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Explaining path-dependence in the evolution of networks. The case of an Electronics cluster in Argentina

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Abstract

One of the current open areas of cluster research concerns the factors driving the dynamics of local inter-organizational networks. Since embeddedness in local networks is considered to be one important dimension of firms? capacity to innovate, understanding their dynamics can also help to interpret a cluster?s development trajectory. Conceptual works about networks in clusters claim that most networks tend to grow according to a very stable pattern, but very little research has analyzed the micro dynamics responsible for the path dependent evolution of local networks in clusters. To address this limitation we develop a novel conceptual framework where we distinguish between micro dynamics that lead to path dependent changes of local networks, and path destructive micro dynamics. We apply Stochastic Actor-Oriented Models (SOAM) for network change to the case of an electronics cluster in Cordoba (Argentina), and find that the cluster is characterized by a path dependent change of its local network, and argue that this is associated to the coexistence of different (path dependent) micro dynamics, such as: reciprocity, preferential attachment, and social and institutional proximity. In contrast, we do not find that firm level agency and inter-firm heterogeneity contribute to generate path destructive processes of network change. This paper provides evidence that contributes to the refinement of the incipient theories about cluster network dynamics and cluster evolution.

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Explaining path-dependence in the evolution of networks. The case of an Electronics cluster in Argentina

1. Introduction

One of the current open areas of cluster research concerns the factors driving the dynamics of local inter-organizational networks (Martin and Sunley, 2006; Glückler, 2007; Boschma and Frenken, 2010; Giuliani; 2010; Martin, 2010; Boschma and Fornhal, 2011; Martin and Sunley, 2011; Ter Wal and Boschma, 2011; Staber, 2011; Balland, 2012; Balland et al., 2012; Li et al., 2012). Since embeddedness in local networks is considered to be one important dimension of firms' capacity to innovate, understanding their dynamics can also help to interpret a cluster's development trajectory. Yet in many cases, conceptual works about networks in clusters claim that, even if at the micro level firms (or other actors) make numerous connectivity choices and changes over time, at the macro level most networks tend to grow according to a very stable pattern. For instance, Glückler (2007) suggests that cluster evolution is likely to be path-dependent and that this, by and large, is the result of retention mechanisms in new tie formation "that cause new ties to reproduce and reinforce an existing network structure" (p. 622). Also Ter Wal and Boschma (2011), who conjecture that the characteristics of networks will change along the cluster lifecycle (CLC), suggest also that, during the growth stage of the CLC, local networks will tend towards the formation of a stable core-periphery structure, where centrally located firms are likely to become even more central through a preferential attachment process and the exit of firms positioned at the periphery of the local network. Later on, towards the mature stage of the CLC, the network might become denser and drive the cluster into lock-in. Previous studies on other contexts than regional clusters also show that networks are stable (e.g. Walker et al., 1997; Uzzi et al., 2002), especially social structures that characterize more mature systems, which "typically display a set of stable, self-reproducing positions occupied by actors with similar network profiles"(Gulati and Gargiulo, 1999, p. 1450).

While most networks are expected to reach a level stability, the micro dynamics of path dependent network change in clusters are still unclear. Network studies suggest that the evolution of the macro structural characteristics of a network is driven by concurrent forces operating at the micro level (Owen-Smith and Powell, 2004; Powell at al. 2005). Some are endogenously induced by the existing network – e.g. past relationships influence future ones (Walker et al., 1997; Gulati and Gargiulo, 1999), while others are exogenously-driven, which means that they are related to the heterogeneity in the internal and individual characteristics of the actors in the network. Hence, the changes occurring in the structural properties of a network are often due to a mix of exogenous and endogenous micro dynamics (Baum and Mezias, 1992; Di Maggio, 1992).

In this paper we ask the following research question: What micro dynamics are responsible for a path dependent evolution of local networks in clusters? To explore this question we develop a novel conceptual framework drawing on earlier network dynamics research, where we distinguish between micro dynamics that lead to path dependent changes of local networks and path destructive micro dynamics. The former are retention mechanisms that result in persistence of ties and consolidation of existing network structures. They include endogeneous micro dynamics such as reciprocity, transitive triplets (closure) and preferential attachment, as well as exogeneous micro dynamics related to a set of proximity effects (social, institutional, geographical and sectoral). Path destructive micro dynamics in contrast contribute to generate variation in the network and to discard existing network structures, generating new network arrangements, and include a set of exogenous micro dynamics connected to entry/exit dynamics, and to inter-firm heterogeneity and firm's individual agency.

We explore the micro dynamics of network change in the context of an electronics cluster in the City of Cordoba, Argentina. The analysis focuses on the cluster information network, which has been studied in 2005 and 2012, a period roughly corresponding to the maturity of the cluster, although the economic fluctuations of the Argentinean economy impede to trace a very clear CLC for this case. The research is based on the collection of data through face-to-face interviews conducted by one of the authors. The survey was based on similarly structured questionnaires, administered to a sample of firms in the cluster in 2005 and again in 2012. Social network analysis (Wasserman and Faust, 1994) is employed to conduct static comparisons between knowledge networks over time, and a class of Stochastic Actor-Oriented Models (SAOM) for network dynamics developed by Snijders (2001, 2005) and colleagues is used to explore the micro dynamics of network change.

We find that the cluster is characterized by a path dependent change of its local network, and argue that this is associated to the coexistence of different (path dependent) micro dynamics, which the SAOM analysis proves to significantly influence the formation of new ties, such as reciprocity, preferential attachment, and social and institutional proximity. In contrast, we do not find that firm level agency and heterogeneity contribute to generate path destructive processes of network change. This paper provides evidence that contributes to the refinement of the incipient theories about cluster network dynamics and cluster evolution.

The paper is organized as follows. The conceptual framework is developed in Section 2. Section 3 present the context and methodology of this study. Section 4 presents and discusses the empirical results. Section 5 concludes the paper.

2. Conceptual framework

The literature suggests that there are certain micro dynamics of new tie formation that are likely to be conducive to a stable and path dependent pattern of macro-level network evolution (i.e. path dependent micro dynamics). There are instead other micro dynamics, which are more likely to generate path destructive patterns of network evolution, and to discard the structural properties of a network at a given point in time (i.e. path destructive micro dynamics) (see Glückler, 2007). Based on prior network research, we identify a set of path dependent vs. path destructive micro dynamics, which are summarized in Table 1 and discussed in the following sections.

[Table 1 about here]

2.1 Path dependent micro dynamics

2.1.1 Reciprocity

Reciprocity has been studied for a long time as mechanisms promoting the formation of new ties in inter-corporate networks (Lincoln et al., 1992; Fehr and Gachter, 2000). In the context of this paper, reciprocity emerges when a firm that has been the recipient of business information from another firm, decides to return (reciprocate) the favour. Reciprocity is common in accounts of industrial clusters (Amin and Thrift, 1994). Smith-Doerr and Powell (2005, p. 20) argue that, in industrial districts, “repetitive contracting, embedded in local social relationships, encourages reciprocity. Monitoring is facilitated by social ties and constant contact.” Likewise, Grabher (1994, p. 181) describes East German regional industry in the 1970s as characterized by the emergence of informal networks, which “provided diffuse infrastructure for barter governed by the principle of reciprocity.” In such contexts, reciprocity is considered to stabilize relationships and increase levels of trust between the parties, creating beneficial repercussions on the quality of the interaction. In this respect, Ahuja et al. (2012) consider reciprocity to be related to the inertia of organizations, which maintain stable routines and relational habits. Hence, we consider reciprocity to be one of the forces that favour path dependent network changes in clusters.

2.1.2 Transitive Closure

Transitive closure increases network cohesiveness. It occurs when a new link is formed between two actors that are already connected to a common third actor. Underpinning transitive closure is what is known in social psychology as “balance theory” (Heider, 1958), which suggests that an individual establishes a new linkage with a third one on the basis of whether, the individuals she/he is already connected to, have positive feelings about (and are themselves connected to) this third person. Basically, the idea is that an individual perceives a sort of psychological pressure from her/his direct contacts (e.g. friends) and is induced to choose new contacts in a way that preserves some consistency and harmony (or balance) within the social group that she/he is part of (Granovetter, 1973). Also, firms may find it very convenient to form relationships with other firms that are already socially proximate (Ahuja et al., 2012). Studies on regional clusters include many stories that are persuasive about the existence and importance of network closure and are indicative of the tendency for firms to become embedded in dense networks (Becattini et al., 1991; Inkpen and Tsang, 2005; Ter Wal, 2011; Giuliani, 2010). One of the main reasons for firms to form triads, is that they represent social spaces where relationships can be monitored easily, which guards against opportunistic behaviour and is likely to give rise to intense exchanges of valuable, tacit and fine-grained knowledge (Uzzi, 1997). Network closure can be considered a stabilizing force in the evolution of networks as it conduces to increasing levels of network embeddedness over time and is therefore likely to promote a path dependent process of network change.

2.1.3 Preferential Attachment

Ibarra and Andrews (1993) and Lazega et al. (2012) among others, suggest that, under conditions of uncertainty and ambiguity, the search of advice is socially-derived. This means that the most centrally positioned actors in a network are those that most rapidly gain reputation because of the information about them that diffuses through their many direct linkages. The most prominent actors are frequently cited, which contributes to their aura. In addition to reducing uncertainty, selection of a prominent actor may be preferred to selection based on quality judgments because the latter “are costly to make” (Gould, 2002, p. 1149). Key to the status effect is the existence of a (socially derived) prominent firm that shapes the evolution of the network in a regional cluster over time, a phenomenon that is often associated with the concept of preferential attachment (de Solla Price, 1976; Barabasi and Albert, 1999). Preferential attachment is based on the idea that firms guided by status when searching for important business information or other assets, will target prominent firms. This behaviour is common among new entrants with no prior knowledge of the other firms in their competitive environment (e.g. Rosenkopf and Padula, 2008). This mechanism of new tie formation does contribute to a rich get richer phenomenon, stabilizing the centrality of the most central actors, and therefore is considered here to be one of the key mechanisms under a path dependent process of network change.

2.1.4 Proximity Effects

Firms contribute to network stability also by binding to similar actors, a concept that sociologists call 'homophily' (McPherson et al., 2001). Similarity leads to inbreeding processes that make interacting parties progressively more similar to each other and distant from other more diverse actors. The search of similar others in studies of regional clusters point at the importance of inter-firm technological overlaps in areas of specialization (Cantner and Graf, 2006; Tallman and Phene, 2007). Hence, a linkage is established when both parties can take advantage of a pool of knowledge that is similarly sophisticated, which will facilitate learning. Such inbreeding on the one hand contributes to hyper-specialized and knowledge-rich linkages, but it also on the other hand causes the tendency to form stable linkages, and to produce a path dependent process of network change whereby novelties and disruptions are made unlikely by the tendency of actors to seek similar others. In a bid to analyze the impact of different types of inter-firm proximities on innovation, Boschma (2005) also argues that too much proximity is responsible for lock in and inertia in clusters. By contrast, creating ties with actors that are dissimilar may spark significant changes in the network (see below).

In this paper we analyze four different sets of proximity effects: social, geographical, institutional and sectoral proximity. By social proximity we refer here to the presence of friendship linkages between local entrepreneurs: extant literature on the sociology of organizations has shown the power of social connections in shaping market transactions and in creating embedded socio-economic structures (Granovetter, 1985; Uzzi, 1997). Ingram and Roberts (2000) find that friendship relationships between managers at competing hotel firms are likely to be robust over time, to a certain extent pointing at the existence of a certain structural stability of business ties when these are backed up by friendship relationships. Also the geographical proximity of firms can entangle the interacting firms into local consolidated network structures, not least because firms may find it easier to interact with their neighbors than to establish distant ties. In contrast, the formation of ties with distant actors may shorten the duration of local ties or may perturb local dynamics (Glückler, 2007). In this paper, we do also analyze the role of institutional proximity, which is generally conceived in terms of belongingness to the same macro-level institutional framework (Boschma, 2005; Balland et al., 2012). Here we give a different definition of institutional proximity, because all firms in the cluster are subject to the same macro-level institutions. We define this kind of proximity in terms of the institutions they are subject to on the basis of their participation (or not) to the directive committee of the local business association (CIIECCA). Elaborating upon institutional theories about isomorphism (DiMaggio and Powell, 1983), it is possible to envisage that firms taking part to the directive committee of a business association are likely, not only to cooperate for the achievement of a common institutional goal, but also to progressively become more similar one to the other, and to strengthen their relationships over time. Finally, interactions among firms that are part of the same sectoral niche (as opposed to other sectors) can also reduce variation in the cluster and favor processes of lock in in the local network .

2.2 Path destructive micro dynamics

2.2.1 Entry-Exit

One of the most disruptive effects on cluster networks can be the entry-exit dynamics of firms. New entrants, as well as the exit of some firms offer opportunities for network change for they can exert destabilizing effects on the pattern of interactions consolidated by incumbent firms. Depending on where they are positioned in the local network, exiting firms may have disruptive effects: if they are highly central actors, their exit may cause a vacuum that remaining firms have to fill by establishing brand new ties. Similarly, new entrants may have to decide about whom to connect to, and their newness means that they are unlikely to embed following local consolidated routines and path dependent connectivity choices. However, entry-exit dynamics are not per se guarantee of path disruptive network change. Exiting firms that occupy peripheral network positions are unlikely to perturb a consolidated network structure. Moreover, as mentioned earlier, new entrants may be ideal candidates for reproducing preferential attachment choices by connecting to the most prominent actors in the network. Hence, although potentially path disruptive, the entry-exit dynamics may also not perturb established path dependent paths of network growth.

2.2.2 Inter-firm Heterogeneity and Firm Agency

Inter-firm differences are often associated to greater degrees of variation in network structure. Firms that are markedly different under one or more dimensions may not connect at all, but if they do their interaction may propitiate radical changes in the network structure, as these actors may become the bridges of previously unconnected communities of firms and entrepreneurs. Relatedly, firm agency is also important in producing changes (Ahuja et al., 2012). Firms that have markedly different characteristics as those of other firms in the cluster, firms that stand out positively – e.g. they are highly entrepreneurial, talented and/or strongly connected to extra-cluster markets and knowledge sources - may bring forward a revolutionary and path destructive as well as path creative processes of change in the local network. In their work on network dynamics and cluster evolution in Dali, China, Li et al., (2012) treat this dimension – which they call “action” – as one of the pillars of a framework to explain cluster evolution. By action they refer to “the individual level evaluation, decision-making and reflexive monitoring through which agents react to existing context and network conditions. This may reflect individualistic learning, strategic action to differentiate products from competition or a deliberate effort to choose a path that only partially reflects the need of the network” (p. 136). In this paper we build on this perspective and look at three dimensions of firm-level heterogeneity and agency: innovation, export propensity and social responsibility. Innovation reflects the capacity of a firm to stand out as compared to the other firms in the cluster in terms of its capacity to create something new and spark innovative solutions to local problems. Export propensity captures the degree of openness of firms to foreign markets, which in the context of this study, also reflects firms' openness to external knowledge about markets, clients and technologies. Finally, we look at a relatively unimportant dimension for small and medium enterprises (SMEs) in the developing world: the social responsibility towards local communities and stakeholders, as we considered it to be a dimension that could mark the difference among the firms in the cluster.

3. Methodology

3.1 The Context

The electronics industry in Argentina is characterized by the presence of many SMEs and a few large firms – recent estimates on the industry suggest that about 80 per cent of the firms in the industry has less than 50 employees (Trends, 2007). From a geographical standpoint, about 75 per cent of the electronics activities are concentrated in the City and Province of Buenos Aires, while the rest is distributed across three regional poles: Rosario, Córdoba and the free zone of Tierra del Fuego, which is specialized in consumer electronics. The electronics industry as a whole targets the domestic market, with about 20 per cent of the firms being export-oriented (Trends, 2007).

In Córdoba, the first electronics companies started up in the 1970s. Three factors seem to have influenced this process: the setting up in Córdoba of a military plant for aircraft production – the Fábrica Argentina de Aviones (FAdeA) (former Fábrica Militar de Aviones) – and the presence of several local universities, which have provided the local area with a pool specialized technical human resources - the first wave of graduates in engineering was in 1968. Also, the Córdoba electronics industry has benefited from Import Substitution (IS) policies that protected the production of consumer products between the 1950 and mid 1970s. According to Berti (2006) before 1975 there were already twenty-two firms in Córdoba, specialized in the production of consumer electronics items (TV, radios, and their components).

During the military dictatorship (1976-1983), changes in macroeconomic policies towards a higher international openness of markets contributed to the out-competition of many electronics SMEs, and to processes of industrial concentration. According to Azpiazu et al. (1992, cited in Berti, 2006), over that period, the electronics component industry reduced its production volumes by 91 per cent, which meant that most of the firms in that sub-sector either closed up their activities or reconverted into importers of electronics components. The Alfonsin Government (1983-1989) has attempted to promote an industrial policy in favor of the electronics and informatics industries. Although largely unsuccessful (Berti, 2006), these policies eventually contributed to create a certain degree of diversification of the industrial activities, and strengthened specific market niches (telecommunication, electro-medicine, computer electronics for industry needs, video-games, etc.) which came to substitute consumer electronics firms. According to Blanco et al. (1986), in 1986 Córdoba counted with twenty-five firms operating in these sectoral niches. Only two of them were firms with more than 150 employees.

The trade and monetary policies of the 1990s contributed to the weakening of SMEs and their local value chains, and attracted foreign investors, which offered better working conditions and therefore attracted the most talented human resources available at the local level. However, to face such difficulties and strengthen local competitiveness, the existing local electronics producers in Córdoba gathered into a new business association (the *Cámara de Industrias Informáticas, Electrónicas y de Comunicaciones del Centro de Argentina* (CIIECCA)). Finally, since the turn of the century, the new macroeconomic policy, the development of new industrial policies and the currency devaluation that followed the 2001 economic crisis, pushed competitiveness in the electronics industry, which resulted in new SMEs being started up in Córdoba. Over the period 2003-2007 the cluster participated to a Cluster Development Program (CDP) co-funded by the Multilateral Investment Fund (MIF), the Inter-American Development Bank (IADB) and by local resources. The CDP, which targeted also other industry clusters beside electronics, was designed to strengthen local linkages and cooperation among private actors, as well as between private actors and local institutions and to ease local firms’ exports and access to new production technologies and organizational innovations.

Figure 1 illustrates the evolution of the cluster over the various macro-economic changes and highlights the fact that during the period of our analysis (2005-2012) the cluster had slowed down in the entry of new firms, which to a certain points at the fact that the cluster has entered a maturity stage of its life cycle.

[Figure 1 about here]

3.2 Data Collection

This study is based on the collection of primary data through interviews to the firms in the cluster. A structured questionnaire has been designed to collect information that allows to address the objectives of this study. The questionnaire has been administered both in 2005 and 2012 to professionals occupying key management positions in the firms (in many cases to the owners themselves) and it included a special section for the collection of network data. Prior to the main fieldwork, the questionnaire was tested in three different interviews and changes have been made according to respondents’ suggestions. Each interview was carried out by an assistant of the person in charge of the 2005 evaluation study and it lasted on average about one hour. The study counts also on a focus group carried out after a first report with the analysis of data had been produced. Due to the lack of an official registrar of companies and census data, to identify the universe of firms that were active electronics service providers or manufacturers in the City of Córdoba, we opted for the CIIECCA as a main source of information, complementing this source with ad-hoc interviews to key-industry informants, who provided us with a comprehensive list of firms active in the electronics industry. Based on these sources, we found that in 2012 the universe of electronics firms in Córdoba was of 47 firms (it was of 50 firms in 2005). We have contacted all of them to proceed with interviews. Our interest in interviewing the universe of firms is that it allows the collection of full network data. We were successful in interviewing 38 firms (80% response rate) in 2012 and 41 firms (82% response rate) in 2005. The total number of electronics firms existing in 2012 that were interviewed in 2005 is of twenty-seven firms, four of which did not allow to be interviewed in 2012. Hence, twenty-three firms have been interviewed in both years, whereas fifteen firms, which have been included in the 2012 study, did not exist (6), or did not answer our questionnaire in 2005 (9). Furthermore, 14 firms that were included in the 2005 study no longer existed or migrated to other industries in 2012.

The questionnaire was designed to collect information about: (i) inter-firm networks within the cluster; (ii) firms' innovative, entrepreneurial and strategic characteristics. Relational data were collected using the roster recall method (Wasserman and Faust, 1994): firms were given a list (roster) of the other electronics firms in the cluster (i.e. the population at the time of the interview) and asked about innovation-related knowledge transfer. In this study we focus on the information network, which maps the exchange of business information among the firms in the cluster. The questions are reported below:

Network questions administered in 2005 and 2012

A- To which of the firms included in List 1 did you transfer business information (e.g. technological advice, marketing advice or any other kind of information that is relevant to the business) in the last three years?

B- From which of the firms included in List 1did your firm receive business information (e.g. technological advice, marketing advice or any other kind of information that is relevant to the business) in the last three years?

Relational data resulting from answers to the relational questions are expressed in a matrix composed of *n* rows and *n* columns, corresponding to the number *n* of firms in the study (e.g. 47 in the case of the 2012 relational matrixes). Each cell in the matrix reports the occurrence of a given relationship existing between firm *i* in the row to firm *j* in the column (0, 1).

The firms that did not answer our questionnaire were also included in the roster, and their relationships have been tracked if the interviewed firms declared to have established a relationship with a non respondent firm. In this research we consider a tie to exist if at least one of the respondents has indicated that tie to exist. We agree that this approach may give rise to concerns about the accuracy of data (Wasserman and Faust, 1994, p. 56), but in this way we obtained relational data about non respondents. We consider that in this study the quality of the relational data is likely to be high due to the fact that we analyze a well bounded system (e.g. the population of firms is known, the numbers are workable, and firms do all belong to the same industry context), which increase the chances that they give good response reliability (Calloway et al., 1993). Furthermore, the stability of our observed patterns of interaction over time (see later sections), the qualitative information gathered during this round of interviews and the focus group encourage us to think that our data are reliable. In particular, the non respondent firms do not appear to possess characteristics that would have influenced network structure in a significant way, and most of the respondents did not even mention them as partners in relationships. This is consistent with our 2005 data, which suggest that they occupied a very peripheral role in the network (Matta, 2011).

Descriptive statistics about our 2012 sample are reported in Table 2. The table shows that our sample is constituted by Argentinean Micro-Small-Medium Enterprises (MSMEs), 35 per cent of which were funded prior to 1990, while the remaining started operations during the 1990s (42%) and in the past decade (24%). Table 2 also shows that the firms in the cluster specialize in different segments of the electronics industry, which range from the production of basic electronics components and circuits to more sophisticated final products such as TLC equipment or electro-medical devices. There are an average of 3-4 firms per market segment and these segments are not part of the same value chain. Next, Table 2 shows that the firms are vertically integrated, performing internally R&D and design activities (92%), manufacturing (97.4%), and marketing and distribution activities (around 90%). This clearly points at a specific characteristics of this cluster, where local division of labor seems to be rather limited, which also differentiates this cluster from the archetype of the Marshallian industrial district, characterized by high division of labor across local firms. As concerns exports, we observe that about half of the firms do not export, and another 30 per cent exports less than 20 per cent of their sales. Only a 14 per cent of the firms are export-oriented, with more than 40 per cent of their sales going to international – mainly Latin American – markets. Finally, only nine firms have at least one patent registered at the Argentinean Patent Office.

[Table 2 about here]

3.3 Data Analysis

The analysis proceeds in two steps. First, a static comparative analysis of network structure in the two periods considered (2005 and 2012) is carried out based on the set of network structure indicators presented in Table 3. The table reports the measures used to analyze the characteristics of the local networks in 2005 and 2012, namely: density, fragmentation, dyad-based reciprocity, number of isolates, size of largest component, and degree and betweenness centralities. All these measures are calculated using the software UCINET.

[Table 3 about here]

Second, we use SAOMs for network dynamics, allow for statistical inference of network dynamics by simultaneously analyzing the impact of different types of effects on network change (Snijders, 2001; 2005; Snijders et al., 2010). There are three classes of effects that SAOM can take into account (see Ripley et al., 2011 for a full description): first, *endogenous or structural effects*, which are a pure derivation of sociological theories and depend on the network itself (e.g. reciprocity, network closure effects, degree-related effects); second, *individual covariate effects*, which account for the characteristics of the actors in the network (e.g. ego-effects expressing the tendency of actors with higher values for a given characteristic to have higher out-degrees, and alter-effects, expressing the tendency of actors with higher values of a given characteristics to have higher in-degrees; etc.); and, third, *dyadic covariate effects*, based on the existence of some kind of proximity or distance between pairs of actors in the network and expressing the extent to which a tie between two actors is more likely when the dyadic covariate is larger.

To assess what effects are likely to drive network change, the SAOM used in this paper relies on a set of fundamental assumptions (which are standard in SAOM estimations):

1. the model is about directed relationships (i.e. a tie goes from actor *i* to actor *j*) and the underlying time parameter *t* is continuous;
2. the changing network is the outcome of a Markov process, which means that the current state of the network determines probabilistically its further evolution, whereas the earlier past plays no role;
3. the actors control their outgoing ties, which means that changes in ties are made by the actors who initiate the tie, on the basis of their and others' attributes and their position in the network, which is the reason why these models are described as 'actor-oriented';
4. at any given moment, one probabilistically selected actor (called ego) may have the opportunity to change one outgoing tie, and no more than one tie change can be made at any moment. This means that two actors cannot decide jointly to form reciprocal ties at the same moment between time *t* and *t+1*. Hence, we do not know the order in which ties are created or terminated between time *t* and time *t+1*.

The actor-based network change process is decomposed into two sub-processes, both of which are stochastic:

5. the change opportunity process, which models the frequency of tie changes by actors (the change rate);

6. the change determination process, modelling the probabilities of tie changes, which depend on the three effects described above (i.e. *structural, individual covariate and dyadic covariates*).

An important aspect related to SAOMs is that they are actor-based simulation models used for statistical inference. This means that the model contains parameters that have to be estimated from observed data by a statistical procedure. This procedure uses the methods of moments implemented by computer simulations of the network change process. The first observed network is used as the starting point of the simulations. The first step in the model is to choose the ego who is allowed the opportunity to make a change – i.e. to initiate or withdraw a tie, or to do nothing. The probabilities of this choice depend on the objective function, which expresses how likely it is that an actor will change her/his network, and is a linear combination of a set of effects:

$$f_i(\beta, x) = \sum_k \beta_k s_{ki}(x)$$

where $f_i(\beta, x)$ is the value of the objective function for actor *i* (the ego); $s_{ki}(x)$ are the effects (selected from among a wide set of *structural, individual covariate* and *dyadic covariate* effects) and the β_k are the statistical parameters for each effect. If β_k equals 0, the corresponding effect plays no role in the network dynamics, if β_k is positive then there will be a higher probability of moving in directions where the corresponding effect will be higher, or the converse if β_k is negative. The estimates of the parameters in the objective function are approximately normally distributed, which means that the parameters can be tested by referring the *t*-ratio (parameter estimate divided by standard error) to a standard normal distribution (Snijders et al., 2010).

The probability that an actor *i* makes a change and chooses between some set *C* of possible new states of the network is given by:

$$\frac{\exp\left(f_i(\beta, x)\right)}{\sum_{x' \in C} \exp\left(f_i(\beta, x')\right)}$$

This formula is used also in multinomial logistic regressions and it means that the probability that an actor makes a change is proportional to the exponential transformation of the objective function of the new network that would result from this change (Snijders et al., 2010).

According to our research questions, in this paper we use the following effects ($s_{ki}(x)$):

(1) Network endogeneous (structural) effects, which we have associated to path dependent network change:

- reciprocity effects: the tendency to reciprocate ties over time;
- transitive triplets: the tendency towards clustering (e.g. friends of friends become friends).
- preferential attachment: the tendency of central actors to become more central over time.

(2) Proximity effects, which we have associated to path dependent network change (and vice versa distance effects are associated to path disruptive network change):

- Social proximity: the tendency of entrepreneurs who are friends in 2005 to form more ties among each other over time;
- Geographical proximity: the tendency of entrepreneurs who are geographically close to form more ties among each other over time;
- Sectoral proximity: the tendency of firms belonging to the same sub-sectoral niche to form more ties among each other over time;
- Institutional proximity: the tendency of entrepreneurs who participate in the directive committee of the same business association to form more ties among each other over time.

(3) Inter-firm Heterogeneity and Firm Agency effects, which we have associated to path disruptive network change:

- Firm-level innovation: the tendency of the most innovative firms (proxied by the number of granted patents from the Argentinean Patent Office) to form more new ties other over time as compared to other firms;
- Firm-level exports: the tendency of the most exporting firms (proxied by a binary variable) to form more new ties other over time as compared to other firms;
- Firm-level social responsibility: the tendency of firms with more intense commitment towards social responsible programs towards the local community (measured on a Likert scale from 1 (min) to 5 (max) based on the company self-assessment)[1] to form more new ties other over time as compared to other firms;

Figure 2 shows the distribution of these three firm-level variables.

[Figure 2 about here]

In the estimation we control also for firm-level variables that might influence the formation of new ties, such as firm size, measured as number of FTE employees, based on the idea that larger firms may have a higher propensity to form more ties. We control also for firm age on the premise that older firms would have had more time to embed themselves socially in the cluster, and for firms' participation intensity in a local cluster development program that took place during the period 2003-2007 (measured by the number of CDP activities each firm took part in the course of the policy treatment). This exercise is based on the 2005 and 2012 dichotomous information networks. The new entrants in the network are treated as structural zeros.[2]

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[1] Respondents have been asked to rate the following statement: "*The firm has undertaken Corporate Social Responsibility programs to improve the living conditions of the local community*" on a Likert scale ranging from 1 (totally disagree) to 5 (totally agree).

[2] A structural zero means that it is certain that there is no tie from actor i to actor j. Structural zeros provide an easy way to deal with actors leaving or joining the network between the start and the end of the observations.

4. Results

4.1 Path Dependent Network Change

In this section we undertake a static comparative analysis between the information networks in 2005 and 2012, based on a set of indicators reported in Table 4. Results show that the macro structural characteristics of the local information network have been subject to some changes over time. In particular, network density has considerably decreased (from a value of 0.17 in 2005 to 0.09 in 2012),[3] and network fragmentation has increased, with the number of isolated firms increasing slightly (from 1 to 3). The observed decrease in network density is to a large extent due to the termination of CDP's networking activities in 2007 (see Section 3.1). However, parallel to the termination of several linkages, new linkages have also been formed: 37 per cent of the ties that are present in the 2012 network are new ties, while the remaining 63 per cent of ties are persistent linkages that were present in 2005. Over the period of analysis we do also observe that the network structure has become more centralized as the GINI coefficient value for degree centrality has increased from 0.40 to 0.54.

[Table 4 about here]

Figures 3 a and 3 b plot the distribution of the degree centrality for both networks, showing a right tail of firms with high degree centrality and a majority of firms with more peripheral positions. Further analysis suggests that the majority of firms holding central positions in 2005 were also central in 2012. Only one of the central firms in the 2012 network is a new entrant (see Section 4.3 on entry/exit dynamics), while two of the central firms in 2005 slightly reduced their centrality in 2012.

[Figures 3a and 3b about here]

[3] We have carried out a bootstrap t-test to check that the two networks' densities are statistically different and found a t-statistics of 2.7, which rejects the null hypothesis of no difference (Snijders and Borgatti, 1999, p. 65).

In spite of the numerous changes occurred in the network, we do not observe here a path destructive process of network change. To the contrary, the key structural features of the network were largely untouched: the network's hierarchical structure has reinforced through time, as reflected by the distribution of firm-level degree centralities, and it has maintained its centralized structure anchored to a group of highly central firms, which have, by and large, persisted through time in that position. On these grounds we argue that the network change in the cluster has followed a path dependent process. In the next session we analyze the micro dynamics underpinning this observed path dependency.

4.2 Results of SAOM Analysis

This section reports the empirical results of the SAOM estimations about the micro dynamics of network change (see Table 5). The rate parameter and density effects are reported by default in this type of estimation. The rate parameter is positive and significant in all models indicating a significant change in the formation of new ties; while the negative and significant coefficient of density indicates that firms tend not to establish knowledge linkages with just any other firm in the cluster (Snijders et al., 2007).

We find that the significant micro dynamics observed here are all associated to a path dependent evolution of network change. Two of the structural effects are significant: reciprocity (β=3.73 and s.e. 0.79), and preferential attachment (β=0.06 and s.e. 0.03). Among the proximity effects we find strong significance for both social (β=1.30 and s.e. 0.54), and institutional proximities (β=0.97 and s.e. 0.28). In contrast, we do not find any significant effect among the firm-level variables: innovation, exports and social responsibility. The model includes also control variables for firms' size, age and CDP participation intensity, among which only the latter turns out significant.

[Table 5 about here]

4.3 The Role of Entry and Exit

The results reported above take no explicit account of the firms' entry/exit dynamics for new entrants are treated as structural zeros in the SAOM analysis (see Section 3.3). This raises the question of whether the characteristics of the network are influenced significantly by relative entry and exit patterns. In our conceptual framework we have suggested that the path destructive role of entry/exit depends largely on exiting firms' position in the network, as well as on new entrants capacity to attract considerable numbers of linkages.

In the context of this study, we should note first that there are some differences in the characteristics of new entrants and those firms that exit: new entrants are slightly larger than firms that exit the cluster, although they are small firms in both cases (9.7 vs 6.3 employees respectively on average). Most of the firms that exit the industry start up new activities in the commercialization of electronics products, and cease manufacturing activities in sub-sectoral niches like automotive electronics, alarms and control electronics, because these industries are declining and are subject to strong international competition. In contrast, most of the new entrants specialize in more dynamic niches connected to TLC activities. Some of them are firms that existed already, but were not geographically located in the City of Cordoba, and in two cases the new entrants are spin-offs of existing firms.

In terms of network positioning (Table 6), we find that exiting firms were slightly more central than new entrants in their respective networks, particularly so in terms of normalized betweenness centrality (8.9 of exiting firms vs. 1.1 of new entrants), which indicates that exiting firms were able to connect otherwise disconnected firms in the network. This result reflects the fact that four of the firms that eventually exited the cluster occupied rather central positions in the cluster. At the same time, however, the centrality values of new entrants and exiting firms did not significantly differ from those of incumbent firms in their networks. Else said, these firms do not stand out as compared to other firms in the network in terms of network positioning, thus generating little opportunities for path disruptive changes in the network. The limited connectedness of new entrants is reflected also by the fact that only three firms were close to the group of most central firm, replacing the positions of the exiting firms mentioned earlier, while the other new entrants simply replaced firms that had exited the cluster and had been located on the periphery of the network. To conclude, we observe that in the context of this research new entrants and exiting firms did not generate disruptive effects on the process of network change, but did rather contribute to maintain a certain degree of stability in the pre-existing network structure.

[Table 6 about here]

4.4 Discussion of Results

In our conceptual framework we have discussed the path dependent vs. path destructive nature of a set of micro dynamics and our empirical results are consistent with that framework. We find that the network change in the electronics cluster of Cordoba has followed a path dependent process, consolidating an existing centralized and hierarchical network structure. Next we find that the formation of new ties in such a network is driven by a set of micro dynamics that we have conceptually associated to a path dependent process of network change, while no path destructive micro dynamics is observed in this case. We find that the firms that are more prominent and capable than others in addressing certain challenges – in terms of innovation, exports and social responsibility – do not spark any significant change in the pre-existing network structure: such firms do not attract or produce a number of fresh ties that can be network destructive or, putting it to the extreme, that can start up a brand new development path in the cluster.

An interpretation is that even the most prominent firms in the cluster do not individually *act* in ways that can shape the local networks and the future settings of the local cluster. Rather, individual agency seems to succumb under the weight of other stronger micro dynamics. In this respect, our result about reciprocity was to be expected because this is typical of directed networks and it is coherent with previous cluster research (Giuliani, 2010). The strengthening of the most central firms under the preferential attachment process is consistent with our observation of the local network becoming slightly more hierarchical over time, and it is also coherent with earlier studies viewing preferential attachment as a key driver of the evolution of networks in clusters (Giuliani, 2007; Glückler, 2007; Boschma and Frenken, 2010; Ter Wal and Boschma, 2011). Next, we do also find that institutional proximity is an important driver of new tie formation, which stresses the "club" nature of social networking processes in line with much of the collective learning approaches to regional studies (e.g. Capello, 1999; Capello and Faggian, 2005). Finally, a powerful path dependent micro dynamic is social proximity: friendship relationships predict the formation of new ties between firms. This result is consistent with the organizational sociology literature, which has long stressed the intertwined relationships between friendship and business ties (Granovetter, 1985), but our analysis points at the downside of social ties, since they are mainly responsible for a path dependent trajectory of the cluster, which, as discussed below can also have detrimental effects for its future competitiveness.

Our discussion here concerns the implications that path dependent micro dynamics have on network change and on the cluster development trajectory. Stability is *per se* not a bad thing. It provides a place with a strong sense of identity, a durable set of interactive routines that can be enriching for the interacting parties, as they can reduce uncertainty, information asymmetries, and breed local trust and confidence. The downside of path dependent network change is that, over the long term, it may bring the network and the cluster to a lock in (Ter Wal and Boschma, 2011), where firms become unable to bring variation and to spark technological or organizational changes in the local context. The problem of lock in has been long debated in the cluster literature, as it is responsible for the incapacity of industrial cluster firms to face international competition, upgrade their technologies and skills and generate new knowledge – especially, but not exclusively, in the context of developing countries' clusters. Hence, a deeper understanding of the micro dynamics facilitating path dependent network changes is important to address its potentially negative consequences. We elaborate this further in the conclusions.

5. Conclusions

5.1 Contributions

One of the currently most debated and least studied issues in regional and innovation studies is network dynamics (Martin and Sunley, 2006; Glückler, 2007; Boschma and Frenken, 2010; Martin, 2010; Boschma and Fornhal, 2011; Martin and Sunley, 2011; Ter Wal and Boschma, 2011; Staber, 2011; Balland, 2012; Balland et al., 2012; Li et al., 2012). We add to this growing body of research by exploring the micro dynamics of path dependent network change in clusters. As predicted by earlier conceptual studies (Glückler, 2007; Ter Wal and Boschma, 2011) we observe in the context of our case study a stable and path dependent pattern in the evolution of the local information network. Moreover, in line with other studies on networks in industrial clusters, we find that network change is due to the co-existence of different endogenous and exogenous micro dynamics: namely, endogeneous micro dynamics such as reciprocity and, to a certain extent, preferential attachment, and exogenous micro dynamics like institutional and social proximity effects. Based on our conceptual framework, we have argued that such micro dynamics are mainly responsible for the path dependent change of the network in the cluster. Our study is also in line with Giuliani (2010), who shows that the *lack* of agency of some firms may be contributing to the path dependent trajectory of the cluster and its network.

Our findings have implications for research on innovation in the context of developing and emerging countries. Much of the literature suggests that emerging/developing economies suffer from severe market failures and institutional weaknesses (Hoskisson et al., 2000). In this context, firms that want to enter the international competition need to cultivate and join different types of inter-organizational networks, e.g. business groups or interpersonal networks, such as the *guanxi* in China. These networks provide access to resources, reduce information asymmetries among firms, enable higher bargaining power vis a vis other market counterparts, increase lobbying power with governments, and allow firms to upgrade their capabilities (Guillén, 2000; McDermott et al., 2009).

However, such networks may also represent a trap for cluster firms, especially when the local development process is intertwined with a path dependent change of local networks. It seems fairly clear that endogeneous micro dynamics as well as social and institutional proximities are unlikely to generate disruptive effects in the local network and, if left operating, they can easily bring to a negative lock in.

In that context, interesting policy questions arise about networking policies and, in general policies oriented at strengthening local social capital. While such policies may well be useful to generate a local process of collective learning, policy makers should be aware of the fact that over the long term there is a risk that the collective system that the policies have contributed to generate may become stagnant if its member are not given the opportunity to introduce variations or to generate disruptive effects to the local network. Connections to extra-cluster actors or attraction of dynamic entrepreneurs or large multinational firms in the local context could be possible way out of a path dependent evolutionary process that is approaching lock in.

5.2. Limitations and Further Research

This paper has some important limitations which provide opportunities for further research but also suggest some caution in interpreting the findings. The study is based on a single case, which means that the results cannot be generalized. Moreover, this research has important data limitations. Since we could not interview the whole population of firms, we have reconstructed the full networks based on respondents' discernment about their ties to non respondents, and based on the insights gathered during the focus group. However, it is fair to mention that our data may not be totally accurate and therefore scholars should consider this limitation when reading our data. Another important critical aspect of this paper is that we do not prove a causal link to exist between the set of significant micro dynamics and the path dependent change of the local network. Based on our conceptual framework, we conjecture such relationship to exist, and we show empirically that our conjecture is plausible, but we necessarily leave to simulation modeling scholars to prove the validity of our model. We did also focus here only on the micro dynamics of new tie formation, while future work will focus on the dissolution of ties – also considering that, in our case, network density has decreased over time. Furthermore, this study also explores only one type of local network - the information network. Future research could explore multiple network dynamics. Finally, our operationalization of firm-level agency has been rather simplistic, and future research should try to capture more inter-firm variation at the cluster level as well as more entrepreneurial attitudes of local managers and entrepreneurs.

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TABLES

Table 1 Path dependent and path destructive micro dynamics of network change

Micro dynamics	**Mechanisms**	**Macro level effect on network change**
Reciprocity	• Stabilization of ties • Mutual relationships	• Mainly path dependent
Transitive Closure	• Stabilization of triads • Social capital	• Mainly path dependent
Preferential Attachment	• Reinforcement of the most central actors	• Mainly path dependent
Inter-firm Proximity	• Consolidation of ties among similar actors • Inbreeding • Stability	• Mainly path dependent • Inter-firm distance may be path destructive
Entry-Exit	• Destabilization of network structures • New ties from previously unconnected actors	• Path dependent and path destructive depending on (i) the position of exiting firms in the network and (ii) the connectivity choices of new entrants
Firm-level Heterogeneity and *Firm-level Agency*	• Bridging distant communities of actors • New combinations of knowledge and resources • Outstanding actors may promote renovation in the network structure and spur changes	• Potentially path destructive

Table 2. Descriptive Statistics (2012)

a) Size	**N**	**(%)**
Micro (0-5 employees)	6	16
Small (6-20 employees)	16	42
Medium (21-150 employees)	15	39
Large (>150 employees)	1	3
b) Year of foundation	**N**	**(%)**
Prior to 1990	13	34.2
1991-2000	16	42.1
2001-2009	9	23.7
c) Sectoral niches	**N**	**(%)**
Electronics components	5	13,2
Measurement devices (e.g. electric weights)	6	15,8
Energy devices (e.g. transformers)	3	7,9
Industrial electronics	6	15,8
Electro-medical devices	4	10,5
Telecommunication (TLC)	3	7,9
TV & radio production (e.g. broadcasting devices, anthems)	3	7,9
Security & Alarms	1	2,6
Audio-visual & entertainment devices (e.g. home theatre, video games)	3	7,9
Distribution services (e.g. ATM)	4	10,5
Industrial control and automation (e.g. CNC, mecatronics)	6	15,8
Others	11	28,9
d) Activities performed internally	**N**	**(%)**
R&D	35	92.1
Design	36	94.7
Manufacturing	37	97.4
Marketing	34	89.5
Distribution and Logistics	18	47.4
Other (professional or technical services)	4	0.1
e) Export	**N**	**(%)**
Only domestic market	15	53.6%
Exporting between 1% and 20% of overall sales	9	32%
Exporting between 20% and 40% of overall sales	0	0%
Exporting more than 40% of overall sales	4	14.4%
f) Patents	**N**	**(%)**
Number of firms with at least one patent	9	23,7%

Table 3 Descriptive Social Network Analysis: Key Measures

Concepts	Description	Measures
(i) Network Characteristics		
1. Density of the network	The overall connectedness of firms in a network.	Network density (*ND*) is defined as the proportion of possible linkages that are actually present in a graph. *ND* is calculated as the ratio of the number of linkages present, *L*, to its theoretical maximum, *n(n-1)/2*, with *n* being the number of nodes in the network (Wasserman and Faust, 1994): $ND = \frac{L}{[n(n-1)/2]}$ It ranges from 0 (total disconnection) to 1 (maximum connection).
2. Fragmentation of the network	The degree to which some firms are disconnected from the network	The number of components (see below) divided by the number of nodes.
3. Dyad based reciprocity	An indicator of the degree to which firms establish reciprocal tie	The number of reciprocated dyads (i.e. two nodes with bi-directional ties) divided by the number of adjacent dyads (i.e. two nodes with at least an uni-directional tie).
4. Isolates	The number of disconnected nodes in a network	Firms with no connections to other firms in the network.
5. Component	A group of firms that are connected in a network	Components are separate sub-sets within a network. The size of the larger component is the number of firms that form part of the largest component.
6. Actor-level degree centrality	Number of ties a firm maintains with other actors in the network	Degree centrality is defined as the number of links incident upon a node (i.e., the number of ties that a node has). The indicator can be standardised by *n*, with *n* the number of nodes in the network: $DC_i = \frac{\sum_i xij}{n-1}$ We do also distinguish between *In-degree centrality*, which measures the extent to which information is acquired by/*transferred to* a firm from other local firms, and *out-degree centrality*, which measures the number of information linkages originating in a firm.
7. Betweenness centrality	Degree of intermediation between otherwise disconnected firms	It measures the degree of interconnectedness of a firm on the basis of its propensity to be in-between of other firms' information linkages.

Table 4 Key Network Characteristics in 2005 and 2012

	2005	**2012**
Number of firms in the network	41	47
Density	0.17	0.09
Fragmentation	0.10	0.14
Dyad reciprocity	0.38	0.76
Number of isolates	1	3
GINI Coefficient on Degree Centrality	0.40	0.54

Table 5 Results of the SAOM Analysis

	Estimate (s.e.)	***Significance***
(1) Endogenous Effects:		
Reciprocity	3.73 (0.79)	***
Transitive Triplets	0.09 (0.08)	n.s.
Preferential Attachment	0.06 (0.03)	*
(2) Proximity Effects:		
Social proximity	1.31 (0.54)	***
Geographical proximity	0.02 (0.02)	n.s.
Institutional proximity	0.97 (0.28)	***
Sectoral proximity	0.41 (0.37)	n.s.
(3) Inter-firm Heterogeneity and Agency Effects		
Firm-level innovation	0.04 (0.26)	n.s.
Firm-level exports	0.30 (0.49)	n.s.
Firm social responsibility	0.13 (0.16)	n.s.
Controls:		
Size	-0.10 (0.51)	n.s.
Age	-0.01 (0.03)	n.s.
CDP Intensity	0.34 (0.13)	***
Density	-4,5139 (0,7097)	***
Rate Parameter	12,9640 (2,5953)	

Note: Results of stochastic approximation. Estimated parameter based on 987 iterations. The convergence of the models was good in all cases (*t*-ratios were all inferior to 0.10 for all coefficients in all models) and no severe problems of multicollinearity were encountered.

*5p<0.05; **p<0.01; *** p<0.001

Table 6 Network Centrality of Exiting Firms and New Entrants

	Normalized Out-Degree Centrality	**Normalized In-Degree Centrality**	**Normalized Degree Centrality**	**Normalized Betweness Centrality**
Exiting firms (2005 values)	0.16	0.11	0,21	8.9
Incumbents (2005 values)	0.17	0.19	0,26	3.6
t-test (p-value)	*0.85*	*0.14*	*0,38*	*0.81*
New entrants (2012 values)	0.60	0.60	0,06	1.1
Incumbents (2012 values)	0.10	0.11	0,12	3.5
t-test (p-value)	*0.21*	*0.16*	*0,16*	*0.24*

FIGURES

Figure 1 The Evolution of the Electronics Cluster in Córdoba, Argentina

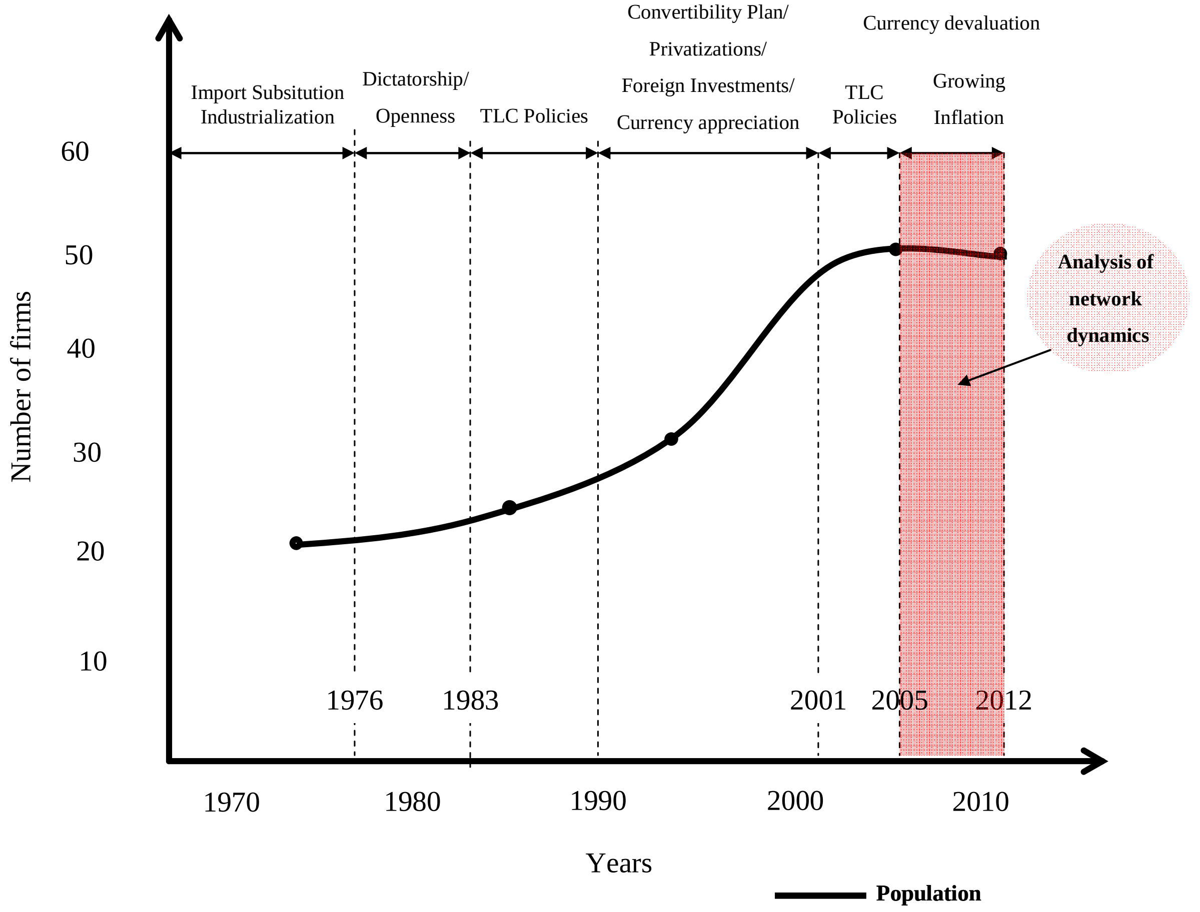


Figure 2 Distribution of firm-level variables: Patents, Exports and Corporate Social Repsonsibility

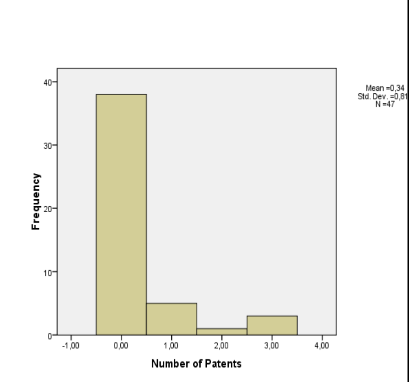
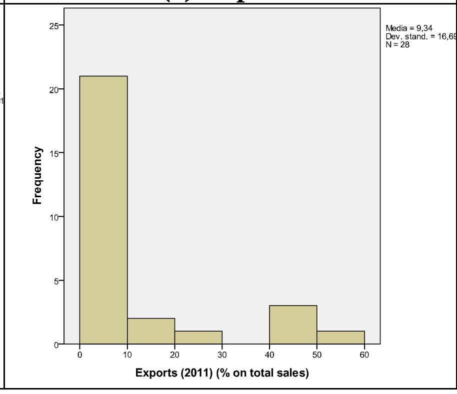
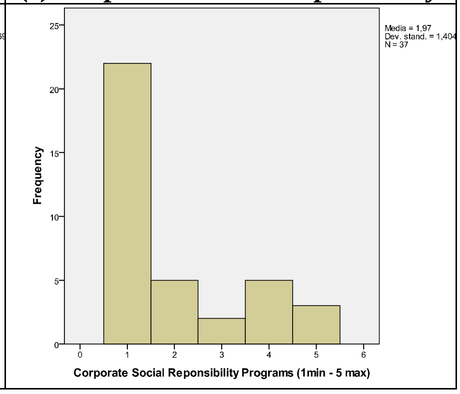
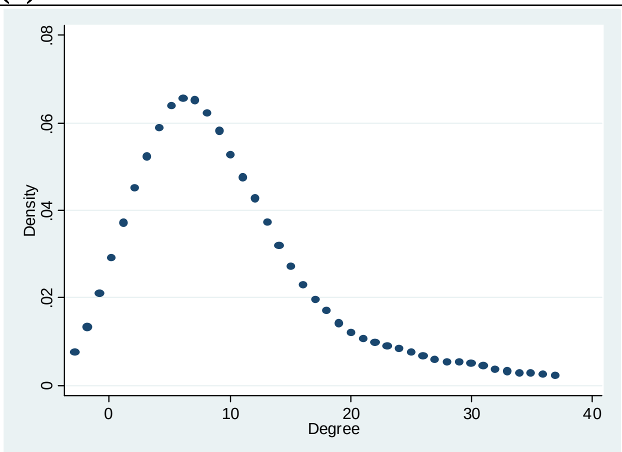
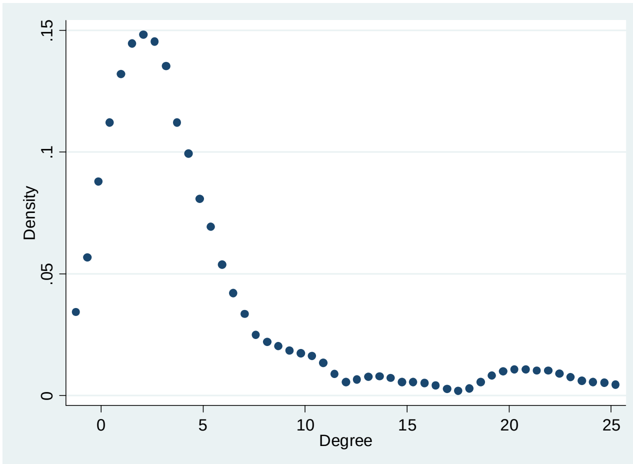
(a) Patents	*(b) Exports*	*(c) Corporate Social Responsibility*
		

Figure 3 Kernel Density Distribution of Degree Centrality for the Information Networks

(a) Information Network in 2005	**(b) Information Network in 2012**
	
Note: The X-axis reports the number of direct ties maintained by each firm (degree centrality)	Note: The X-axis reports the number of direct ties maintained by each firm (degree centrality)