to ask whether changes in partners depend on the firm’s position within the network.

The rationale underlying this model is that the technical network is just one realization, and might occur by chance. To see to what extent the technical network diverges from a random network, the study generates a number of random networks through Markov chain Monte Carlo maximum likelihood estimation. The study compares parameters in the simulated and real networks. This procedure repetition provides a good representation of the real network.

ERGM requires the study to add variables in consecutive blocks to test these variables’ relative contributions. The baseline model includes the individual covariates or firm-level attributes. The intermediate model incorporates the dyadic covariates, whereas the endogenous forces join the model in the final stage. As Goodreau (2007) indicates, this procedure accurately assesses network forces' role in explaining firm characteristics and relational attributes. Following Hunter et al. (2008), the study discards model fit statistical measures because of data interdependency. Instead, the study checks goodness-of-fit (GOF) plots comparing the real network with a set of simulated networks.

Table 2 here.

As the data in Table 2 illustrate, results are consistent with expectations. Both cognitive and institutional proximities exercise a significant negative effect on the creation of linkages ($p<0.01$ and $p<0.10$, respectively). Results support H1 and H2. Conversely, the geographical and social dimensions enhance linkages. The significant result at $p = 0.01$ and $p = 0.1$, respectively, endorse H3. Likewise, organizational proximity fosters common learning and knowledge sharing within cluster boundaries ($p<0.01$).

Control variables provide interesting insights into the selective nature of the network formation process. While age fosters the creation of linkages at $p< 0.10$, the absolute difference between partners generates the opposite effect ($p<0.01$). This evidence indicates that the status effect shapes the advice dynamics. Well-known firms have more linkages, but connections are less likely to occur between older and more recent units. In addition, only the out-effect of the absorptive capacity attribute yields a negative significant effect ($p <.01$), indicating that firms showing strong knowledge bases are more selective and less advice seeking.

The sensitivity diagnosis corroborates results' strength. The auto-correlation coefficients among various intervals are close to 0, with the exception of the first auto-correlation coefficient, which always takes the value of 1. Furthermore, Gewerke statistics, which are relatively comparable to Z statistics, yield non-significant values for $p < 0.10$. The Akaike Informative Criterion (AIC) and the Bayesian Information Criterion (BIC), which are model fit measures that rely on independent data, exemplify improvements in measures of model fit. AIC and BIC commonly compare nested statistical models like ERGM. Nevertheless, this study relegates both AIC and BIC measures (Hunter et al., 2008). Instead, the study uses parameter traces and GOF plots comparing real network characteristics with those of simulated networks based on each model. In addition to being stable and convergent, the model has reasonable horizontal traces. Although thorough observation of the different network parameter plots reveals some disparities, the study's main interest lies in the hypotheses regarding actor traits.

Further statistical analysis shows to what extent cognitive and institutional proximity favor organizational proximity in advanced cluster life stages. The quadratic assignment procedure—a non-parametric technique that scholars apply to relational data—permits the regression of a dependent matrix on one or more independent matrices. The dependent variable is organizational proximity, and the independent variables are the other proximity dimensions and a matrix reflecting age difference between firms. Correlations between independent variables range from 0.01 to 0.05, indicating no problems of multicollinearity.

Table 3 here.

Table 3 displays QAP regression results for the knowledge network. GOF values reveal that the model offers a good explanation for the phenomenon under study. Results confirm the expectations regarding the role of institutional and cognitive proximities in reinforcing organizational proximity. Both forms of proximity enhance the organizational dimension. ERGM results reveal the positive effect of organizational proximity on the likelihood of interacting with other firms, thereby confirming H4.

6. Discussion and conclusion

This study focuses on the dynamics of network formation in mature and declining clusters, using ERGM and data from a foodstuff cluster in Spain. The baseline model explores the propensity of firms to establish and receive ties based on firm-level attributes, whereas the intermediate model also controls the effect of proximity dimensions.

Empirical findings confirm that proximity dimensions interrelate and affect the technological knowledge network dynamics. Firms benefit from sharing information because this knowledge-sharing process may allow joint problem solving and common innovation practices. The potentially negative effects of a proximity excess constitute another important factor. In the network under study, too much cognitive and institutional proximity degrades the formation of intra-cluster linkages. Firms know the high cost of networking, and hence carefully choose their technological partners, namely those whose cognitive maps are complementary. The lack of suitable rules and regulations undermines the generation of new linkages and fosters the dissolution of former partnerships. An obsolete institutional framework leads to dysfunctional business relationships, hindering cooperation and knowledge transfer.

From another perspective, two or more forms of proximity are necessary to sustain network formation. Results imply that social, organizational, and geographical proximity may take over from former proximity forms that have now become barriers for cooperation. An excess of proximity in lengthy interactions may negatively affect linkages creation but may also enhance the effect of relating proximity dimensions. The models' combination shows how institutional and cognitive proximity contribute to the emergence of organizational proximity. Furthermore, findings show that two or more forms of proximity may complement each other. Other proximity dimensions offset the detrimental effects that certain proximity forms cause.

These findings have certain limitations. First, they derive from informants' perceptions and self-report data regarding previous behaviors. Hence, memory errors and omissions may exist. Methodology mitigates these potential deficiencies, but lapses in aspects such as the valuation of linkages may arise. Nonetheless, relying on informants' memories is necessary to obtain information about the whole intra-cluster network, even though doing so implies a trade-off between robustness and completeness.

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Table 1. Descriptive statistics of the sample

Characteristics	Number of firms (%)
Employees	
10	10(27.8)
10<X≤25	7(19.4)
25<X≤50	10(27.8)
50<X≤100	6(16.7)
100< X	3 (8.3)
Sales (thousands Euros)	
X ≤1.000	10(27.9)
1.000<X≤3.000	12(33.3)
3.000<X≤6.000	7(19.4)
6.000< X	7(19.4)
Year of creation	
Up to 1970s	15(41.7)
1980s	4(11.1)
1990s	10(27.8)
2000s	7(19.4)
International operations	
Exporters	16 (44.4)
Importers	19 (52.8)
Exporters/Importers	84.2
Business activities	
Manufacturers	26 (72.2)
Suppliers	10 (27.8)

Legal structure	
Corporation	17 (47.2)
Limited liability	15 (41.7)
Others	4 (11.1)
Local organizations membership	
POD (denomination of	22 (66.1)
origin)	24 (66.7)
TDC (business association)	
City	
Xixona	36 (100)

Table 2. ERGM technical network

	Baseline model	Intermediatemodel	Final model
	B (p-value)	B (p-value)	B (p-value)
Mutual	***0.91	***1.15	***1.58
Age	***-0.04	**0.05	*0.03
Age (abs.diff)	***-0.22	***-0.16	***-0.11
Absorptive capacity (in)	***0.43	**0.39	0.12
Absorptive capacity (out)	***-0.82	***-1.02	***-0.44
Supplier	0.13	*0.16	0.10
Geographical proximity		**-0.74	***-1.62
Cognitive proximity		***-0.77	***-.57
Institutional proximity		*-0.22	*-0.23
Organizational proximity		***1.25	***1.30
Social proximity		*0.60	*0.61
GWESP (2.5)			***0.21
CTriple			***-0.33
GWINDegree (0.7)			4.90
GWOUTDegree (0.7)			***-2.49
AIC	1488	1420	1339
BIC	1519	1476	1416

Significance codes: *** p < 0.01; ** p < 0.05; * p < 0.1

Table 3. QAP logit regression results

	Estimate	Exp(b)	Pr(<=b)	Pr(>=b)	Pr(>=|b|)
Intercept	-20.13	1.81e-09	0.401	0.59	0.42
Institutional proximity	1.60	4.94e+00	0.96	**0.04	*0.09
Social proximity	-14.67	4.28e-07	0.32	0.68	0.32
Cognitive proximity	1.73	5.61e+00	0.96	**0.04	*0.09
Geographical proximity	14.18	1.44e+06	0.54	0.46	0.47
Age (abs. Diff)	0.01	9.88e-01	0.29	0.71	0.38
Goodness of fit statistics					
Null deviance: 1746.73 on 1260 degrees of freedom Residual deviance: 150.7278 on 1254 degrees of freedom Chi-squared test of fit improvement: 1596.003 on 6 degrees of freedom, p-value 0 AIC: 162.7278 BIC: 193.561 Pseudo-R^2 Measures: (Dn-Dr)/(Dn-Dr+dfn): 0.56 (Dn-Dr)/Dn: 0.91 Total fraction correct: 0.99					

Significance codes: *** p < 0.01; ** p < 0.05; * p < 0.1