Small worlds, inheritance networks and industrial clusters

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ABSTRACT

The performance of firms within industrial clusters has been the subject of a multitude of studies. The organizational attributes inherited by spinoffs from parent firms is one explanation behind performance premiums. This paper examines the relationship between a spinoff’s network and its geographic location in an industrial cluster. We hypothesize that there is a negative relationship between a spinoff’s network efficiency and its distance from the cluster’s centroid. Although recent literature infers that the transmission of knowledge in industrial clusters is accomplished via inherited network ties, this has not been directly measured. This paper aims to fill that research gap. We find that, after controlling for firm size, parent size and age, there is indeed a statistically significant and negative relationship between network efficiency and geographic distance to a cluster’s core.

KEYWORDS

Industrial clusters; small-world networks; pulled spinoffs; firm heredity; localization economies

JEL CLASSIFICATION

B52; L26; O33; R30

1. Introduction

Prior research in the industrial lifecycle literature infer that network ties, which act as transmitters of knowledge, are more efficient within industrial clusters (Carias and Klepper 2010; Klepper 2010; Boschma and Wenting 2007; Buenstorf and Guenther 2011; Wenting 2008). However, there have been few studies that explicitly identify and measure these networks. This paper aims to fill that research gap by measuring the networks of individual firms to test the relationship between network efficiency and geographic location. Specifically, we test whether centrally-located firms within a cluster have more efficient knowledge networks. Hence, this paper focuses on the dynamics of the interplay between tacit information embedded in the form of networks and geography. Due to its knowledge-intensive nature and given its stage in the industry lifecycle, this paper addresses the Stockholm ICT cluster.

The industry lifecycle approach (Klepper 2002, 2011) considers knowledge as a fundamental component to cluster growth. Industrial clusters are the product of a Darwinian process where successful firms spawn from incumbent firms in the area (Gompers, Lerner, and Scharfstein 2005). These spinoffs inherit the knowledge and routines of their parent firms. A cluster thus emerges as spinoffs choose to locate in the same area as their parent firms (Klepper 2007; Dahl and Sorenson 2009), the success of
which is the result of one (or few) parent firms that have passed on their capabilities to spinoffs through various generations. Studies show that spinoff firms located in the same area as their parent firm perform better than non-clustered firms (Klepper 2007; Dahl and Sorenson 2009). One typical explanation is that the cluster performance premium is the result of knowledge transfers. As local knowledge regarding market niches and emerging technologies are more likely found within the confines of the firm, a main argument is that firms within an industrial cluster can exploit local knowledge and connections via network ties. These network ties are the result of the entrepreneurial spawning process itself.

Clustered firms are thus more likely to exhibit greater inter-firm network connectivity, and these networks are assumed to serve as vehicles for inter-firm knowledge transfer. However, such network effects remain a hypothesis, and have so far have only been inferred rather than measured. Nonetheless, such effects are assumed to be a valid explanation of the cluster. Thus, we test if surviving firms located closer to the cluster core have more efficient knowledge networks (that is, networks that exhibit a high level of local connectivity and global reach), thereby capturing the assumed performance premium that explains the presence of industrial clusters. Hence, the novelty of this paper is that it measures and tests a micro foundation of firm-level gains from industrial clusters that are a consequence of historical industrial dynamics. Although prior studies have focused on collaboration networks (Giuliani 2007; Morrison 2008; Boschma and Ter Wal 2007; Lambiotte et al. 2008; Liben-Nowell et al. 2005), so far little attention has been given to inherited networks that are the result of historical inter-firm relationships. Such networks are not pursued but innate and the result of events such as those that arise from entrepreneurial activity and the spinoff process.

Using longitudinal data of establishments in the Stockholm region from 1990 to 2010, we identify an inter-firm network based upon the historical relationships of spinoffs and their parent establishments. Based on this, we measure the small-world properties of establishments’ networks, which reveal the level of local network clustering (or ‘cliquishness’) as well as the level of global network connectivity. Such a measure also describes the robustness and resilience of an establishment’s network, i.e. where small changes in the network do not fundamentally impact an establishment’s networked relationships. The small-world measure serves as a proxy for network efficiency of potential knowledge flows. The main advantage of this is that it allows us to empirically test the relationship between a direct measure of potential knowledge flows and location on firm-level data. In this view, the main hypothesis is that there is a negative relationship between the small-world properties of an establishment’s network and its distance from the core of an industrial cluster.

This paper is structured as follows. A theoretical framework will first provide an overview of the literature regarding networks and firm location, and how the industrial lifecycle process may provide a different perspective on how one may regard knowledge networks. This is to give a real-world interpretation of a small world network, which we will also cover in brevity. We will then turn to a description of the data and conceptualize the network of analysis. We then analyze the relationship between geography and network connectivity using a beta regression, a type of two-part fractional response model. The final section concludes.
2. Theoretical background

2.1. Networks and firm location

The use of network analysis for the study of knowledge transfer in industrial clusters is not new. Giuliani and Bell (2005), in a study of the Chilean wine cluster, found that knowledge is not diffused evenly throughout clustered firms but within a core group of firms that have the biggest knowledge-sharing network. Giuliani (2007) again found this pattern with wine clusters in both Italy and Chile. Morrison (2008) reached a similar conclusion in a study of an Italian furniture district, as well as Boschma and Ter Wal (2007) with Italian footwear firms. Thus, knowledge transfer between firms is not purely the result of geographic proximity but due to underlying knowledge channels that may result from co-location.

Further studies examine the relationship between geography and a firm’s knowledge network. Giuliani (2013) found that the persistence of knowledge ties among Chilean wine firms is the result of co-location, and Balland, Belso-Martínez, and Morrison (2016) found that among the Spanish toy cluster, physical proximity is an impetus for technical knowledge networks (but less so for business knowledge networks). Similarly, Juhász and Lengyel (2017) observed that among clustered printing firms in Hungary, geographic proximity increases the probability of tie creation among firms (although geography does not influence the persistence of those ties). Furthermore, Broekel, Fornahl, and Morrison (2015) found that clustered German biotechnology firms hold more favorable positions in national knowledge networks.

In the same vein, Funk (2014), in a study of the US nanotechnology sector, found that efficient network systems only benefit firms located in close proximity, while geographically less proximate firms benefit from inefficient networks. However, Funk (2014) considered intra-organizational networks rather than those between firms, and thus within the context of information diversity and exchange on the firm-level. What unites these studies is the use of collaboration data and the subsequent study of networks that are actively-sought. Using a similar perspective, but outside the collaboration network approach, Lambiotte et al. (2008) and Liben-Nowell et al. (2005) examine the relationship between social networks and geographic distance, and find an inversely proportional relationship. But this again comes with the rationale that individuals are more likely to actively form links with one another if they are in close geographic proximity. These studies do not directly address knowledge networks of a passive and resultant codification that is of historical consequence, i.e. one derived via inheritance.

In fact the closest study this paper can be compared to is that of Ter Wal (2013), who compared clustered IT and life science firms in Sophia-Antipolis. While the IT sector saw the emergence of a robust local network over time, this was not observed in the life sciences sector. Although Ter Wal (2013) used a similar approach as the above studies (i.e. the observing of knowledge networks that are actively explored and sought out), it was found that the emergence of local spinoffs provided a key role in establishing links between inventors in the IT sector, where such industry lifecycle dynamics were comparatively stronger. Of note, it was observed that the knowledge network in the IT sector consisted of shortcuts between subgroups of firms, a structure resembling a small worlds network.
Hence, we already know about the relationship between actively sought collaboration networks and the location of clustered firms. This paper takes a different approach that considers the history and origins of the firm. What follows is a description of a network that identifies familiarity of knowledge and routines, *passed down through generations of firms*. Put differently, an inter-firm knowledge network that is antecedent, pre-existing and the result of the industrial lifecycle itself.

### 2.2. Networks and the Entrepreneurial Spawning Process

Much of the evolution of industrial clusters can be explained by the entrepreneurial spawning process, which involves the establishment of a new firm by a former employee of an incumbent firm in the same geographic area. These spinoff firms often have experience in the same or a related industry as the parent (Klepper 2006). Although the spawning process is by no means the *only* means of firm entry in industrial clusters, much of the relatively superior attributes and abilities of firms within such areas can be explained by such a mechanism (Klepper 2007; Boschma and Wenting 2007; Heebels and Boschma 2011). This paper focuses on ‘pulled’ spinoffs, whose parents continue to exist after the new firm enters the market and whose founders originate from the incumbent firm (Andersson and Klepper 2013).

The entrepreneurial spawning process, and the resulting pattern of surviving firms, may therefore be described as Darwinian in nature. Boschma and Frenken (2003), Klepper (2007) and Buenstorf and Klepper (2009) provide a thorough overview of this process, in what can be interpreted as the dynamics of spatial clustering. The firms that produce the products most adapted to market demand grow the fastest. These successful firms spawn more spinoffs. These spinoffs inherit the capabilities of the parent firm, and because of this, firms spawned by more successful firms tend to be more successful themselves. The process enters into a geographic sense through means of the home advantage effect. Dahl and Sorenson (2012), using data on Danish start-ups, find that entrepreneurs display a certain degree of geographic inertia when choosing a location for their firm. Following on from Michelacci and Silva (2007) and Dahl and Sorenson (2009), they tend to establish their firms in areas which they have lived in for a long time. This may be either down to entrepreneurs’ deep understanding of the local market or connections to family and friends. Entrepreneurs acquire their experience from incumbent firms in the area, which deepens the entrepreneurs’ understanding of that given industry. Thus, start-ups in an industry tend to emerge in regions that already have a high number of similar firms, even if locating close to similar industries offers no hypothetical advantage. The cluster is therefore a path dependent process which is a function of the location decision of successful parent firms.

Industry knowledge easily transmitted via inheritance may consist of goods, markets, production routines, and sources of supply. Crucially, an entrepreneur’s decision to locate in a given geographic area arises out of knowledge of prospective hires. A familiar source of new hires is the entrepreneur’s prior employer, and, perhaps to a lesser extent, other nearby firms in the same industry (Carias and Klepper 2010). It thus follows that firms in the same region as its founder have a greater capacity for hiring employees in the same industry (Dahl and Sorenson 2010). Carias and Klepper (2010) test this theory by comparing spinoffs that operate in the same industry as their parents with those that do not. Using
Portuguese data, they find that entrepreneurs that start firms in the same industry as their prior employer are more likely to be located in the same geographic area. They are also more likely to employ workers from their prior employer as well as other firms from the area. Knowledge of this nature, which is the result of experience, is more likely to be inherited through experience rather than actively sought out. Furthermore, knowledge can flow both ways. Agrawal, Cockburn, and McHale (2006) showed that prior employers maintain their relationships with former employees, and these enduring social relationships contribute to knowledge flows from individuals to their former workplaces. Thus, spinoffs in clusters are more likely to have more cohesive networks. Better firm performance results from cohesive networks which are in-turn a consequence of location decision. A firm’s knowledge, whether in terms of the local labor market or its given industry, could be thought of as the result of that firm’s relationship with the rest of the inter-firm network. This network is in-turn a result of historical relationships. If a node of a network can be thought to represent a workplace establishment, the network’s links represent historical firm-to-firm relationships, and it is through these links that knowledge transmits.

Given these dynamics of spatial clustering, there have been a number of empirical regularities found in prior research. Firstly, spinoffs, as a result of the industrial background and inherited endowments of the entrepreneur, tend to outperform other types of new firms. This pattern has been observed in country studies in Denmark (Eriksson and Kuhn 2006; Sørensen and Phillips 2011), Norway (Hvide 2009), Sweden (Andersson and Klepper 2013), Brazil (Muendler, Rauch, and Tocoian 2012), Portugal (Baptista and Karaöz 2006) and the United States (Elfenbein, Hamilton, and Zenger 2010). Secondly, we know that spinoffs within clusters tend to outperform spinoffs outside clusters, as seen in the Detroit automobile industry (Klepper 2007, 2010), the Silicon Valley semiconductor industry (Klepper 2010), the UK automobile industry (Boschma and Wenting 2007), the Akron tire industry (Buenstorf and Klepper 2009), the German machine tools industry (Buenstorf and Guenther 2011), the Dutch publishing industry (Heebels and Boschma 2011) and the global fashion industry (Wenting 2008). Given these stylized facts, the question remains whether spinoffs that have survived the initial selection pressures found within clusters, as well as possessing the necessary attributes for exploiting the benefits found within, have superior knowledge and routines inherited from previous incumbent firms. Put another way, are the micro foundation firm-level gains of spinoffs in industrial clusters the result of underlying genealogical networks? If we were to identify and measure such networks, we would then be able to empirically test such a relationship.

1This may also extend to knowledge spillovers. Geographic proximity is said to have a profound impact on how agents interact despite recent technologies that enable face-to-face communication over long distances. The advantages of geographic proximity still have a major effect on industrial cluster formation despite such technologies (Hoekman, Frenken, and Van Oort 2009). This is because face-to-face interaction is comparatively beneficial for effective learning (Boschma and Frenken 2010). Indeed, Arzaghi and Henderson (2008) find that, even in a high-density area such as Manhattan, geographic proximity leads to enhanced local productivity in industries where exchange of information is paramount. The returns to geographic proximity rapidly decrease as firms locate further away from the central cluster.

2The benefits of proximity and contact between organizations, rather than within, can arise out of the dissimilarity of information. Agents within an organization often have little to share, as they possess highly similar knowledge sets. In a Schumpeterian context, the sharing of knowledge between organizations may lead to more radical, rather than incremental, innovations. This is due to the combination of technologies that are disparate to a degree but nonetheless related in a cognitive context.
2.3. Small world networks – conceptual issues

The question therefore remains on how an ‘efficient’ network, that is, one in which facilitates a favorable level of knowledge transfer, is structured. To put it succinctly, an efficient network is one which ‘has a perfect balance between local necessities and wide-scope interactions’ (Latora and Marchiori 2001, 3). Of course, one could consider a network where all agents are connected with each other, thereby making any discussion of network structure irrelevant. However, such networks can also be considered costly, as agents would not only have to maintain the myriad of links but also elicit the information gleaned from such a network which may require a close to infinite absorptive capacity.

One may also envisage a network structured with the view that agents will choose to attach themselves to another agent that possess the greatest number of existing connections. This is known as the preferential attachment model, proposed by Barabasi and Albert (1999). Agents attaching themselves to ‘hubs’ gives them the shortest path length to other agents in the network. Viewing a network in this context is more in tune with firm strategy, i.e. the deliberate seeking out of new connections. However, this is not a consequential context of network analysis, i.e. where network ties form out of the result of a firm’s historical and evolutionary path. Although a network may resemble that of a preferential attachment model, analyzing it in such a sense is misleading as the underlying fabrication of the network may have been the result of dynamics that run counter to that model’s assumptions.

In an economic context, we may view efficiency as the capacity of knowledge percolation as well as the stability and robustness of that capacity. Thus, we require a network model that not only describes the efficiency of firms with respect to the rest of the network, but does so on both a global and local level. It should be emphasized that in the context of this paper, we seek to measure the efficiency of individual firms, and not the network as a whole. This efficiency measures the small world properties of those firms.

The small worlds network structure is a formalization by Watts and Strogatz (1998) based on the ‘six degrees of separation’ experiment conducted by Stanley Milgram in the 1960s, and may be defined as a network in which nodes are linked by a short chain of acquaintances. A small world network is one which displays a high degree of reachability (i.e. the ease of reaching one part of the network to another) and cliquishness (i.e. local groups of nodes with a high familiarity of one another). Thus, firms that exhibit higher small world properties will supposedly have a better understanding of their industry, as they have better and wider-reaching knowledge of other firms. But crucially, the efficiency of the knowledge pathway does not fall away upon minor structural changes to that industry, if that structural change is not too severe. The efficiency of information transfer, whether in terms of knowledge of other firms’ employees or tacit information relevant to the industry, is linked to a node’s small world properties on both a local and global scale.

With reference to Figure 1, the model is as follows. Consider \( N = 360 \) nodes arranged in a hypothetical ring-like lattice. Each of these nodes have an undirected link with their

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3In reality such networks rarely form. Ter Wal (2009) and Giuliani (2007) point out that well-connected agents rarely accept unlimited networking proposals and will only select those that give them the greatest return. Thus, firms constrain themselves in terms of the number of network connections they can make. Furthermore, geographic distance gives rise to costs incurred as a result of attaching to any network. Therefore, agents will typically connect to nodes of lower degrees if these are more proximate in any dimension (Boschma and Frenken 2010, 128). Although it is often in the interests for an agent to join a network, they do so based on their own cost constraints, dictated by their cost set.

4An undirected link is one that has no orientation.
We begin with a perfect lattice (rewiring probability = 0), with \( N = 360 \) nodes and \( K = 720 \) links, with each node connected to its closest two neighbors only. Thus, average local efficiency is very high but average global efficiency is close to zero.

\[
\text{Average } E_i^l = 0.7222
\]
\[
\text{Average } E_i^g = 0.0566
\]
\[
\text{Average } SW_i = 0.2022
\]

Rewiring each node (with a probability of 0.05) gives a network displaying the properties of a small world network. Global efficiency of many nodes increase, but at the slight expense of local efficiency. The overall effect, however, is an increase in \( SW_i \).

\[
\text{Average } E_i^l = 0.5026
\]
\[
\text{Average } E_i^g = 0.1689
\]
\[
\text{Average } SW_i = 0.2738
\]

A random network (rewiring probability = 1). Global efficiency continues to rise but at a detrimental effect on local efficiency. \( SW_i \) tends to be negligible.

\[
\text{Average } E_i^l = 0.0033
\]
\[
\text{Average } E_i^g = 0.2444
\]
\[
\text{Average } SW_i = 0.0284
\]

Figure 1. From a perfect lattice, to a small world, to a random graph.

immediate \( k \) neighbors. We consider the case with each node connected to four (i.e. \( k = 4 \)) of its immediate neighbors only. This setup, known as a perfect lattice, demonstrates zero randomness as each node exhibits precisely the same relationship with its neighboring nodes in the network. As each node is connected to all its \( k = 4 \) neighbors, we get what resembles a ‘clique’. At this stage, nodes are locally efficient as they can reach proximate nodes with few steps, but they are not globally efficient as to reach the other side of the network requires many steps. The number of links, or geodesic distance, \( d_{ij} \), between neighbors is therefore small, but large for nodes on opposing sides of the network.
Given this perfect lattice, and with a fixed probability, each link is rewired to a different and random node in the network. In this example, this probability is $p = 0.05$. For a node that exhibits rewiring, this reduces local efficiency at the expense of creating a short-cut to another section of the network. Global efficiency for the given node, as well as for its neighbors and nodes on its own side of the network, increases. Likewise, this also increases the global efficiency of nodes on the receiving end of the network. If we were to continue with this process, average global efficiency of the network increases at the expense of average local efficiency.

Further rewiring the network leads to a structure that resembles that of an Erdős and Rényi (1959) nature, or a ‘random graph’. In such a case, cliques completely diminish as the local pattern of the original perfect lattice falls away. Average global efficiency tends to its maximum limit, while average local efficiency tends toward zero. Thus, a small world network is one where we introduce some randomness but not too much. A node with high small world properties can reach another part of the network within a relatively short geodesic distance and this ease is not hindered by hypothetically removing a node within its immediate network. Hence, both reachability and cliquishness are equally important.

Uzzi and Spiro (2005), in a study of the small world properties of collaboration networks, found an inverse U-shaped relationship between small world properties and performance measures, with the argument that networks with very high levels of cohesiveness lead to the sharing of overly similar information and arriving at a point of creative rigidity. Novel ideas fall away as new talent gets locked out. However, the network used in this paper considers new firms as given, with the Schumpeterian assumption that young and pulled spinoff firms come into the market precisely because they have arrived upon a new and radical idea that is perceived as profitable.5

3. Network topology

What follows is a network modeled as both a neural network as well as a social one. The aim is to convey a firm’s passive position in an overall knowledge network structure. At the same time, the network serves to depict the potential social connections between firms, as those embedded in similar knowledge sets are more likely to have a greater knowledge of each other’s employees with similar skills. Thus, what follows is not a social network in its strictest sense, but a system to map cognitive relations.

3.1. Network rules

This paper considers a network6 with nodes, representing establishments, that have at least one link. An establishment (or workplace) differs from a firm in that it has a specific geographic location (as a firm may be composed of many establishments).

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5Another issue that makes comparison to Uzzi and Spiro (2005) problematic is their use of a bipartite network (i.e. being linked in to a network via a group or organization. A ‘network where production is team-based and roles are specialized, decentralized, and interdependent...the optimal level of success increases with a medium level of small world connectedness and product cohesion’ (Uzzi and Spiro 2005, 493–4). The network used in this paper on the other hand is unipartite, and made up of distinct establishments.

6The network is both of one-mode (in which nodes are connected via a direct relationship) and bipartite (which considers the connection of two nodes via a given attribute) type. The bipartite relationships are however transformed to unipartite ones.
Whether a link exists between two nodes is based on several conditions, which shall be described here as well as summarized in Table A1 (appendix).

The primary rule is that of spinoffs. Consider an individual that has a position of managerial seniority within a workplace. Such a position not only entails an adequate level of understanding about the inner workings of the workplace and the firm, but also a good knowledge of the workplace’s industrial connections as well. If that individual makes the decision to leave the firm and establish a new firm, she will inherit the knowledge of the incumbent workplace’s connections. Thus, the spinoff firm will not only establish a direct link with its mother firm, but the parent firm’s links also. Figure 2 provides an example of how a network may evolve out of the result of an entrepreneurial spawning process over time.

For the sake of simplicity in this example, let us assume that all firms have only one workplace. Let us consider a firm, labeled A on figure\(^7\) 2, that spawns two firms, B and C in period \(t + 1\). In addition to a link established with their parent firm A, the two spinoffs also form an indirect link between themselves, a network formation assumption previously applied by Lengyel and Eriksson (2017). As they had spawned in the same period, one can assume that the two new firms have intimate knowledge of each other. This results in links established between the two spinoffs and the parent firm. In period \(t + 2\), firm B spawns firms D and E. Likewise, D and E form an indirect link with each other. In addition, these two new spinoffs inherit\(^8\) links from their parent firm B, and thus form indirect links to firms A and C. This further exacerbates the complexity of the network. This increasing complexity continues through \(t + 3\) and \(t + 4\) provided no firms exit. Thus, although inheritance plays an important role in the structure of the network, it’s not the only role. One cannot rule out other relationships that would enable the same type of inter-firm familiarity, such as the ‘sibling’ type of relationship that arises between two spinoffs that spawn from the same parent firm and in the same time period.

On Figure 2 one may observe that firm A spawns F in period \(t + 2\), while spawning B and C in period \(t + 1\). Spawning in two different time periods alters the subsequent pattern of network formation. As F spawned later than B and C, it does not form links with those firms.\(^9\) The assumption of intimate knowledge of fellow spinoffs is somewhat weaker if firms spawn in different time periods. As firm F spawns its own firms in \(t + 3\) and \(t + 4\), the resultant network exhibits a ‘branching’ effect. We may interpret this as the regional branching process as described by Boschma and Frenken (2011). Largely a chance event, we propose that a firm spawning over different time periods increases the probability of industrial partitioning. It may be seen on Figure 2 that the resulting

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\(^7\)As well as the specific links described in this section, Figure 2 also features additional links, for the sake of illustration.
\(^8\)All of these links follow the same parent-spinoff rules described here.
\(^9\)The system of inheriting links is to ‘reward’ firms for their heritage, a way of embedding them in the history of their knowledge and routines. This is to avoid the ambiguity of assigning weights. Of course, one could assign weights to links (taking into account entropy), but this would require further assumptions regarding the nature of those weights. We could also assign weights to nodes, but there would again be an added ambiguity to what those weights mean for the rest of the network, and to what extent.

\(^9\)Note that this ‘sibling’ rule only takes effect with spinoffs established in the same time period as well as those that share the same parent. We have deliberately avoided any arguments concerning this relationship in lagged time periods as this would introduce a critical assumption that would not be easily backed up due to the ambiguity of memory (and memory itself may be dependent on a range of further factors, such as start-up size, the nature of the founder, etc.).
network in $t + 4$ is composed of two broadly separate clusters joined together at firm A (and nowhere else). This is an important result and has implications on the local efficiency of nodes.

The three other rules, while not directly the focus of this paper, cannot be ignored. If we were to consider a network that maps the transmission of routines via parent-spinoff relationships, one cannot overlook similar transmissions via alternative linkages. Two of these concern workplace mergers and splits, which work in a similar fashion as spinoffs. In the case of mergers, two or more nodes become one, taking all their associated links with them. For splits, a single node splits into two or more nodes, each of which inherits the links of the former firm (which may or may not be defunct). Lastly two workplaces can have a link between them if they are both part of the same firm. We can assume that if two workplaces within the same sector share ownership, they will have a degree of organizational proximity that allows for an adequate sharing of information. In such a relationship, we will not assume inheritability of past links. To avoid adding assumptions to the model, these relationships (firm splits, mergers and same-firm establishments) take on the same weight as parent-spinoff linkages.

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10 All of which are direct, one-mode relationships.
11 This is a bipartite relationship.
12 Such cases consist of multiple workplaces under one firm, for example branches of the same company. A new workplace will form links to all other workplaces within the same firm, but will not take inherit links to outside firms. Thus we assume a more local relationship vis-à-vis the other network rules. A subsequent spinoff from such a workplace, however, would inherit the firm’s links.
13 Assigning weights to different types of link would be problematic as the underlying subject (knowledge transmission) is unquantifiable.
these various network rules listed in Table A1, the parent-spinoff rule binds the network together.\textsuperscript{14}

The rules produce a network that is neither additive nor subtractive.\textsuperscript{15} The average number of links per node in the network may grow or shrink depending on the underlying trend of industry structure. Indeed, it is conceivable that the nodes in the network may exhibit small world properties at one point in time but then begin to disintegrate into a random network at a later point in time. The average number of links per node, and therefore small world properties, are therefore not merely the result of the mere sails of time but the entrepreneurial spawning process itself.

3.2. Network characteristics

To gauge both historic and current relationships between workplaces, we use micro data from Statistics Sweden (SCB) with regard to ICT workplaces located throughout Sweden. This data not only contains information regarding workplace entry and exits but also the nature of those entries and exits, which in-turn serve to describe the relationships between workplaces as well as trends of the industry lifecycle.

This paper considers the main component of the network as the population of study. The main component of the network is its largest connected set of nodes. Small world studies by Davis, Yoo, and Baker (2003), Uzzi and Spiro (2005) and Gulati, Sytch, and Tatarynowicz (2012) use the same approach. A disjoint network rules out analyzing small world network properties as small world networks consider a connected network (Gulati, Sytch, and Tatarynowicz 2012). Including isolated nodes as well as smaller components would be fallacious as they are unreachable. The size of the network’s main component undergoes a somewhat abrupt phase transition throughout the years of study, which may be seen in Figure 3.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{figure3.png}
\caption{Percentage of nodes within the main component.}
\end{figure}

\textsuperscript{14}Considering other link types separately would result in a disjointed and therefore incomparable network. When considering a small world network, the whole should not be seen as a sum of its parts.

\textsuperscript{15}Furthermore, the durability of links are infinite as to preserve memory. If a firm exits, knowledge of that firm does not necessarily cease, i.e. the knowledge network of the exited firm’s neighbors remains in place. Given the inheritability of links, removing an intermediary is irrelevant.
In the early years of analysis, from 1991 to 1995, the percentage of nodes part of the main component is relatively low, and this percentage remains more or less unchanged for these years. From 1995 to 2001, however, an abrupt phase transition occurs, with roughly 40% of nodes part of the main component from 2001 onward. Again, post-phase transition, this level remains stable. One possible explanation for this phase transition may lie with the changing nature of the ICT industry, as the wide-spread use of the Internet took off during the phase transition period resulting in an explosion of ICT firms. A more mathematical explanation, however, lies with the nature of assembling random networks. Part of the trend before 2001 can be the result of assembling the network data; indeed, inter-workplace relationships would be masked in earlier years due to limited information, as network data for this paper begins in 1991. Information regarding the relationships between workplaces before this year is therefore absent and in-turn limits the size of the observed main component. Moreover, the phase transition from 5% to roughly 40% from 2001 is a result of the natural properties of random graphs Kauffman (1995). This phase transition from 2001 is when the network becomes autocatalytic, i.e. the point at which the main component of the network becomes self-sustaining. As the number of nodes in the network continue to increase, the percentage of nodes within the main component remains constant. One may also suggest that the upward trend before 2001 is a result of the underlying industrial lifecycle. For this reason, and to eliminate any bias arising from small network size, regression analysis will be restricted to observations for the years 2001 onward.

3.3. Measuring the potential for knowledge flows with small world networks

The traditional method of measuring small world networks is by using average path lengths and clustering coefficients, the measures used by Watts and Strogatz (1998) to introduce the model. These two measures, however, are best suited for networks that assume the percolation of one packet of information. For analysis of 'real world' industrial networks such as that in this study, it’s more appropriate to view the network as a percolator of concurrent packets of information. This is known as a parallel network. Thus, efficiency, as introduced by Latora and Marchiori (2001), offers additional advantages such as dropping restrictions on the system such as connectedness and sparseness.

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16Kauffman (1995, 57) shows that there is an abrupt change in the size of the main component when the ratio of nodes and links passes 0.5, thereby resulting in the s-shaped curve.
17This is when the main component becomes defined as a giant component. Formally, this is when the total number of links (both within and outside the main component) reaches a condition where a threshold, $c$, is greater than half the the number of nodes in the entire network, $n/2$, and where $4c - 2n = \text{Nodes in the Giant Component}$ (Bollobás 2001). Considering the first year of observation, 1991, $c = 31.5$ and $n/2 = 366.5$, this condition does not suffice. However for 2001, $c = 5.086$ and $n/2 = 4,235$, the condition holds.
18A parallel system is one where all nodes concurrently exchange packets of information. This differs from a sequential system, i.e. where only one packet of information relays throughout the network. Measuring a parallel rather than a sequential system is advantageous as it allows for the presence of 'bad' nodes that are less able in transmitting information. An example given by Latora and Marchiori (2001) is the Internet. The presence of some slow computers does not diminish the efficiency of the entire Internet, but rather goes unnoticed as the rest of the system engages in the exchange of thousands of packets of information efficiently. This assumption of a parallel system also extends to biological networks as well, especially those that concern neural pathways of the brain. Thus, we can maintain the same measurement of a network while allowing for the possibility of 'bad' nodes.
Let $d_{ij}$ represent the geodesic distance, or shortest path, between two nodes $i$ and $j$. Thus if a link directly connects nodes $i$ and $j$, then $d_{ij} = 1$. If node $i$ is two links away from node $j$, then $d_{ij} = 2$ and so on. The efficiency, $\epsilon_{ij}$, of communication between nodes $i$ and $j$ is thus inversely proportional to the shortest distance between them, i.e. $\epsilon_{ij} = \frac{1}{d_{ij}} \forall i, j$. Geodesic distance takes the value $\pm \infty$ if no path exists, and therefore $\epsilon_{ij} = 0$. $\epsilon_{ij}$ describes the relationship between two nodes. To describe the negotiability of the entire network, we formally define global efficiency\textsuperscript{19} of node $i$ as:

$$E_i^G = \frac{1}{N - 1} \sum_{j \neq i \in G} \frac{1}{d_{ij}}$$  \hspace{1cm} (1)$$

An ideal network, i.e. one which has all of its nodes connected to all other nodes, will have an average $E_i^G$ equal to one.\textsuperscript{20} Thus, $0 \leq E_i^G \leq 1$. Again, a network with a relatively low global efficiency is one that would resemble a lattice, while a high average global efficiency (and hence a high level of average reachability) is one which could either imply a small world network structure or a random graph. To differentiate between the two, we formally define local efficiency as:

$$E_i^L = \frac{1}{N_i(N_i - 1)} \sum_{j \neq k \in G} \frac{1}{d_{jk}}$$  \hspace{1cm} (2)$$

Local efficiency\textsuperscript{21} exclusively addresses the local subnetwork of node $i$, which is in-turn comprised of its neighborhood while excluding node $i$ itself. In this paper, this neighborhood has an order of 1, i.e. only its immediate neighbors. Local efficiency thus tests if removing node $i$ has any impact on the connectivity of node $i$'s immediate neighborhood, and thus the local subnetwork’s resilience. A network with a high average local efficiency (implying a high level of average resilience) indicates either a perfect lattice or a small world network, but not a random graph.

As we use the same principles in calculating global and local efficiency, they are directly comparable and take on the range of $0 \leq E \leq 1$, and therefore use the same scale. However, global and local efficiency, as measurements taken separately, do not concretely conclude the nature of a node’s relationship to the rest of the network. As seen in Table 1, the value of such measures only serve to exclude one possibility of a node’s nature. Thus, we extend the measures of efficiency introduced by Latora and Marchiori (2001) by introducing the small world metric\textsuperscript{22}:

| Table 1. Comparative network measurements. |
|-------------------------------------------|
| Measurement | Perfect lattice | Small world | Random Graph |
|------------|----------------|-------------|--------------|
| Global efficiency | Low | High | High |
| Local efficiency | High | High | Low |
| Small world metric | Low | High | Low |

\textsuperscript{19}This may be seen as an alternative to the more traditional measure of average path length.

\textsuperscript{20}For this reason, and the fact that networks in this paper are characterized as unweighted, efficiency measures are not normalized.

\textsuperscript{21}This an alternative to the more traditional measurement of transitivity, or the clustering coefficient.

\textsuperscript{22}There are other micro-level small world measures in the literature, for example the modularity index as introduced by Girvan and Newman (2002). A metric composed of efficiency measures, however, dispenses with the need of creating network partitions and considers each node in their own right.
Equation (3) is simply the geometric mean of the global and local efficiency of a given node $i$. Such a measurement not only gives us a conclusive indication of the nature of node $i$’s relationship to the rest of the network, but also provides a measurement that uses the same scale as both efficiency measures (and thus $0 \leq SW_i \leq 1$). A geometric mean also provides a ‘punishing’ effect for disparate values of local and global efficiency. Furthermore, we have a single dependent variable that is of use in a regression analysis.

We recalculate the small world metric $SW_i$ for each year $t$, for all establishments $i$. The assembled network as it appears in $t = 2010$, using the rules listed in section 3.1 (and summarized in Table A1, and not just those pertaining to spinoffs), may be seen in Figure 4, which illustrates the main component of ICT firms in Sweden. This graph, which maps the network with larger network clusters toward the middle and smaller

\[
SW_i = \sqrt{E_i^G E_i^L}
\]  

(3)

Figure 4. Main component of the network, 2010.

\footnote{Note that this is for the purpose of illustrating the small world metric with a given network structure. This network changes with every year of observation, and hence the small world metric for each establishment may change also.}

\footnote{Using the Yifan Hu proportional layout algorithm.}
networks clusters toward the edge, shows that establishments with higher values of $SW_{2010}$ tend to locate toward the middle of the graph (where larger local network clusters tend to be more prevalent).

4. Empirics

4.1. Spinooffs

This paper considers pulled spinoffs, from the ICT sector, as the subject of study. Spinoffs, in a general sense, are firms that can be conclusively traced back to a single older firm and whose startup was conceived through Schumpeterian motivations. For this general category, and using data drawn from the Swedish employer-employee matched database for the period 1990–2010, we may identify spinoffs using three criteria.

First, spinoffs must originate within the same 2-digit Statistical Classification of Economic Activities in the European Community\(^{25}\) (NACE). As the starting sample is already restricted to observations with NACE codes defined as KIBS activities within the ICT sector (as in Table A2, see appendix), this condition is automatically met. Second, data with respect to the professional status (and hence whether they are defined as an entrepreneur) of each individual is used to determine the establishment’s founder. Statistics Sweden determines an individual’s employer (establishment/firm) annually by his or her place of work in the month of November (Andersson and Klepper 2013). If identified, that founder’s establishment in the previous year of observation is then identified to be the spinoff’s parent firm. Thirdly, and if data regarding professional status is not available, the most common prior year establishment of all employees of the spinoff is used to identify the parent firm. This method is similar in scope to that used by Eriksson and Kuhn (2006) and Andersson and Klepper (2013). If the above three conditions fail to identify a parent firm, the new establishment is considered as an ‘other’ and does not exhibit the same network rules.

In addition to being classified as spinoffs, this paper considers new firms in its strictest sense. That is, spinoffs must be new in a Schumpeterian manner, and created out of the pursuit a new idea or market niche. Therefore, using the methodology of Eriksson and Kuhn (2006), a further distinction is made to separate pulled spinoffs from pushed spinoffs. Some spinoffs come into being out of a result of the exit of its parent firm. These are pushed spinoffs, and these are identified as such if its parent firm ceases to exist at the time of the establishment’s startup. If the parent firm continued to operate at the time of formation of the new establishment, then the spinoff is classified as a pulled spinoff. It is pulled spinoffs that are of the focus of this paper, and the only type of spinoff considered in statistical analysis.

Table A3 in the appendix lists the number of new spinoffs for each year of analysis, 2001–2010. In this paper, we will consider pulled spinoffs whose ages range from 3 to 6 years only. The reason for this is two-fold. First, we consider age 6 to be the upper benchmark in terms of ‘young’ establishments. After this age, we can assume that a firm cannot be considered a ‘start-up’ in an evolutionary sense, as product lines become

\(^{25}\)In terms of the 2002 (revision 1) classification, which is only available for the years 2002 to 2010 (when it was revised again). For years before 2002, the 1992 NACE classification was used and translated from its 2002 categories.
4.1.1. **Data description**  
The Stockholm region represents the greatest concentration of ICT firms in Sweden. This is not only in the ‘largest city’ sense but also in terms of relative concentration.\(^{26}\) Furthermore, by focusing on one location we can consider the immediate spatial effects of an industrial cluster. Thus, young pulled spinoffs (ages 3 to 6) within Sweden’s main component of ICT firms after 2001, and located within Stockholm County, are the focus of this paper. A summary of the dependent and independent variables used in this regression may be seen in Table 2. Here, we describe each in turn.

In section 2.3, we introduced the small world metric as the geometric mean of global and local efficiency. This allows an assessment of small world properties that addresses both local and global characteristics without giving weight to either. This also gives precedence to scale, and normalizes the two measures into one and thus \(SW_i \in 0, 1\). Kernel density plots for local and global efficiency as well as the resultant small world metric may be seen in the appendix (Figure A1). The non-normal nature of the small world metric is due to frequent observations of zero for local efficiency. Such observations are those that locate on the peripheries of local network clusters. On the other hand, nodes on the periphery of the whole network tend to have a very low global efficiency (but never zero), while those located in the network core display a relatively high global efficiency.

The sample’s descriptive statistics may be seen in Table 3. For \(SW_{it}\) to be equal to one, a firm would need to exhibit a global efficiency of one, i.e. have a direct link to every other firm in the network, which would mean the whole network would be its immediate neighborhood. Furthermore, all firms in its immediate neighborhood would have to have a connection with each other, generating a local efficiency of one. For this reason, although such high values of \(SW_{it}\) are hypothetically possible, it’s highly unlikely.

High local efficiencies, i.e. those that are equal to one, are more common in establishments with smaller immediate neighborhoods. This has some intuition, as

| Variable  | Description |
|-----------|-------------|
| \(SW_i\)  | Small world metric, composed of the geometric mean of global and local efficiency, at time period \(t\) |
| Distance\(_j\) | The Pythagorean distance from the cluster’s centroid, at time period \(t\). Centroid recalculated each year of observation. |
| Parent Size\(_i\) | The firm’s parent’s size, measured in number of employees. Recorded at time of spinoff. |
| Founding Size\(_i\) | The firm’s size, measured in number of employees, at the time of spinoff |
| Size\(_i\) | The firm’s size, measured in number of employees, at time period \(t\). |

\(^{26}\)See Lindqvist, Malmberg, and Sölvell (2008) and Karlsson, Mellander, and Paulson (2004) for further discussion.
the bigger the clique, the more unstable it is likely to be. It is therefore not too surprising that local efficiency is not normally distributed. A normally distributed global efficiency is however more intuitive as it is more of a direct reflection of a firm’s centrality. Those in the ‘middle’ of the network are more likely to display higher global efficiency than those at the edge.

In addition to information regarding workplace entries and exits the data also contains information regarding geographic location, in this case on a X- and Y-coordinate basis. To calculate the distance of an establishment from the geographic cluster’s centroid, we take the Pythagorean length from it. Thus, Distance\textsubscript{it} of workplace \(i\), is the Euclidean distance (i.e. ‘as the crow flies’) from the centroid of the industrial cluster in the year of observation \(t\). One unit equates to one meter. In any given year, a cluster’s centroid is the mean X- and Y-coordinates of all establishments within the confines of the county’s administrative boundary.\textsuperscript{27} Stockholm County, with spinoffs (in the given year) highlighted, may be seen in Figure 5. From the descriptive statistics, we can see that the distance from the cluster’s centroid is highly varied, ranging from 153 meters to around 59 km. The area of Stockholm County is considerably larger than the city of Stockholm itself, with much of it rural. This enables us to consider the industrial cluster in a continuous sense, allowing for a gradual decline in firm density.\textsuperscript{28} In addition to the expansion the cluster, it also becomes somewhat denser (this may be seen in Figure A2 in the appendix). Overall, the level of clustering has exhibited an increasing trend over the time period of study as the average distance to the centroid has gradually diminished. This is especially pronounced at around the year 2000. We expect the relationship between distance and small world properties to be negative and non-linear, with a diminishing effect with respect to distance, and we thus take the logged transformation of Distance\textsubscript{it} for our analysis.

In addition to the main variables of interest, we also allow for additional variables that may serve as control variables to account for any change in small world properties that are not the result of changes in distance from the centroid. The size of the parent establishment at the time of spinoff, Parent Size\textsubscript{i}, can be said to have a positive impact on the small world properties of a pulled spinoff as nodes that represent larger firms are more likely to have more links. The spinoff firm then inherits these links from the parent. We also consider the

\begin{table}[h]
\centering
\begin{tabular}{lrrrrrr}
\hline
Variable & Mean & S.D. & Min & Median & Max & Skew \\
\hline
SW\textsubscript{it} & 0.20 & 0.17 & 0.00 & 0.24 & 0.47 & −0.10 \\
Distance\textsubscript{it} & 8846.17 & 7860.28 & 153.16 & 7318.52 & 58987.37 & 2.10 \\
Parent Size\textsubscript{i} & 288.40 & 379.07 & 2.00 & 128.00 & 1909.00 & 1.95 \\
Founding Size\textsubscript{i} & 3.00 & 8.35 & 1.00 & 1.00 & 95.00 & 7.96 \\
Size\textsubscript{it} & 4.41 & 13.17 & 1.00 & 1.00 & 217.00 & 9.39 \\
Local Efficiency\textsubscript{it} & 0.38 & 0.37 & 0.00 & 0.33 & 1.00 & 0.38 \\
Global Efficiency\textsubscript{it} & 0.17 & 0.04 & 0.08 & 0.17 & 0.27 & −0.14 \\
ln Distance\textsubscript{it} & 8.69 & 0.97 & 5.03 & 8.90 & 10.99 & −0.59 \\
ln Parent Size\textsubscript{i} & 4.78 & 1.47 & 0.69 & 4.85 & 7.55 & −0.28 \\
ln Founding Size\textsubscript{i} & 0.41 & 0.83 & 0.00 & 0.00 & 4.55 & 2.43 \\
ln Size\textsubscript{it} & 0.57 & 1.02 & 0.00 & 0.00 & 5.38 & 1.92 \\
\hline
\end{tabular}
\caption{Descriptive statistics of sample.}
\label{tab:descriptive_stats}
\end{table}

\textsuperscript{27}Coordinates are based on the SWEREF99 coordinate system. This is very close to the WGS84 coordinate system, with slight adjustments.

\textsuperscript{28}We define the geographic boundary of analysis at Stockholm County, as extending this further would potentially blur the analysis with the potential effects of neighboring ICT clusters such as those of Uppsala and Nyköping.
size of the establishment at the time of spinoff, Founding Size\textsubscript{i}. One may infer that the larger the establishment, the more likely it will form (and inherit) new links throughout the industry. Furthermore, and perhaps more crucially, the network of the firm’s neighborhood may strengthen with size, which in-turn implies an increase in the firm’s network resilience (in the form of local efficiency) and thus an increase in its small world metric. Inferring the sign of this coefficient, however, is complex and will be discussed later. We also account for the size of the spinoff firm itself, Size\textsubscript{it}, in its year of observation. This is to account for any effects in addition to those of Founding Size\textsubscript{i} that may occur over the following ages of observation (and provided the firm survives).

All three size variables are measured in terms of the number of employees, and logged to reflect nonlinearity with respect to the variable in question. Like the effect of increasing distance, it is not unreasonable to suggest that firm size and parent firm size have a diminishing effect on the networking properties of a firm as decreasing returns to scale set in after a certain point with respect to size.

4.2. Results

Section 2 showed that the dependent variable, SW\textsubscript{it} lies in the unit interval [0,1]. Regressions that use such data are often heteroscedastic and have asymmetric distributions. For this reason, we employ a beta regression\textsuperscript{29} model as proposed by Ferrari and Cribari-Neto (2004) with a specification as seen in equations (4) and (5).

\textsuperscript{29}The beta regression requires the dependent variable to be in the interval (0,1). To transform from the unit interval [0,1], we employ the method used by Smithson and Verkuilen (2006), i.e. $(SW_{it}(n - 1) + 0.5)/n$. 

![Figure 5. The geographic cluster of ICT firms in the Stockholm area, 1995 and 2010.](image-url)
ln \frac{\mu}{1 - \mu} = \beta_0 + \beta_1 \ln \text{Distance}_{it} + \beta_2 \ln \text{Parent Size}_i + \beta_3 \ln \text{Founding Size}_i + b_4 \ln \text{Size}_{it} \quad (4)

\ln \phi = -\gamma_0 - \gamma_1 \text{Local Efficiency}_{it} - \gamma_2 \text{Global Efficiency}_{it} \quad (5)

In addition to the main response coefficients of interest (which are part of the mean model in equation (4)), beta regressions also allow for the inclusion of phi coefficients, which make up part of the precision model in equation (5). Here, \( \mu \) and \( \phi \) denote the mean and precision parameter of SW\(_{it} \) respectively.\(^{30}\) Phi coefficients, as introduced to the beta regression model by Simas, Barreto-Souza, and Rocha (2010), allow for further adjustments to correct for dispersion. As we can account for much of this dispersion from the two efficiency measures that compose SW\(_{it} \), we include both variables for estimation of phi coefficients. We use a logit link function to relate the mean of the response variables to the linear predictor\(^{31}\) and a log link function to relate the precision parameters to its linear predictor. This gives us the transformations of the dependent variable in Equations (4) and (5). The interpretation of the mean model is like that of a logistic regression. For example, consider two spinoffs, \( i \) and \( j \). If spinoff \( i \) is located 1% further away from the cluster’s centroid compared to spinoff \( j \), the ratio between firm \( i \)'s expected SW\(_{it} \) (i.e. \( \mu \)) and the difference to a ‘perfect’ SW\(_{it} \) (i.e. \( 1 - \mu \)) would be \( e^{\beta_1} \). Using the estimate of \( \beta_1 \) (from Table 4), this ratio would be \( e^{-0.0220} \), or 0.9782. In other words, the odds of achieving a ‘perfect’ SW\(_{it} \) of 1 for spinoff \( i \) would be 0.9782 of spinoff \( j \).

**Table 4. Beta regression results.**

| Coefficients (mean model with logit link): | Dependent variable: SW\(_{it} \) |
|------------------------------------------|---------------------------------|
| ln Distance\(_{it} \)                   | -0.0220** (0.0112)              |
| ln Parent Size\(_i \)                   | 0.0520*** (0.0087)              |
| ln Founding Size\(_i \)                 | -0.0642** (0.0317)              |
| ln Size\(_{it} \)                       | 0.0280 (0.0233)                 |
| Intercept                                | -0.5117*** (0.1181)             |

| Phi coefficients (precision model with log link): |                                |
|-----------------------------------------------|--------------------------------|
| Local Efficiency\(_{it} \)                   | 6.8969*** (0.1283)              |
| Global Efficiency\(_{it} \)                  | 9.8313*** (1.2962)              |
| Intercept                                     | -2.5319*** (0.2102)             |

Number of observations 1155

*** and ** denote statistical significance at the 1% and 5% levels respectively. Clustered standard errors in parentheses.

\(^{30}\)Formally, we derive these from \( E(SW) = \mu \) and \( \text{VAR}(SW) = \mu (1 - \mu) / (1 + \phi) \).

\(^{31}\)Other link functions were used, i.e. probit, cauchit, log-log and conditional log-log. These led to minimal impact on the results however, so the logit model is reported here.
To reiterate, establishments with an age in the range of 3 to 6 are included in the sample, and all observations are from the years 2001 to 2010 when the main component of the network takes the form of its autocatalytic state. We run a pooled regression (with observations grouped by firm) and therefore use clustered robust standard errors. As we assume that there are no universal effects over time, $t$ is not considered. The results of the regression are presented in Table 4, with standard errors in parentheses. Apart from the phi coefficients, all variables are in their logged form to not only reflect diminishing effects of the variable in question but also to normalize their distributions.

For the mean model, the coefficient estimates are statistically significant, and the signs of the coefficients are in-line with expectations. Overall, they are consistent with the hypothesis that, when considering younger spinoff establishments aged 3 to 6 years, there is a negative relationship between an establishment’s network efficiency and its geographic distance to the core of an industrial cluster. In other words, establishments exhibit diminishing small world properties as they locate further away from the cluster. Thus, based on a network composed of the historical organizational relationships between establishments, those further away from an industrial cluster are less efficient with respect to the transmission of cognitive skills than those closer to the core. Hence, with all else being constant, we may say that firms within the cluster benefit from knowledge transfer while those located outside of it benefit less so. The network is thus, arguably, an explanation of the cluster itself and represents the firm-level gains from being part of the industrial cluster.

Thus, one might say that networking benefits arise in spinoffs that are in close proximity to one another. With the ICT sector, which relies on specialized labor inputs that engage in non-routine tasks, small spatial scale matters. Location within a cluster is perhaps a more valid discussion than the location in or out of one. This argument resonates with earlier studies. Arzaghi and Henderson (2008) found that, regarding advertising agencies in southern Manhattan, there is a sharp and rapid decay with respect to the benefits associated with proximate neighboring firms. There is a distinct concession of benefits received when moving from the core to the fringe, which follows the model by Lucas and Rossi-Hansberg (2002). Externalities arising from proximity begin as large but quickly evaporate, even within the small confines of southern Manhattan. Similarly, Larsson (2017) found that, with occupations involving non-routine activities, human capital externalities decline sharply with distance from central business districts. Thus, the steeper the decline of knowledge transfers in space, the greater the incentives for clustering in space.

The estimate for the effect of parent size on an establishment’s small world metric is also consistent with theory. A positive sign of the coefficient illustrates the positive impact of link inheritance upon the small world properties of new spinoffs, with $SW_{it}$ increasing further upon larger parent sizes. This is hardly surprising given that larger spawning establishments are more likely to have more global links to inherit. This in-turn leads to an increase in global efficiency for spawned establishments. Moreover, the current size of firms has no statistically significant impact on its small world properties. One can infer that the effects of firm size on network efficiency can already be accounted for with the firm’s parent size and founding size. Furthermore, given that the firms in the sample are between the ages of 3 and 6, we can also infer that, perhaps,
a firm’s small world properties imbues in its early years and subsequent changes in firm size has no discernible effect.

What at first seems counter-intuitive is that the coefficient for founding size is negative, indicating that smaller spinoffs, as soon as they come into existence, are more likely to have larger small world metrics. Note that this is the founding size of spinoffs, and not establishments in general. Thus, this does not necessarily counter the result of the coefficient of parent size. To explain why this coefficient is negative, one must return to the nature of the network itself. The literature suggests that larger firms tend to spawn less often, and smaller firms tend to spawn more often. Gompers, Lerner, and Scharfstein (2005) found that smaller firms, that is, those with 100 or less employees tend to experience a substantially higher rate of entrepreneurial spawning as smaller firms serve as incubators where employees acquire the knowledge and skills needed to start a new firm. Figure 6 compares the timeline of two cases. If larger firms spawn spinoffs that inherit their parents’ characteristics, those spinoffs will also spawn less often. On the other hand, smaller firms will spawn firms that in-turn spawn more often. The result is a more complex network on the local level. This increases local efficiency in smaller firms (but not necessarily global efficiency), which in-turn gives rise to higher levels of small world properties. Thus, even if smaller spinoffs don’t survive as long as larger firms, they are still more locally efficient.

One can thus envisage a more complex chain of inherited network ties for smaller firms than that of larger firms. This increased level of complexity is prominent at the local level, and hence smaller firms exhibit higher local efficiency and thus small world characteristics. In an evolutionary sense, one can envisage the need for inter-firm knowledge and communication as a survival need. The lack of in-house and self-contained research incentivizes the smaller firm to seek industry knowledge outside the firm. Large surviving firms, on the other hand, while more likely to exhibit increased global efficiency, have less need of complex and local inter-firm connections as their research is more self-contained.

![Figure 6](image-url) The emergence of local efficiency among smaller firms.
5. Concluding remarks

Recent literature suggests that new firms, in the form of spinoffs, tend to be more successful inside industrial clusters than outside of them. Networks facilitate transmission of knowledge of other firms, and this knowledge may be in the form of other employees as well as industry-specific information. Network efficiency, resulting from historical parent-spinoff ties, serve as a cluster performance premium. This paper has filled a research gap by measuring these networks to show that firms that enjoy more efficient networks are more likely to be located within a geographic cluster of firms from the same industry.

Using matched employer-employee data spanning from 1990 to 2010, we compiled a network model that captures the small world properties of firms as a proxy for the capacity and resilience of knowledge percolation. By controlling for firm size as well as the size of the parent firm, we can conclude that firms lose their capacity to gain industry-specific knowledge as they locate further away from the industrial cluster. Thus, the surviving firms that locate within the core of that cluster are those that have the endowments associated with the inherited organizational abilities of their parent firms, coupled with the perks of remaining within the cluster via home advantages. Surviving firms that locate away from the geographic cluster have less inherited industrial links with other firms. This relationship between geography and knowledge percolation capacity exists irrespective of any externalities gained purely by location choice but rather due to the firm’s background.

This paper adds to the literature in evolutionary economic geography. Generated inheritance networks have not been considered in detail in prior research, and this paper uses a longitudinal approach to do so. We may view a firm’s network not as a result of the firm’s actions or strategies, but a consequence of its own history. Here, we may see the firm’s network and its geographic location as two dimensions of the firm’s environment. The geographic location, in the form of Stockholm’s ICT cluster, hosts the network needed for firms to be successful. Thus, we can say that rather than surviving firms adapting to their environment, it is the environment that has adopted surviving firms (Alchian 1950). In the context of this paper, firms do not ‘choose’ their network, but realize it when the firm comes into being. If firms that locate within geographic clusters are more successful than those that locate outside of them, this is the result of the suitable characteristics of the environment that adopted them.

This adoptive approach opens further potential areas of research. At present, while there is a magnitude of studies that focus on firm entry (Agarwal et al. 2004; Shane 2000; Gompers, Lerner, and Scharfstein 2005; Klepper 2009) and firm growth (Beaudry and Swann 2009; Maine, Shapiro, and Vining 2010), and firm survival (Andersson and Klepper 2013; Eriksson and Kuhn 2006), there has been relatively little recent research with regard to the role of networks. Both Lengyel and Eriksson (2017) and Ter Wal and Boschma (2011) examine the effect of network structure on innovation and subsequently firm performance and regional growth. However, there has been relatively little research on the role of inherited, genealogical networks on firm performance. For example, one may seek to explain how geographic distance impacts the survival rates of spin-off firms via their networking abilities, and how this may change depending on the background of the entrepreneur. Other areas of potential research may include an
expansion of the inheritance network model itself. In this paper, we have, for the sake of limiting critical assumptions, considered unweighted links. Further research may shed light on the role of memory, thereby assigning weights to inherited links. In addition, the effect of different link types (spinoff, merger, etc.) on efficiency may be of interest, as well as an investigation to the comparative strength of such links. In a practical sense, however, this may entail measurement of the unquantifiable. Nonetheless, the inheritance network approach provides a promising tool in the study of clusters and evolutionary economic geography.

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Appendices

Table A1. Network formation rules with respect to each type of new establishment.

| Type of new firm                  | Link inheritance | Additional rules                                           |
|----------------------------------|------------------|-----------------------------------------------------------|
| Spinoffs (pulled and pushed)     | Yes              | No                                                        |
| Mergers                          | Yes              | The nodes of merged establishments become one              |
| Splits                           | Yes              | Upon a split, a link is formed between each of the splits |
| New establishments in a common   | No               | New links with other establishments with a common firm    |
| firm                             |                  | No                                                        |
| Other firms (de novo, etc.)      | No               | No links upon foundation                                  |

Note: classification of new firms may overlap, and therefore may follow multiple rules

Table A2. NACE codes for ICT sector KIBS.

| NACE (2002) | NACE (1992) | Activity                                         |
|-------------|-------------|--------------------------------------------------|
| 72,100      | 72,100      | Hardware consultancy                            |
| 72,210      | 72,202      | Software consultancy and supply                 |
| 72,220      | 72,201      | Data processing                                 |
| 72,300      | 72,301      | Other software consultancy and supply           |
| 72,400      | 72,400      | Database activities                              |
| 72,500      | 72,500      | Maintenance and repair of office, accounting and computing machinery |
| 72,600      | 72,600      | Other computer related activities                |

Table A3. Number of new spinoffs in each year of analysis (2001–2010).

| Year | Giant component | Entire network |
|------|-----------------|----------------|
| 2001 | 205             | 520            |
| 2002 | 149             | 398            |
| 2003 | 153             | 406            |
| 2004 | 162             | 435            |
| 2005 | 141             | 389            |
| 2006 | 155             | 468            |
| 2007 | 198             | 559            |
| 2008 | 227             | 540            |
| 2009 | 146             | 516            |
| 2010 | 185             | 630            |

Figure A1. Kernel density of efficiency measures and the small worlds metric.
Figure A2. Mean distances from cluster centroid, 1991–2010.