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**KNOWLEDGE GROWTH THROUGH INTER-
ORGANIZATIONAL KNOWLEDGE RECOMBINATION:
AN ANALYSIS OF THE US SEMICONDUCTOR INDUSTRY
BETWEEN 1976 AND 2002**

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Introduction

In their effort to generate novel productive knowledge, firms are largely dependent on the network of inter-organizational relations they are embedded in (Lundvall 1988), and this is especially true for firms operating in industries where knowledge is widely dispersed, complex, and rapidly expanding (Powell et al., 1996). Whether through formal strategic alliances (Eisenhardt and Schoonhoven, 1996; Powell et al. 1996), technology partnerships (Hagedoorn and Schankenraad, 1994), collaboration in research projects (Shan et al., 1994), or board interlocks (Goes and Ho Park, 1997), inter-organizational networks diffuse relevant knowledge across network members that could hardly be gained through arms-length market exchanges. Accordingly, in recent years a considerable body of theoretical and empirical research has accumulated that explains which characteristics of a firm's network position promote firm's inventive performance (see Borgatti and Foster 2003 for a review).

While this line of research has proved enormously useful, a limit is that it is based on an essentially static perspective, which portrays inter-organizational networks as structures merely funnelling knowledge flows across network members. The present article aims to extend this perspective by emphasizing that in addition to a structure of knowledge conduits (Owen-Smith and Powell 2004), inter-organizational networks encompass knowledge wellsprings, i.e. active sources of knowledge generation. An example may serve to clarify our point. In 1975 Chuck Peddle, the founder of MOS Technology, developed and patented a microprocessor chip called 6502. Its speed, power and low cost not only appealed Steve Jobs and Steven Wozniak, future founders of Apple Computers, who included this technology in their first Mac, but also produced a whole series of related inventions by MOS Technology's competitors (such as, for example, the model Zilog Z80 patented by Zilog in the late seventies). As this example shows, while the structure through which knowledge circulates throughout an inter-organizational network tends to remain stable (Walker et al. 1997), organizations continuously learn from each other and generate new knowledge in a self-reinforcing cycle; therefore, the knowledge-access benefits accruing to a focal firm through its network do not only depend on its network position, but also on how much and which new knowledge is being generated by the firm's network contacts.

In setting out to analyze inter-organizational networks from this broader perspective, the article aims to provide three main contributions. First, we will show how the inventive performance of a firm is affected by dynamics of knowledge growth that take place among a firm's network contacts, net of the

effects of structural characteristics of firm's own network position. That is, we will argue and demonstrate that holding constant a firm's positional characteristics, its inventive performance varies as a function of the knowledge generated by its contact firms. Second, we will show that by taking into account these dynamics of network-level knowledge growth, new insights can be gained about the effects deriving from a firm's network position; in particular, by looking at inter-organizational networks as encompassing both knowledge conduits and knowledge wellsprings, we will shed new light on the important debate on the putative effects of network closure and network brokerage. Third, we will provide evidence that due to the self-reinforcing mechanism behind these network-level dynamics, firms tend to cluster into either fast-growing or sluggish sub-networks.

The article proceeds as follows. We begin by explicating the notion of knowledge growth as recombination (Fleming 2001), on the basis of which we flesh out our hypotheses on the effects of inter-organizational networks on firm-level inventive performance. Subsequently, we propose that the causal mechanism by which network-level knowledge growth dynamics affects firm-level knowledge growth can be straightforwardly modeled by means of a "network autocorrelation" (Leenders, 2002). Next, we illustrate our data, which describes all patents and patent citations made in the semiconductor industry between 1975 and 2002, and we discuss why it provides an appropriate empirical setting for our test. Finally, we discuss the results of our analyses, we elaborate on the implications of our study, and we point out the next steps that need be taken to improve on this line of research.

1. Theory and hypotheses

Particularly in high-technology industries (Rosenkopf and Nerkar, 2001), business performance is strongly related to a firm's ability to constantly generate new useful technological knowledge. For that reason, the mechanisms by which new technological knowledge is generated have received increasing attention in recent years. To date, a good deal of consensus has formed around the view that knowledge generation is a problem-solving process wherein solutions are discovered through recombinant search (e.g., Fleming 2001). From this perspective, inventions stem either from the novel combination of knowledge embedded in existing technological components (Gilfillan, 1935; Schumpeter, 1939; Usher, 1954; Nelson and Winter, 1982; Basalla, 1988, Weitzman, 1996; Hargadon and Sutton, 1997; Fleming, 2002) or from reconfigurations of existing combinations (Henderson and Clark, 1990). Recombinant knowledge inputs are often taken from technological solutions developed within the boundaries of a firm (Katila, 2002; Katila and

Ahuja, 2002; Nerkar, 2003). Recombinant search, however, can also involve knowledge residing across firms (Rosenkopf and Nerkar, 2001; Song et al., 2003) or even across industries (Katila, 2002).

Effectively recombining knowledge inputs into a useful invention requires familiarity with those knowledge inputs. Familiarity, in turn, increases with a firm's mastery of the scientific and engineering know-how embodied in the technological solutions wherein knowledge inputs reside, as well with firm's memory of both failed and successful recombination efforts involving those technological solutions (Hargadon and Fanelli, 2002). For both these reasons, the greater is a firm's experience in recombining knowledge inputs generated by a given source, the more effective tends to be the process of recombinant search. Thus, to the extent that a firm's knowledge inputs are generated outside a firm's boundaries, firms embedded in a stable network of inter-organizational knowledge flows tend to be better innovators than firms whose exchanges are based primarily on arms-length relations (Powell 1990).

As said, we aim to develop the argument that inter-organizational networks encompass both knowledge conduits and knowledge wellsprings. That is, we posit that the knowledge inputs a firm has access to through its network depend not only on the position the firm occupies within the network, but also on how actively a firm's network contacts generate new knowledge. Therefore, regardless of a firm's position within its inter-organizational network, we expect a firm's inventive performance to be enhanced to the extent that the firms it regularly takes knowledge from are themselves innovative; further, we argue that the impact of a contact firm on the focal firm is determined by the frequency with which the latter takes knowledge from the former. Hence, we propose the following hypothesis:

HYPOTHESIS 1: *Ceteris paribus*, a firm's inventive performance increases with the inventive performance of its contacts, where the relative impact of each contact firm is determined by the frequency with which the focal firm takes knowledge from it.

If it true that a firm's inventive performance depends on the inventive performance of its contact firms, then it is also true that inventive performance at the level of a firm's inter-organizational network is driven by a self-reinforcing dynamics. That is, each increase in performance taking place within a firm's ego-network will enhance, directly or indirectly, the inventive performance of all other firms in the ego-network; similarly, each decrease in the inventive performance of a firm will hinder to some degree the process of knowledge generation of the whole network around the firm. We reckon that if this self-

reinforcing process of knowledge growth is sufficiently strong relative to exogenous antecedents of firm's inventive performance, then we should be able to discern empirically that firms that are closely connected to one another exhibit more similar inventive performance than disconnected firms. Hence, we propose the following hypothesis:

HYPOTHESIS 2: Clusters of closely connected firms should exhibit either a predominantly high or a predominantly low inventive performance

As said, prior research has debated extensively whether inventive performance is facilitated when a firm occupies a brokering or, conversely, a closed position within an inter-organizational network. From the perspective developed in the present paper, it can be argued that a key contingency determining which of the two positions is most beneficial is the inventive performance of the firms within a firm's ego-network. Following the brokerage argument, we take the position that firms bridging otherwise unconnected sub-networks access a broader variety of knowledge elements, which enhances their inventive performance by securing a broad spectrum of recombinant inputs (McEvily and Zaheer, 1999; Zaheer and Bell, 2005; Rosenkopf and Nerkar, 2001; Song et al., 2003). There is a limit to this principle, though, because firms have limited absorptive capacity (Cohen and Levinthal, 1990), and hence they can handle on so much variety in their recombinant search (Fleming 2001). When a focal firm's contacts generate knowledge at a fast pace this limit is soon reached, because the variety of knowledge to be handled goes through the ceiling when many distinct knowledge trajectories evolve rapidly. Therefore, we expect brokering firms to be able to rip the knowledge-access benefits inherent in their diverse ego-network only to the extent that their contacts generate new knowledge at a relatively low pace. Conversely, we expect firms to be able to more easily exploit the knowledge advances made by their contact firms when the latter are tightly related to one another and, hence, their trajectories of knowledge growth are overlapping. In this case, indeed, the new knowledge generated by a focal firm's contacts is likely to be absorbed more easily and, thus, the benefits deriving from network-level knowledge growth should be ripped more fully. These arguments lead us to formulate our third and last hypothesis.

HYPOTHESIS 3: The positive effect of network-level inventive performance on a firm's inventive performance varies inversely with firm's network brokerage

In Equation 1, y is a vector measuring the inventive performance of each firm in a focal firm's network; W is a weight matrix specifying the impact that the inventive performance of each contact firm has on the inventive performance of the focal firm; and ρ is the network autocorrelation parameter to be estimated within a regression setting (along with a vector X of exogenous independent variables). As it appears, through this network autocorrelation model we can estimate the extent to which a focal firm's inventive performance varies with the inventive performance of the firms in its ego-network, where the impact of each contact firm is assumed to be proportional to the frequency with which the focal firm takes knowledge from it.

3. Data and methods

Since the pioneering works of Schmookler (1966) and Scherer (1965), a large body of research has used patent data to study technological innovation and economic development. Patent data have received much attention because they are systematically compiled, they have detailed information, and they are continuously available over time. In each patent document, there is information concerning the patenting firm, the inventor, the geographic location of the patenting firm, the technology classes the patent belongs to, and the so called patent's prior art – i.e., the citations a patent makes to earlier patents it built on. In this study, we use patent and patent citations data both to trace the inter-organizational network of knowledge flows and to gauge firms' inventive performance, focussing on the US semiconductor industry in the period between 1976 and 2002.

3.1 Tracing inter-organizational knowledge flows

Because a patent's prior art indicates which earlier patents the focal patent built on, prior art has been extensively used to trace knowledge flows across individuals (Nerkar and Paruchuri, 2003), firms (Mowery et al., 1996; Stuart and Podolny, 1996; Song et al, 2003; Rosenkopf and Almeida, 2003), industries (Griliches and Lichtenberg, 1984; Scherer, 1984), and countries (Jaffe, Trajtenberg and Henderson, 1993; Branstetter, 1996). We follow this same methodology to reconstruct the network of inter-organizational knowledge flows in the US semiconductor industry. In particular, we look at the patents granted to a focal firm, and trace all citations each of these patents makes to earlier patents; because for each patent we know the patent holder, we are able to reconstruct the network of inter-organizational knowledge flows, where the value of a tie is determined by the number of patent citations made by a focal firm to each contact firm

within a given time interval.

While using a patent's prior art to trace knowledge flows has many advantages, it also has problems. For example, some citations are strategically introduced in a patent's prior art to prevent litigation; moreover, quite a large share of patent citations are introduced by the patent examiner after the patent has been applied for, and thus can hardly be regarded as indicative of the knowledge inputs the inventor recombined. Therefore, assuming that every patent citation is indicative of a knowledge input recombined in an invention yields a risk of both Type I and Type II errors (Alcacer and Gittelman 2004). Nonetheless, the huge body of research using patents' prior art to trace knowledge flows guarantees that while somewhat problematic, patent citations are reliable indicators of knowledge flows; furthermore, direct validation studies have concluded that patent citations are "a valid but noisy measure of technology spillover" (Jaffe et al., 1998: 198).

3.2. Measuring firms' inventive performance

As mentioned, we also use patent data to gauge firms' inventive performance. In so doing, again, we follow a long-established methodology. For an invention to be patented, it must consist of knowledge that is new, non trivial, and applicable. Accordingly, patent counts are generally regarded as a valuable proxy for measuring knowledge growth if the success, or impact, of each patent is taken into account (Griliches 1990). If a patented invention consists of knowledge that is useful for the generation of subsequent inventions, it will be cited. To say it with Gittelman and Kogut (2003, p. 380): "...because certain patents open richer technological veins, the subsequent advances in related technical knowledge encourage more innovative efforts in that area and, hence, more patents. These, in turn, cite the initial patents that opened this avenue of technological innovation. It is this feedback that carves a trace in the patent patterns." Accordingly, a widely used indicator of the impact of a patent on the advancement of knowledge is counting the number of citations it received, which is called forward citations (Griliches 1990). As an indirect validation that a patent's forward citations capture knowledge contribution, forward citations were found to be positively related to received royalties (Giummo 2003); to intangible assets, controlled for R&D expenditure (Hall cum suis 2004); to the value of a patent in the eyes of the patent holder (Harhoff et al. 1999); and, to the social value of a patent (Trajtenberg 1990). Forward citations were also directly validated as a measure of knowledge contribution through surveys of inventors and experts by Albert cum suis (1991), and by Jaffe cum suis (2000), and to the best of our knowledge, out of a large body of empirical research no

published study has disconfirmed the validity of this measure. Therefore, to gauge a firm's inventive performance within a given time interval, we use the number of forward patent citations received by the patents granted to that firm within that time interval.

3.3. Selection and classification of firms

We focus our analysis on the US semiconductor industry in the period between 1976 and 2002, for four main reasons. First, patenting is extensively carried out in the semiconductor industry, and all major firms, regardless of national origin, patent their inventions in the USPTO (Almeida and Kogut, 1999). Second, inter-organizational collaboration, personnel mobility and knowledge sharing through communities of practice are in part and parcel in the semiconductor industry, which makes inter-organizational knowledge flows particularly salient. Third, several studies have validated the use of patent citation data to track knowledge flows across company boundaries, as well as firms' inventive performance, within this industry (Appleyard 1996; Mowery, Oxley and Silverman, 1996; Almeida and Kogut, 1999; Almeida and Phene, 2004; Stuart, 2000). Fourth, the semiconductor industry is driven by a fast-growing technology, and firms' ability to continuously and speedily improve on their technological knowledge is absolutely crucial for them to be able to command a competitive advantage. We selected target firms by following Hall and Ziedonis (2001), and matched Compustat and USPTO data for 180 firms that actively patented for at least three years between 1976 and 2002. Our sample is consistent with both recent works in the semiconductor industry (Henisz and Macher, 2004) and with the list of semiconductor firms monitored by Dataquest, a specialized market research provider. Furthermore, we used business directories (Who owns Whom US, UK and Asia), industry sources (ICE annual volume 1997) and prior research (Hall and Ziedonis, 2001) to identify the founding date of each firm, and to define whether a firm is an integrated device manufacturer, a fabless firm, or a vertically integrated producer. We classified as other all-remaining types (foundries, equipment firms producing components for semiconductor firms, and service providers other than fabless).

3.4 Modelling the evolution of the inter-organizational network

As said, we model the network of knowledge flows connecting the firms operating in the semiconductor industry from 1976 and 2002. Consistent with prior studies (e.g., Schilling and Phelps 2007), to capture the evolution of this inter-organizational network we partition the observation period into 3-years interval. As argued by Stuart and Podolny (1996), 3 years is roughly

the time that a particular product, design or process remains “new” in the semiconductor industry (e.g., each next-generation computer memory lasts approximately 2.5 years on average). Figure 3 provides a visual representation of the network based on patent grant date¹, depicting the pattern of knowledge flows in the US semiconductor industry in the period 1976-2002. We visualize firms as closer together when they are highly connected by knowledge spillovers, and farther away when they are loosely connected or disconnected². As our sample is characterized by entry and exit of firms in each time windows, we summarize the basic statistics of the 9 networks in Table 1.

3.5 Operationalization of the variables

Dependent variable

Firm inventive performance ($INNOV_{it}$): For each 3-year interval as defined above, we measured firm’s inventive performance as the sum of forward citations (excluding self-citations) received by the firm’s patents during the first 5 years after each patent’s grant. Measuring firms’ inventive performance on the basis of the citations received within a five-year interval could engender an error, since Hall et al. (2001) showed that it takes 90 years to catch 90% of all citations received by an average patent. In order to assess the severity of this error, we rank-ordered the firms in our sample based on the sum of citations their patents received during our earliest time window (1976-1978), and then we rank-ordered them again based on the sum of citations the same patents received throughout our entire observation period, i.e., from 1976 to 2002. Spearman’s rho correlation of the rank orders turned out to be as high as 0.982 ($p < 0.0001$), suggesting that using 5-year intervals to measure forward citations is warranted.

¹ Often, patent’s application year is used instead of patent’s grant year. While we do not expect any significant change to occur as a consequence of this alternative choice, we will repeat our analysis using application date.

² Clearly, this choice yields a bias if the pattern of citations in early periods of observation differs from more recent pattern in a systematic way. In order to assess the magnitude of this bias, we used Quadratic Assignment Procedure (Simpson, 2001) to regress the most recent 3-year window (2000-2002) on the network based on the whole 27-year observation period (1976-2002). The correlation coefficient between the two network configurations is 0.876 (p value 0.0082). Based on these results, we concluded that a network representation based on a 3 years is almost as unbiased as one based on the whole time period.

Explanatory variables

Network's inventive performance(INTERDEP_{it}): As said, we modelled the influence exerted on a firm's inventive output by the inventive output of its ego-network by means of a network autocorrelation measure, as defined by Equation 1. The network autocorrelation measure was operationalized as follows. To build the weight matrix, W_t , we took all patents granted to any of the firms in our sample during each 3-year interval. On the basis of those patents, for each firm in our sample we summed the citations made to all other firms, thereby measuring the flow of knowledge running to the citing firm from each cited firm. Thus, a tie weight (w_{ijt}) between firm i and firm j indicates the number of times i cites j during time interval t ⁶. Finally, to make sure that our measure is independent of the size of a firm's patent portfolio, for each 3-year time interval we row-normalized the weight matrix. The normalized matrix indicates, for each firm, what proportion (p_{ijt}) of its total backward citations is made to each of the remaining firms. Therefore, our autocorrelation measure is computed as follows:

$$\text{INTERDEP}_{it} = \sum_{j: j \neq i} p_{ijt} \text{INNOV}_{jt} \quad [2]$$

Structural holes (STHO_{it}): To compute firm's network brokerage, we followed Burt (1992) and measured the extent to which a firm bridges structural holes in its ego-network.

Structural holes X Network's inventive performance (STHOxINTERDEP_{it}): To model how the effects of structural holes on a firm's inventiveness change with the inventive performance of the firm's ego-network, we constructed an interaction term between structural holes and network autocorrelation. To overcome potential collinearity, the term was mean-centred (Aiken, West and Reno, 1991)

Control variables

Industry inventive performance(SPILLOVER_{it}): To compute the effects of diffuse knowledge spillovers taking place in the semiconductor industry over and above of the ones channelled through the inter-organizational network, for each 3-year interval we computed the average inventive performance of all nodes in the network, excluding the focal firm.

Firm patent (NPAT_{it}): To account for firms' accumulated expertise in inventive processes (Phene et al., 2006), we use the number of patents granted to them within a given time window.

Corporate R&D intensity (RD_{it}): Measures of R&D expenditure have frequently been used as a proxy for a firm's technological resources (e.g., Montgomery and Hariharan, 1991), as well as a measure of the investments a firm makes in the production of technological knowledge (Cohen, 1995). Hence, we controlled for R&D expenditure, which we expressed as the logarithm of firms' R&D expenditure (in million of dollars) during the pertaining time interval⁷. Where R&D data were not available (12 cases), we used a regression imputation procedure to impute the data for this variable based on other firm-level information.

Firm size (SIZE_{it}): A firm's size is likely to influence its inventive performance in several ways. For example, it has been argued that learning, scale, and scope advantages enhance firm's innovativeness in large organizations (Cohen & Levin, 1989; Henderson & Cockburn, 1996). Large firm size can also hinder innovation, though. Evaluation of R&D projects in large organizations is difficult, which lowers incentives and reduces the productivity of individual researchers (Cohen, 1995). Empirical results on the effects of size on product innovation have been mixed, possibly reflecting these multiple underlying mechanisms. Although most studies have reported positive effects (e.g., Henderson and Cockburn, 1996), some studies have found a negative effect (Mansfield, 1968), or no effect at all (Clark, Chew, & Fujimoto, 1987). We measured size as the number of corporate employees (thousands). When employment data were not available, we used a regression imputation procedure to impute the data for this variable based on other firm level information, using STATA ice function. A total of 74 values were imputed.

Firm age (AGE_{it}): Prior research agrees that firm age is negatively related with inventive performance, because established firms have a higher tendency to incur learning traps than start-ups (Levinthal and March, 1993; Ahuja and Lampert, 2001). Older firms tend to create innovations that are less influential on subsequent technological development (Phene et al., 2006). To control for these effects, we computed firms' age as the number of years since firm founding.

Firm Type (IDM_{it}, FAB_{it}, VI_{it}, OTHER_{it}): We built a set of dummies to control whether firms are an

integrated device manufacturer, a fabless, a vertically integrated semiconductor producer or an equipment/foundry.

Citations made (CMADE_{it}): We computed a firm's total citations made to earlier patents, to make sure that our network variables based on backward citations are not influenced by differences in firms' propensity to cite.

Self citations (SELFRATIO_{it}): Since all the network and patent measures are computed excluding self cites, we believe it is important to account for the latter. Furthermore, firms using their own knowledge are generally regarded as particularly able to exploit and appropriate their technological inventions (Hall et al. 2001). To measure the extent to which a firm relies on its own previous knowledge, as opposed to external sources, for each firm in each time interval we compute the ratio between backward self-citations and total backward citations.

Technological diversification (TECHDIV_{it}): Prior work has found a positive effect of technological diversification on innovativeness (Phene et al. 2006). To control for this effect, we calculate the Herfindal index of technological diversification of a firm patent portfolio (i.e., one minus the sum of the squared share of patents in each USPTO patent class).

Geographical diversification (GEODIV_{it}): Prior work has shown mixed evidence regarding the relationship between geographic diversification and knowledge creation. We follow Ahuja (2000) and compute the Herfindal index of geographic diversification of a firm patent portfolio (i.e., one minus the sum of the squared share of patents in each country). Patents were assigned to countries based on the first inventor's nationality.

Time dummies (1979-1981_i, 1982-1984_i, 1985-1987_i, 1988-1990_i, 1991-1993_i, 1994-1996_i, 1997-1999_i, 2000-2002_i): We also introduced a set of dummies to control for the effects of time, and for all possible time-varying exogenous factors (e.g., marcoeconomic fluctuations).

4. Results

We report summary statistics and correlations between the key variables in Table 2. Eleven firms make no citations at all to our initial sample firms; hence, we excluded them from the regression analysis. Moreover, for 26 firms we do not have data covering more than one three-year period; because we adopt fixed-effect estimation, these observations are dropped. Finally, for 241 firm-period data points we could not observe information regarding sales, R&D and employment, but only patenting activity. This is because, in the pertaining periods the firm was active but not publicly traded. Given that these observations did not meet the requirements for imputation, we decided to drop them. As a consequence of these choices, our regression analyses are based on 143 firms, yielding a total of 610 firm-period observations.

The dependent variable in this study, $INNOV_{it}$, is a count variable and takes on only nonnegative integer values. The linear regression model is inadequate for modelling such variables because the distribution of residuals will be heteroscedastic and non-normal. Since our variable shows high variance relative to the mean, we used negative binomial regression analysis (Cameron and Trivedi, 1986). We estimated both fixed effects and random effects models. In Table 3, we report the results of our analyses. Model 1 is a baseline model. All controls behave as expected, with exception of size that has a negative effect on firms' inventive performance. All time dummies are positive and significant, apart from the dummy referring to the last period; in this last case, the negative sign reflects data truncation. In model 2, we introduce our SPILLOVER variable, representing the average aggregate knowledge output of all nodes in the network excluding the focal firm, and which therefore indicates industry-level inventive performance⁸. The effect on firm's inventive performance is significant and negative ($p < 0,0001$). The result hints to the effect of competition for knowledge among firms (Podolny et al. 1996). This result is important because it shows that the knowledge produced by other firms can damage a focal firm if the latter is not able to absorb and build on that knowledge.

In model 3, we introduce our network autocorrelation parameter (INTERDEP). As we predicted, the inventive performance of a focal firm is positively and significantly associated with the inventive performance of the firm's ego-network ($p < 0,0001$). Thus, firms significantly benefit from the inventiveness of the firms in their inter-organizational network, and the benefit brought to a focal firm by each contact firm is proportional to the extent to which the focal firm recombines knowledge from it. Because these network-level dynamics are underpinned by a self-reinforcing mechanism, we argued that we should detect empirically clusters of fast-growing firms,

and clusters of sluggish firms. To be able to detect these clusters, we partitioned the sample into 4 quartiles based on their average inventive performance over the observation period. Figure 5 is obtained through a Spring Embedding algorithm and represents the top performing 25% firms as blue nodes, and the 25% slowest growing firms as red nodes. The second and fourth quartiles have been removed from the picture to increase the contrast between fast-growing and sluggish firms. In the network depicted in Figure 5, the distance between firms is proportional to the frequency of knowledge flows between them. As it appears, this representation confirms that inventive performance is clustered, with fast-growing firms occupying central positions in the network and reciprocally feeding each other's inventive performance. Low-growth firms, conversely, cluster at the border of the network. While this graph provides suggestive evidence, rather than strong test of our hypothesis, it does indicate quite clearly that the phenomenon we are after exists.

Model 4 introduces our structural holes variable (STHO). Confirming the brokerage argument, the effect is positive and significant ($p < 0,001$). Hence, bridging knowledge from organizations belonging to disconnected sub-networks induces a variety effect that fosters inventive performance in the focal firm. Model 5 introduces the interaction effect between structural holes and network autocorrelation (STHOxINTEDEP). The sign of the coefficient is negative and statistically significant ($p < 0,016$), as is also confirmed by the two-way interaction graph reported by Figure 4. Therefore, confirming our hypothesized explanation, the effects of brokering structural holes on a firm's inventive performance are positive when the firm's contacts grow relatively slowly; however, as a firm's contacts start to generate new knowledge at a fast pace, absorbing and recombining their knowledge becomes increasingly difficult and, therefore, at some point the effects of structural holes turn negative.

5. Discussion

In this article, we argued that a vantage point can be gained by extending the currently predominant perspective on how inter-organizational networks affect firm-level inventive performance. Namely, we argued that in addition to a structure of knowledge conduits, inter-organizational networks encompass knowledge wellsprings, i.e. active sources of knowledge generation. Therefore, what a firm is able to invent depends significantly on the new knowledge that is pumped, at any point in time, into its network of stable inter-organizational network relations, and not only on characteristics of the position the firm occupies therein. In setting out to analyze inter-organizational networks from this broader perspective, the article

provided a threefold contribution. First, we showed that the inventive performance of a firm is affected in a statistically significant way by dynamics of knowledge growth taking place among firm's ego-network contacts. This means that firm's inventive performance varies as a function of the knowledge generated by its contact firms. Importantly, this effect holds true even controlling for a number of possible alternative explanations, including the structural characteristics of firm's own network position.

Second, we showed that by taking into account these dynamics of network-level knowledge growth, new insights can be gained also on the effects deriving from a firm's network position, in particular network closure and brokerage. Namely, we argued and demonstrated that due to their limited absorptive capacity, brokering firms are able to rip the knowledge-access benefits inherent in their diverse ego-network only to the extent that their contacts generate new knowledge at a relatively low pace. Conversely, firms are able to more fully exploit the knowledge advances made by their contact firms when the latter are tightly related to one another and, hence, their trajectories of knowledge growth are overlapping.

Third, we showed that the knowledge-access benefits inherent in inter-organizational networks are underpinned by a self-reinforcing process. That is, each increase in performance taking place within a firm's ego-network will enhance, directly or indirectly, the inventive performance of all other firms in the ego-network; similarly, each decrease in the inventive performance of a firm will hinder to some degree the process of knowledge generation of the whole network around the firm. As a consequence, firms that are closely connected to one another exhibit more similar inventive performance than disconnected firms, and thus the inter-organizational network tends to partition into fast-growing and sluggish sub-networks. From a strategy perspective, this finding seems relevant. Given that firms are steadily embedded in their ego-network of inter-organizational relations, much of their fate is likely to be determined by whether they belong to a fast-growing or to a sluggish one. From a methodological perspective, we used flows of articulated technological knowledge to define inter-organizational networks, on the basis that knowledge can be exchanged, voluntarily or involuntarily, only if the firms share common practices and tacit knowledge (Brown and Duguid, 2001). Our work suggests that a study based on networks defined by inter-firm flows of codified and technical knowledge leads to results comparable to studies based on social relationships across actors. Hence, we believe that innovation network research could gain a vantage point by shifting the focus from the social dimension of networks to their knowledge dimension and from modelling knowledge flows directly. Moreover,

network autocorrelation models have been largely employed to study social influences or economic geography, but far less used for studies on innovation and knowledge flows, where correlation across units is often seen as a methodological problem to tackle. We believe that the use of these models can contribute to modelling innovation dynamics in contexts where interdependencies are pervasive.

Our study points to some important implications. Our approach points out that technological capabilities growth is a collective phenomenon, as each firm outcome is affected by the growth of other players; moreover, firms that are capable to source knowledge from high growth player benefit from the endogenous mechanism largely. As a practical implication, our results points to the importance of strategic knowledge sourcing on firm innovative performance. We suggest that firms should source knowledge from proximate, fast growing technological players to benefit from growth externalities; moreover, we highlight that bridging diverse knowledge sources is a viable strategy to innovation but, as technological growth pace of sources increases, the beneficial effect of variety is offset by an increasing difficulty in knowledge absorption, recombination and use. Firms in a high pace technology based industry should carefully manage their technological partner choice in order to balance these effects.

5.1 Limitations of the study

The study is still in a preliminary phase and, of course, has a number of limitations. Most of our conclusions rely on patent data, whose validity as proxies of knowledge flows has been debated. Firms may display systematic differences in their propensity to seek patent protection for important technical advances. More importantly, patents are by definition examples of codified knowledge, and citation measures therefore may not capture flows of the tacit knowledge that often forms the basis for firm-specific capabilities. Tacit knowledge flows are virtually impossible to measure, however, and we rely on the assumption that the codified knowledge, represented by patents, and tacit knowledge are complements, rather than substitutes, and that codified knowledge flows and the tacit knowledge flows of interest are closely linked. There is considerable support for this assumption (Patel and Pavitt, 1994).

Network stability is an issue that is worth further discussion. The semiconductor industry during our observed time-span was characterized by turbulence and by a high number of entry and exits in every time window. For this reason, network structure was quite unstable, and measuring growth in a dynamic sense, as difference between outputs at different times, would have led to the loss of a high number of

observations. Since we aim to explain knowledge growth, the next step would be to isolate a subperiod between 1976 and 2002 (characterized by more stability) and test our theory within a more fully dynamic frame.

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6. FIGURES AND TABLES

Figure 1: Example of recombination patterns across firms.

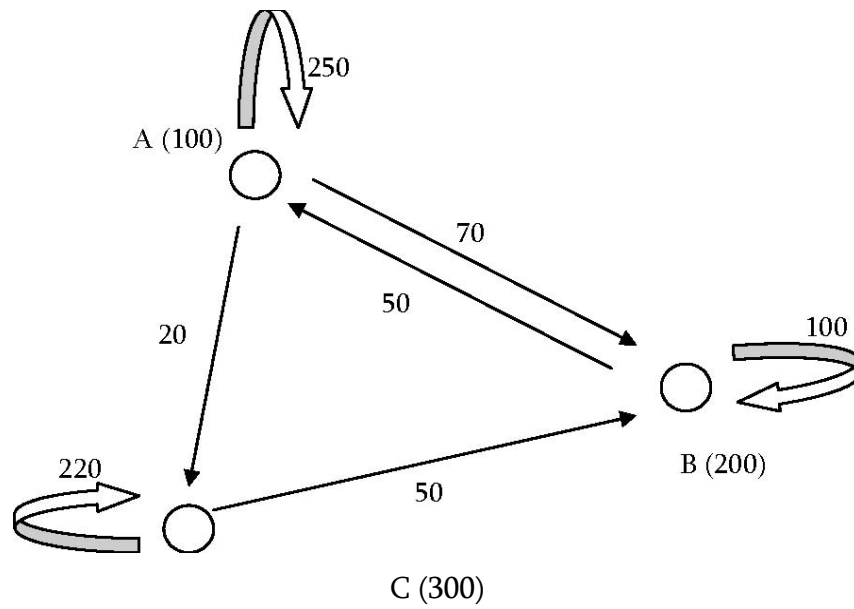


Figure 2: Semiconductor patents, yearly trend Figure 3: Network of knowledge flows between semiconductor players 1976-2002. Figure 4. Two-way interaction graph

Semiconductor patents Yearly trend

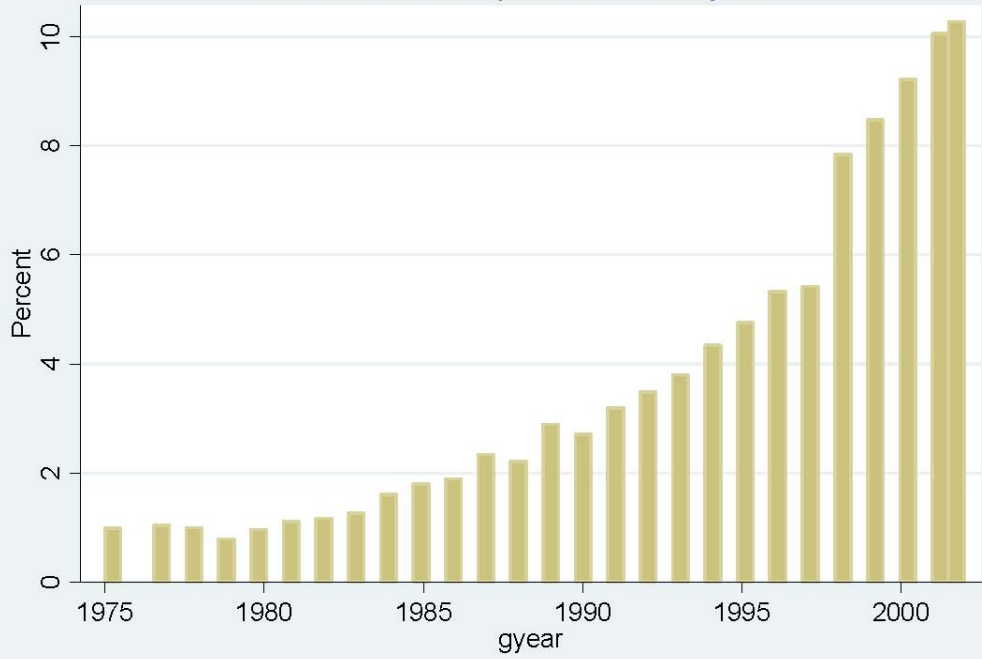


Figure 3: Network of knowledge flows between semiconductor players 1976-2002.

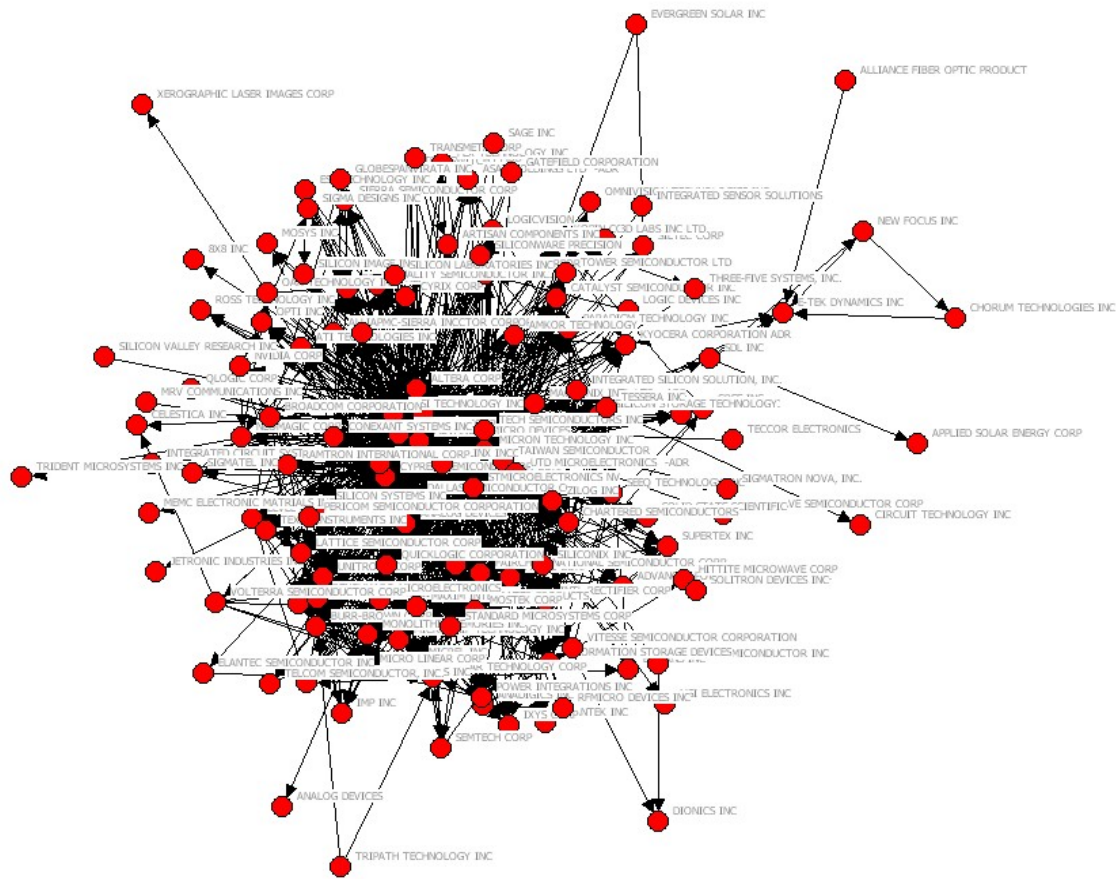


Figure 4. Two-way interaction effect between structural holes and network autocorrelation on inventive performance

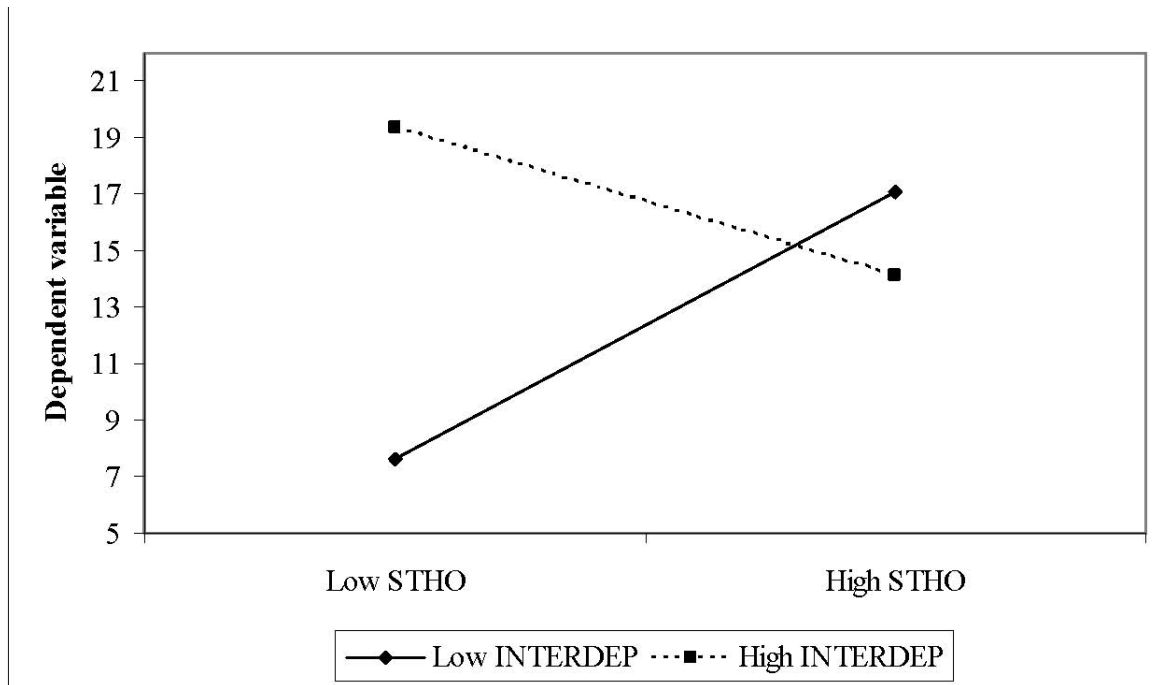


Figure 5: Network of knowledge flows between semiconductor players 1975-2002: faster growing quartile in blue, lowest growing quartile in red.

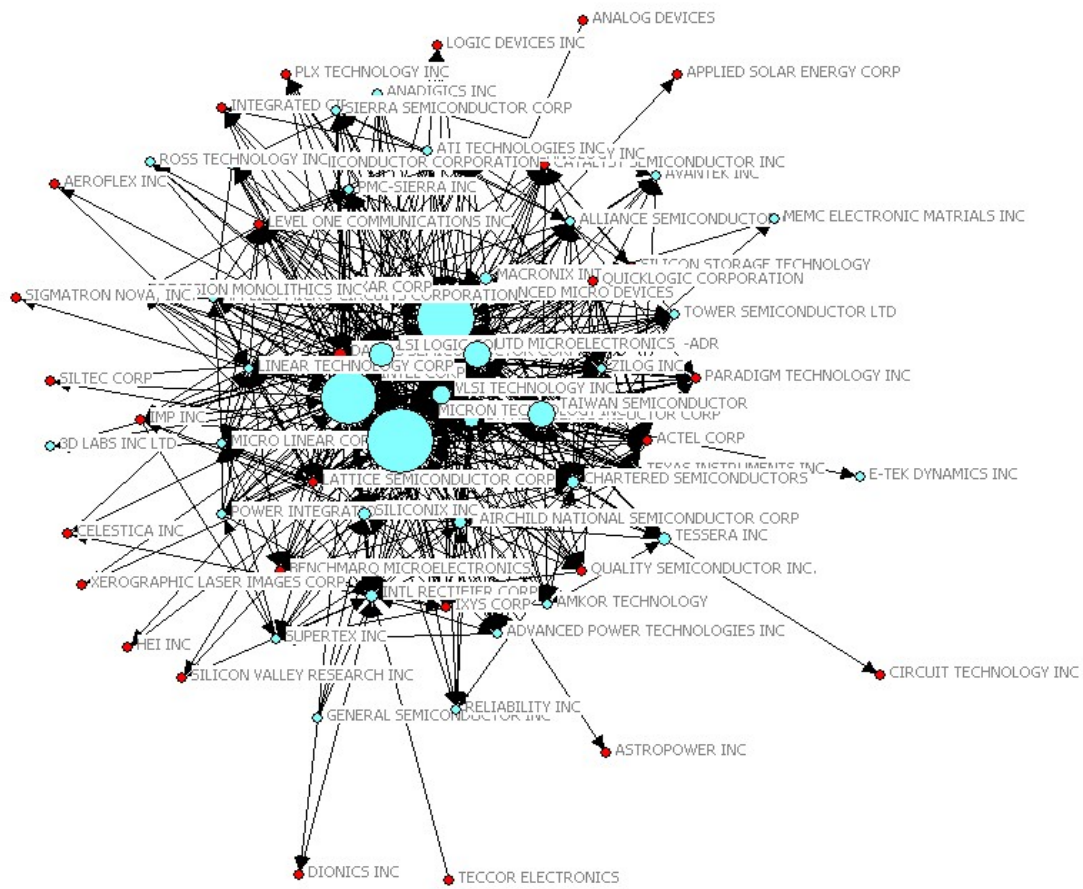


Table 1. Summary citation statistics by firm type and time interval

Period	Nodes	fabless	IDM	Other	Vertically integrated	Entry	Exit
1976-78	41	4	19	6	12	-	-
1979-81	43	5	21	5	12	7	5
1982-84	48	8	21	7	12	8	3
1985-87	71	17	29	12	13	25	2
1988-90	91	23	38	17	13	27	7
1991-93	121	34	50	24	13	31	1
1994-96	128	44	48	23	13	15	8
1997-99	161	61	54	33	13	35	2
2000-02	173	65	59	36	13	13	1
Total	877	261	339	163	114	161	29

Table 3: Results of Negative Binomial Regression for Number of Citations (* p<10%, ** p<0,05, ***, p<0,01)

	Fixed effects				
	Model 1	Model 2	Model 3	Model 4	Model 5
	INNOV	INNOV	INNOV	INNOV	INNOV
Constant	-178,062 (0.21171)***	0.16061 (0.34444)	0.39272 (0.31646)	-0.21577 (0.36191)	-0.05684 (0.36066)
AGE	0.01360 (0.00541)**	0.01688 (0.00571)***	0.02232 (0.00511)***	0.02291 (0.00508)***	0.02398 (0.00505)***
SIZE	-0.07142 (0.05453)	-0.02272 (0.05254)	-0.05329 (0.05084)	-0.05092 (0.05080)	-0.04580 (0.05042)
RD	0.47960 (0.04529)***	0.43986 (0.04396)***	0.38537 (0.04151)***	0.36499 (0.04136)***	0.36617 (0.04094)***
SELFRATIO	-0.00012 (0.00004)***	-0.00007 (0.00004)*	-0.00004 (0.00004)	-0.00004 (0.00003)	-0.00004 (0.00003)
NPAT	0.00018 (0.00005)***	0.00015 (0.00005)***	0.00014 (0.00005)***	0.00013 (0.00004)***	0.00014 (0.00004)***
TECHDIV	0.33634 (0.16011)**	0.36580 (0.15956)**	0.51879 (0.16318)***	0.49325 (0.16432)***	0.51981 (0.16532)***
GEODIV	-0.60637 (0.12494)***	-0.60549 (0.12385)***	-0.50302 (0.11671)***	-0.45503 (0.11463)***	-0.45363 (0.11454)***
CMADE	0.00005 (0.00002)**	0.00003 (0.00002)	0.00001 (0.00002)	0.00002 (0.00002)	0.00001 (0.00002)
VI	-0.73327 (0.33193)**	-0.71110 (0.32999)**	-0.43593 (0.31997)	-0.34131 (0.32121)	-0.29388 (0.31645)
OTHER	0.71283 (0.26014)***	0.63521 (0.26092)**	0.78814 (0.25853)***	0.76220 (0.25480)***	0.75243 (0.25744)***
IDM	-0.29653 (0.17116)*	-0.37642 (0.17492)**	-0.20970 (0.17328)	-0.22606 (0.17319)	-0.21994 (0.17353)
period7981	-0.41683 (0.17724)**	-0.49737 (0.15345)***	-0.48399 (0.13970)***	-0.49456 (0.13365)***	-0.49720 (0.12768)***
period8284	-0.30994 (0.16972)*	0.69240 (0.19946)***	0.85447 (0.18058)***	0.81678 (0.17120)***	0.84406 (0.16404)***
period8587	-0.12243 (0.15921)	141,609 (0.25578)***	155,487 (0.22917)***	149,436 (0.21753)***	154,546 (0.21006)***
period8890	-0.01915 (0.16154)	182,102 (0.29969)***	192,016 (0.26601)***	179,854 (0.25378)***	187,006 (0.24623)***
period9193	0.28568 (0.16682)*	293,424 (0.41524)***	295,805 (0.36317)***	277,051 (0.34683)***	291,007 (0.33931)***
period9496	0.52338 (0.17099)***	619,639 (0.81011)***	636,461 (0.71020)***	608,065 (0.67360)***	642,979 (0.66327)***
period9799	0.23550 (0.18699)	478,830 (0.67808)***	476,670 (0.59209)***	446,403 (0.56509)***	479,892 (0.56216)***
period0002	-127,878 (0.22087)***	-154,591 (0.19919)***	-168,814 (0.18308)***	-191,296 (0.19169)***	-196,653 (0.18949)***
SPILLOVER		-0.00452 (0.00061)***	-0.00544 (0.00057)***	-0.00535 (0.00054)***	-0.00552 (0.00052)***
INTERDEP			0.00008 (0.00001)***	0.00008 (0.00001)***	0.00008 (0.00001)***
STHO				121,566 (0.37564)***	100,360 (0.37843)***
STHOxINTERDEP _{it}					-0.00012 (0.00005)**
Observations	610	610	610	610	610
Number of group(cusip)	143	143	143	143	143
Log likelihood	-2380.903	-2357.35	-2330.258	-2324.4275	-2321.72

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%