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# ENTRY DESPITE THE NETWORK :
# THE RELATIONSHIP BETWEEN NETWORK STRUCTURE AND ENTRY PATTERNS
# IN AN EMERGENT ORGANIZATIONAL POPULATION.

Sophie Manigart, University of Ghent, Belgium

Koenraad Debackere, University of Louvain, Belgium

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Mail address : Sophie Manigart
University of Gent
Hoveniersberg 4
B – 9000 Gent
Belgium
Tel. : (32)9/264 35 08
Fax : (32)9/264 35 77
e-mail : sophie.manigart@rug.ac.be

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## ABSTRACT

Organizational ecology and social network theory are combined to explain entry patterns. We hypothesize that entry rates are influenced by the structure of collaborative networks within the market, particularly their stability and prestige. The hypotheses are tested and partly supported in the emerging population of Dutch venture capital companies.

**Organizational ecology, networks, entry**

## INTRODUCTION

What are the processes underlying organizational entry into new markets ? To answer this question, much thought has been devoted to the relationship between market structure and entry behavior (Bain, 1956 ; Baumol, 1982 ; Hannan and Freeman, 1989 ; Haveman, 1993). In these studies, entrants are both existing organizations which enter the new market through diversification (e.g. Mitchell, 1989 ; Haveman, 1993 ; Mitchell and Singh, 1993) and organizational foundings (e.g. Feeser and Willard, 1990).

In their quest to unravel the relationship between market structure and organizational entry, organizational ecologists have shown that the number of organizations in the total market, in different strata of the market and in various geographical locations affects entry rates (e.g. Barnett and Carroll, 1987 ; Hannan and Carroll, 1992 ; Lomi, 1995). Economic approaches, on the other hand, have highlighted how market structure influences entry through economics of scale and scope, absolute cost advantages or capital requirements (e.g. Tirole, 1988). Although both streams of though have contributed significantly to our understanding of market entry, it is the central thesis of this paper that these insights can be improved in at least two ways.

First, by introducing the construct of the ‘social capital’ of organizations (Burt, 1992 ; Coleman, 1988 ; Granovetter, 1985), we develop the hypothesis that the structure of the market is only partially captured by organizational density and market concentration. The network of relationships amongst different actors in the market is hypothesized to be an important structural market characteristic that may influence the rates of entry.

Second, most research that has looked into inter-organizational networks has focused on an analysis of 'local' networks that have developed around specific organizations (e.g. Freeman and Barley, 1990 ; Jarillo, 1988 ; Mintz and Schwartz, 1984). However, when relating market entry to network structure, it is obvious that not only are organizations part of complex and often intertwined networks of interrelationships, but that the networks themselves are also likely to exhibit structural characteristics that are invisible from the perspective of any single organization caught in the network but nevertheless strongly influence entry patterns.

## ENTRY AND POPULATION DENSITY

Organisational ecology (Hannan and Freeman, 1977, 1989) shows that the founding of organizations depends to a large extent on the number of organizaitons that already exist in the population of interest, i.e. the organizational density. Initially, when density is low, each founding eases subsequent foundings (Hannan, 1986 ; Hannan and Carroll, 1992), because the simple prevalence of a form tends to give it legitimacy (DiMaggio and Powell, 1983). Moreover, the training ground for qualified personnel grows (Brittain and Freeman, 1980) and the supporting environment is widened and strengthened (Garud and Van de Ven, 1989). Though, once a threshold of organizations of a certain kind exists, the legitimation effect saturates and does not increase further (Hannan and Carroll, 1992 :51). In this approach, population density is a proxy variable for the legitimation process, which is not directly observable nor measurable.

As the density increases further, competition for limited resources becomes the prevalent environmental force, inducing a negative relationship between density and founding rates, everything else equal (Hannan and Carroll, 1992 :95). Given a set of environmental conditions that sets a carrying capacity – i.e. the maximum number of organizations in a certain population that can thrive on the limited resources available (Hannan and Freeman, 1989 :123-129) -, the more abundant the number of competitors, the fiercer the competition will be and the lesser the incentives for new organizational entries. Moreover, new organizations compete with established ones that have survived selectionist pressures and that are likely to fit well with the environment (Hannan and Freeman, 1977, 1989). Thus, the founding rate declines as the number of organizations increases in the high density range. Both processes, legitimation and competition, lead to an inverted U-shaped relationship between population density and founding rate, called the 'density dependence model' (Hannan and Freeman, 1989).

## ADDING NETWORKS TO THE MODEL

The density in a population is one measure that captures the legitimation and competition of a new form. We now hypothesize that, beside density, the formation of networks in the population is important in explaining entry patterns. Lomi and Larsen (1996:1289) have shown through simulations that 'vital population rates' such as birth and death rates are "a function of how individual organizations connect to their local environment (that is, to other organizations in their neighborhood)". Networks capture relationships among organizations : "The basic assumption of network relationships is that one party is dependent on resources controlled by another, and that there are gains to be had by the pooling of resources" (Powell, 1990 :303). Furthermore, organizations engage in relationships built on mutual trust to overcome their ability to anticipate uncertain results (Barney and Ouchi, 1986 ; Larson, 1992 ; Pisano, Shan and Teece, 1989).

Whereas population ecology stresses the primacy of environmental forces on organizational existence, social ecology points to the proactive networks that organizations build in order to cope with those forces (Astley and Fombrun, 1983 ; Coleman, 1988 ; Emery and Trist, 1973 ; Granovetter, 1985). Social ecology builds on the assumption that no single organization possesses the necessary financial and technical capabilities to thrive in a competitive environment. Therefore, cooperation offers a viable alternative to gain access to complementary assets and skills. Cooperative links may be established with competitors in the same population or with key actors in the population's environment ; Baum and Oliver (1992) have shown that the more formal relations exist with the environment, the higher the founding rates. Especially in emerging and turbulent industries, incumbents perceive an urgent need for cooperation to overcome the goal uncertainty and complex and indivisible problems they face (Cohen and Levinthal, 1990 ; Gray, 1985).

However, the cooperative strategy of each organization is likely to be influenced by the structure of the network in the population (Barley, Freeman and Hybels, 1992). This has major implications for potential entrants. As they often lack (some of) the resources required to compete successfully in the new market, a cooperative arrangement may provide the best solution to overcome entry barriers imposed by a lack of know-how, economies of scale and scope, or complementary assets (Gray, 1985).

The more cooperative arrangements already exist in a population of organizations, the more difficult it is expected to be for new entrants to enter the market. Entrants lack organizational legitimacy to overcome barriers to forge relationships with existing organizations. Indeed, network partners have to invest considerable amounts of time and energy in developing a viable cooperation (e.g. Larson, 1992 ; Powell, 1990). The more viable network relationships already exist in the industry, the harder it will be for entrants to team up with existing organizations, as partnering is likely to be restricted to organizations that can contribute significantly to their goals. As a consequence, only those organizations which possess assets complementary to those of the incumbents will face opportunities to enter the cooperation. Recognition of entrants will depend upon the prestige and legitimacy of the organizations, but this is precisely what most potential entrants lack. Hence our first hypothesis, which – it should be stressed – is conditional on the density dependence model :

Hyp. 1 : The more cooperative agreements exist in a population, the more entry into the population will be deterred.

Apart from the number of existing network relations in a population, we hypothesize that the duration of the existing relations will influence the entry rate. Indeed, it will be even more difficult for a potential entrant to establish a link with an incumbent if this incumbent is already involved in long time, stable relationships with other organizations. The more a population is characterized by long term relationships, the more entry will be deterred. Hence,

Hyp. 2 : The more stable the cooperative arrangements are, the more entry into the population will be deterred.

The stability of the cooperative arrangements in a population has several dimensions : the average duration of relationships and the spread of the duration. A longer average duration is likely to negatively influence the entry rate ; a higher variation of the duration, on the other hand, is likely to positively influence the entry rate. Indeed, a high variation of duration implies that a number of organizations have not yet established stable, long term relationships. Therefore, there still exist opportunities to team up with these organizations.

Hyp. 2a : The longer the average relationship between members in a population is, the lower the entry rate will be.

Hyp. 2b : The more the duration of relationships between members in a population varies, the higher the entry rate will be.

Researchers further agree that the actions of prestigious organizations influence the actions of other organizations in the market (Burns and Wholey, 1993 ; Haveman, 1993 :598). However, it is at this point not clear how reputation or prestige of high-status incumbents influence foundings or entries (Amburgey and Rao, 1996 :1272). We hypothesize that the higher the average prestige of organizations in an industry is, the lower the entry rate will be. Indeed, as prestige is an element which entrants normally lack, it will be more difficult to enter an industry where the average prestige is high.

Hyp. 3a : The entry rate into a population is lower when the average prestige of the members in the population is high.

How does the dispersion of prestige throughout the industry affect the rate of entry ? More precisely, is an industry structure where prestige is concentrated among a few organizations more favorable to potential entrants than a structure where prestige is rather equally spread across incumbents ? DiMaggio and Powell (1983) emphasize the role of prestigious organizations in attracting new entrants. As potential entrants often face considerable 'searching costs', they will tend to evaluate the overall attractiveness of an industry against the prestige position of a limited number of organizations. When prestige is more or less equally spread across incumbents, no highly visible corporate elite of prestigious organizations exists. The industry structure is fragmented and the appeal to potential entrants to mimic prestigious incumbents is hence minimal.

Hyp. 3b : The entry rate into a population is higher when the prestige of the members in the population is concentrated into a few highly visible organizations.

## RESEARCH SITE

Foregoing hypotheses are empirically tested in the emerging population of venture capital (VC) organizations in the Netherlands from 1970 to 1990. Acting as financial intermediaries, VC companies provide equity or quasi equity financing to unquoted companies. Their main objective is to achieve long-term capital gains to remunerate risks. In addition, VC companies can provide active management support for investees (Sapienza, Manigart and Vermeir, 1996). A formal VC industry emerged in the U.S. in the late 1940s when some wealthy families institutionalized their investment process (Bygrave and Timmons, 1992 :17-19). It was only in the early 1970s that this type of investment was copied in Europe.

Development capital, provided to mature companies, constitutes the bulk of the investments of VC companies (Ooghe, Manigart and Fassin, 1991 :393). We have chosen the population of Dutch VC companies, because it is one of the most developed in Europe (Ooghe, Manigart and Fassin, 1991). The restriction to a single country is no problem, as the investment and finance patterns reveal that this industry was nationally oriented for the time-period considered here. The observation period covered in this study allows to study the emerging phase of an industry (Manigart, 1994).

Networking to scan investment opportunities, shared investments and joint counseling in overseeing funded ventures are central to doing business in this market (Bygrave, 1988 a and b). Indeed, many of the reasons Powell indicates to explain the emergence of cooperative arrangements [“…to gain fast access to new technologies or new markets, to benefit from economies of scale in joint research and/or products, to tap into sources of know-how located outside the boundaries of the firm and to share the risks for activities that are beyond the scope or capability of a single organization” (Powell, 1990 :315)] apply to the VC industry. For instance, risk sharing is crucial. The money a single VC company can invest is usually limited ; therefore co-investing with other VC companies in a target company is interesting. Second, Bygrave (1988a :112) found that “the principal reason for co-investing was… to share expertise”. The time needed to screen a proposal is a critical resource for VC companies. Achieving economies of scale during the screening of investment proposals is therefore advised. Sharing information and expertise with other VC companies, whose judgment is trusted, is thus desirable.

## THE VARIABLES

The first phase of the data collection process consisted in identifying all VC companies that entered the industry between 1/1/1970 and 31/12/1990. Directories on the VC industry were the main data sources : Venture Economics' European Guide to Venture Capital (1985 and 1988), European trade directories and journals (from 1983 until 1992) and the membership directories of the European Venture Capital Association and of the Dutch VC association.

A problem with these data sources is that they only began to appear in the 1980s. As a consequence, we lacked information on the VC industry in the 1970s. This information gap was therefore covered by consulting early studies on the VC industry in The Netherlands, as well as yearly accounts of the major VC companies, which provided enough information to cover the first decade considered in this study. These sources are further complemented with trade journals, newspaper articles, etc. Moreover, telephone interviews were conducted with industry watchers in order to complete the data and with managers from the companies for which information was missing. This approach resulted in a dataset of 104 entries in the Dutch VC industry between 1970 and 1990.

Table 1 lists the basic statistics of the independent variables (panel A) and their correlations (panel B).

- Insert Table 1 about here –

*Dependent variable*

The dependent variable is the time interval between two entries ; the day of the firm's legal establishment is taken as the entry date for newly founded firms, while the day of the first investment is taken as the entry date for existing companies. Exact entry dates (year, month and day) are known for 75 of the 104 VC companies, the year and month of entry is known for an additional 17 companies, while for 10 companies only the entry year is known. Finally, for two companies nothing is known about their entry date. When the exact entry date (year, month and day) is unknown, a random entry day and/or month (drawn from a uniform distribution to assure that every day has an equal chance of being chosen) is assigned to complete the entry dates (Hannan and Freeman, 1989:210).[1] For the two VC firms for which the year of entry is unknown, the first year in which some data source mentions the existence of the firm is taken as the entry year. Similarly, for a company that disappeared, but for which the exact year of exit is unknown, the last year in which its existence is reported is taken as the last year of its organizational life ; it is necessary to know the exact day of exit in order to calculate the independent Density variable. When two VC companies enter the industry on the same day, it is assumed that one of the two (assigned at random) entered half a day earlier than the other (Hannan and Freeman, 1989:211). There were never more than two entries recorded on one day.

- Insert Figures 1 and 2 about here –

In figure 1, we show the evolution of the yearly number of entries and exits. In the first decade, entries were uncommon. In 1980, a period of rapid growth of the VC industry occurred ; while the first decline in the number of entries appeared in 1987. The first exits occur in 1985 ; in 1988 and 1989 the number of VC organizations that ceased their activities was relatively high.

[1] In order to assess how the results are affected by the random assignments for the missing dates, three datasets with different random entry dates are constructed and similar analyses are performed on all three. This approach provides a test of the sensitivity of the results to missing data and shows that the missing data do not influence the results.

*Density variables*

Density and density$^2$/1000 are calculated as the sum of all entries minus all exits that occurred before the entry of the particular VC company. In figure 2, we show the end-of-year density for each year of observation. The density rises sharply until 1988, when it reaches a peak ; the number of VC companies is slightly lower in 1989 and 1990.

*Network variables*

Two VC firms are said to have a network relationship when they co-invest in the same investee company (Bygrave, 1988a) ; their relationship lasts as long as their co-investment. This, of course, captures only one of possible network relationships that may exist between VC companies ; it is, however, the most visible and has perhaps the most impact on the achievement of the companies. Data on co-investments within the VC industry are gathered from the Gilde Guide (1992), which lists all the publicly known deals with the year of investment and exit and with the Dutch investors. Not knowing the internationally syndicated deals is no problem, as only a very small percentage of the deals before 1990 had an international focus. The network variables are computed on a yearly basis. The variables are lagged one year : all entries in year 19XX are assigned the value of the variable in year 19XX-1. This leads to high correlation ratios (see table 1, panel B).

The degree of connectedness, the stability of network relationships and the variation of the prestige are computed, based on co-investment patterns. The degree of connectedness is measured in two ways : we will use an absolute measure and a relative measure. The absolute measure is simply the count of the absolute number of network relationships that exist in the industry. From the moment that two VC companies co-invest, a network relationship exists.

This variable varies between 2 and 205, with an average of 54 co-investments. As relative measure we use the percentage of companies in the market that have no ties to any other company in the industry (the so-called isolates), relative to the total number of companies in the industry. The higher this percentage, the lower the connectedness of the population. Hypothesis 1 thus suggests a negative relationship between the entry rate and the number of co-investments, and a positive relationship between the entry rate and the percentage of isolates. The minimum percentage of isolates is 15%, the maximum percentage (in the first years of the existence of the industry) is 80%.

The stability of the network agreements is measured as follows. We first identify each year strongly connected cliques of organizations, where a strongly connected clique is defined as a group of companies which have network agreements with all other companies in the group (Burt, 1991:116). The algorithm SUBGRAPH CLIQUES of the social network program STRUCTURE is used to identify the strong cliques. For every company in a clique, we count the number of years that that particular company is member of the clique. The average duration of clique membership is computed as the average duration of all companies that belong to a clique in a certain year. The higher the average duration, the more stable the network relationships in the industry are. It varies between 1.4 years and 12 years, with an average of 4.2 years.

The variation of the duration of clique membership is measured as the average duration, divided by its standard deviation. It varies between 0.75 and 10.0, with an average of 3.5. A low variation occurs when the average duration is low, but its standard deviation high and vice versa.

Finally, no consensus exists on what prestige exactly is or how it can be measured. Both size and profitability have been used as proxies for organizational prestige (DiMaggio and Powell, 1983 ; Haveman, 1993). Size stands for visibility and 'visible' organizations receive a great deal of prestige (Scott, 1992). Profitability is a reflection of success, which in turn is one of the building blocks of prestige (Burns and Wholey, 1993). However, in emerging industries neither size nor profitability of the incumbents is stable or transparent. Therefore they may not be suitable indicators of prestige. Social network research has shown that organizations that have a thorough understanding of their environment also occupy a central place in their respective industry networks (Bonacich, 1987 ; Davis, 1991). Centrality provides access to information that flows through the network (Useem, 1984). As a consequence, Davis (1991) concludes : "By maintaining ties to a large number of other organizations, more central firms are able to notice and respond to environmental changes more rapidly…. In addition, centrality indicates a firm's status and the degree to which it is integrated into the corporate elite." Hence, we will use network centrality as a valid operationalization of the prestige construct.

Social network theorists, though, have defined network centrality in a number of different ways (Knoke and Kuklinski, 1983). Freeman et al. (1991:141-142) distinguish two major approaches to network centrality : "First there are those who view an actor as central in a social network to the extent that he or she is somehow 'close' to everyone else in the network…. The second intuition grows out of the idea that people are somehow central to the degree they stand between others on the paths of communication." The first approach stems from the idea that an actor who is close to other actors in a network will have more power, more prestige and more influence than the others (Bonacich, 1987 ; Burt, 1991). The second approach views central actors as those who can facilitate or inhibit the communication of others (Freeman, 1978). Hence, they can either be a weak tie fulfilling a broker role or a strong tie, connected to many other companies (Granovetter, 1974).

As we are interested in the type of centrality that enhances prestige or status in an industry, we use the centrality indices that originate from the first approach. Among those indices, we have chosen the most simple one. We calculate the prestige of every VC company in every year of its existence by dividing the number of VC companies that co-invest with the VC company and divide it by the number of VC companies that could have co-invested with that company (i.e. Density-1). The average prestige in a certain year is then the average of the prestige of all VC companies ; it is clear that this variable will be low when there are few co-investments. It varies between 1.8% and 16%. The variation of the prestige is the average prestige, divided by its standard deviation ; it varies between 45% and 96%. This is an indicator of the concentration of prestige among the different organizations in the industry. A high variation ratio implies that average prestige is high and spread evenly across the industry actors ; a low variation ratio occurs when average prestige is low, but concentrated in a few organizations.

*Control variables*

A set of population-specific control variables is constructed, in order to capture changes in the carrying capacity. When the carrying capacity of the environment changes, the entry rate is also expected to change. When resources become more abundant, the carrying capacity rises, implying that the number of organizations that can thrive increases. An increased carrying capacity will thus have a positive effect on the founding rate. Roure, Keeley and Van der Heyden (1990:247) found that the European VC industry is resource-driven : VCists “place the burden for regulating the flow of funds totally on the prospective investors in VC”.

Previous studies found three variables that are likely to affect the capital available to the VC industry in the US (Bygrave and Timmons, 1992:Chapter 11) : the risk free interest rate, the level of the stock market activity and the creation and activity of a secondary stock market.

An increasing risk free interest rate will decrease the capital available for VC investments, as this raises the required return on the VC investment. The measure used here is the inflation corrected long-term government bond rate. Finally, it is likely that investment opportunities are more abundant when the global economic environment, measured by the inflation corrected Gross National Product (GNP), is high. Thus, it is assumed that a growing GDP will have a positive effect on the entry rate of VC companies.

The creation of a secondary stock market creates an interesting exit route for VC investments, effectively raising the expected return on investment (Roure, Keeley and Van der Heyden, 1990). This attracts more capital to the industry and thus raises the carrying capacity and the founding rate. Therefore, we construct a dummy variable, which is set to 1 if the VC is created after the start of the secondary stock market in The Netherlands (the ‘Parallelmarkt’) on 28/1/1982, otherwise its value is set to 0. Finally, a buoyant stock market increases the expected return ; therefore, the stock market index of the main Dutch stock market is used as an indicator (no index of the ‘Parallelmarkt’ exists).

The macro-economic control variables are measured at the end of each year ; they are taken from the Statistical Yearbooks of the European Commission (for the various years present in the VC dataset). The variables are lagged one year : all entries in year 19XX are assigned the value of the covariate in year 19XX-1. This increases the correlation of the covariates (see table 1, panel B).

## Model specification

When modeling the entry of organizations in a population, the level of analysis is the population (Hannan and Carroll, 1992 :236). In our analyses, we deal with repeated events occurring to the population of interest (Allison, 1984 :51). This kind of process is easily modeled as an arrival or point process (Cox and Isham, 1980 :2). The entry rate is the dependent variable in the analyses. The baseline for comparison is the constant rate, time-independent Poisson model [$\lambda(t)=C$], also called the exponential model (Allison, 1984 :23), which describes a series of events, distributed randomly across time.

In order to introduce heterogeneity into the baseline stochastic model, the entry rate is specified as a function of explanatory variables, $\lambda(t)=\log(\beta x)$, where x is a vector of covariates and $\beta$ the vector of parameters to be estimated, showing the effects of the covariates (Tuma and Hannan, 1984 :Chapter 6). The log-linear form is preferred, because it assures that all predicted rates will be nonnegative. This is a desirable characteristic, as negative entry rates are meaningless.

More explicitely, the full model is our analyses is as follows :

$$\lambda(t)=\log(\alpha_1\text{Density} + \alpha_2\text{Density}^2 + \alpha_3 \text{ Network variable}) \log(\beta x)$$

The density dependence model suggests that $\alpha_1>0$ and $\alpha_2<0$.

The entry rate is estimated in continuous time (event history analysis), as the entry time of the Dutch VC companies is known precisely. The observation period is divided into the intervals between the events, in casu the founding of a VC company (Allison, 1984 ; Kalbfleisch and Prentice, 1980). Each interval is treated as a separate observation (Kalbfleisch and Prentice, 1980:185). The interval representation of the Poisson model is given by the probability density function of the intervals T between two subsequent events, when the intervals between any two events are independent and identically distributed (Cox and Lewis, 1966:22) (t=time) :

$$fT(t)= \lambda e^{-\lambda t}, t>0 \qquad \text{with } E[t]=1/\lambda, \text{var}(t)=1/\lambda^2$$

The parameters are estimated with LIMDEP (Greene, 1992). We use the SURVIVAL function ; likelihood estimation techniques are used. Likelihood estimators are asymptotically unbiased, normally distributed and have minimum variance (Tuma and Hannan, 1984:120). Moreover, they allow for the treatment of censored observations in the continuous time analyses, thereby using all available information (Tuma and Hannan, 1984:120). Censoring, however, is not an important problem when analyzing the whole population. There are 104 observations in the dataset and only 2 censored intervals : the first one and the last one. Two likelihood estimation techniques are used : Maximum Likelihood (ML) (Kalbfleisch and Prentice, 1980:119) and Cox’s Partial Likelihood (PL) (Cox, 1972 ; Kalbfleisch and Prentice, 1980:127-132). In the latter, no explicit function of time on the entry rate is assumed, while this is implicit in the former.

We then adopt following approach. First, the models are estimated, assuming that the entry rate is constant over time, conditional on the control variables. This baseline model does incorporate neither density variables, nor network variables. Second, density and density squared are included in the models in order to test the density dependence model. Third, the network variables are added on at a time, in order to test the hypotheses. We never include more than one network variable in the models, as the correlation between all the independent variables becomes very high (see table 1, panel B).

## RESULTS

Table 2 gives the estimates, obtained with Maximum Likelihood estimation techniques. Partial Likelihood estimation techniques give comparable results, which are not given here, due to space limitations. The first model is the baseline model, which includes only the control variables.

- Insert Table 2 about here -

It is clearly shown that the density dependence model significantly helps to explain the entry rate into the Dutch VC industry. Adding the population density and density squared as explanatory variables improves the models significantly ($\chi^2$ = 14.54, $\Delta$d.f.=2, p<0.001). The coefficients of the density variables have the signs, suggested by the density dependence model, and are significantly zero (p<0.0001). This implies that the population density has an inverted U-shaped effect on the entry rate of Dutch VC companies in the early development of the industry and supports the first hypothesis. The maximum effect of the density occurs when there exist 66 VC companies. As this is well within the observed density range, the effect of a rising density is legitimative in a first phase and competitive in a second phase, as expected.

Adding the network variables (models 2 to 7) does not affect the relationship between the population density and the entry rate. The population density effect is stable and significant in all models estimated ; the maximum effect of the density occurs in a range from 66 companies to 77 companies. Our results thus give full support to the density dependence model.

Adding the absolute number of co-investments in the population (model 2) does not improve the model significantly compared to model 1 ($\chi^2$ = 0.48, Δd.f.=1, n.s.) ; the coefficient of this variable is not significant. Hypothesis 1a is not supported in the population of Dutch VC companies. Adding the percentage of isolates (model 3), which is a relative measure, improves the model ($\chi^2$ = 2.83, Δd.f.=1, $p<0.1$) ; the coefficient of this variable is significant. Consistent with hypothesis 1b, the percentage of isolates has a positive effect on the entry rate : the higher the relative proportion of companies without any tie to other companies in the industry, the easier it is to enter the industry. Conversely, the more companies co-invest with at least one other company, the more difficult it is to enter the industry. Our findings suggest that the fact that some organizations have a high number of links with other organizations does not influence the entry rate. However, when a lot of organizations have no links at all, there exist opportunities for entrants to forge links with those isolates ; this thus positively influence founding rates.

Hypothesis 2 is tested by adding the clique duration variables in models 4 and 5. Adding these variables does not improve the model significantly (average clique duration : $\chi^2$ = 1.60, Δd.f.=1, n.s. ; variation of clique duration : $\chi^2$ = 0.35, Δd.f.=1, n.s.). The coefficient of the average clique duration is significant, but in the opposite direction than hypothesized. The stability of relationships is thus not important in explaining the rate of entry into the Dutch VC industry.

Models 6 and 7 test hypothesis 3. Adding average prestige to the density dependence model, improves the model marginally significantly ($\chi^2$ = 2.50, $\Delta$d.f.=1, p=0.11) ; the coefficient of the average prestige variable is significantly negative. The variation of the prestige is added in model 7 ; this does not improve the density dependence model significantly ($\chi^2$ = 1.52, $\Delta$d.f.=1, n.s.). The coefficient of the variation variable is, however, significantly negative. Our results indicate that the higher the average prestige is in the Dutch VC industry, the less companies are inclined to enter this industry, consistent with hypothesis 3a. However, model 7 suggests that the variation of prestige in an industry may be equally important in explaining the entry rate. A low variation ratio, i.e. a low average prestige, but concentrated in a few players (a high standard deviation of prestige), leads to a higher entry rate than a high variation ratio, caused by a high average prestige equally spread over all companies. Hypothesis 3b thus receives moderate support.

## DISCUSSION AND CONCLUSION

Network forms of organizations have aroused major interest both with management scholars and practitioners. The basic idea underlying the forging of network arrangements is that there are gains to be had by the pooling of resources, as many problems simply exceed the capacity of any single organization to control. Organization ecology has been able to show how population-level variables affect founding and entry rates into specific organizational populations. In this paper, we have shown that the network structure at the population level influences entry rates. Under certain conditions, the network structure inhibits or enhances organizational entries. Thus, this study is complementary to Baum and Oliver (1992), who have shown that the relations with the environment outside the population of interest influence founding rates.

Besides replicating and validating the density-dependence model for entry rates, we found strong evidence that a low percentage of isolated organizations in a population deters entry into that population. Hence, the more organizations have ties to other organizations, the more difficult it is to enter the population. The macro-level network pattern in the population exerts a significant influence on the micro-level phenomenon of organizational entry.

This influence might be further explained as follows. As the potential entrants often lack at least some of the resources necessary to compete successfully in the new market, their ultimate survival may depend on their possibility to engage, within a short delay of their entry, into network-like arrangements with incumbents. In this way, they may get access to know-how, economies of scale and scope or complementary assets they lack. This, however, will be less likely when a large number of organizations have already ties with other organizations. In other words, the degrees of freedom for a potential entrant to engage into network-like arrangements decrease as the connectedness of the population's overall network structure increases. As a consequence, entry barriers rise.

In addition, we found weak support for the influence of network prestige on entry behavior. A high concentration of network prestige lowers entry barriers ; a high average prestige, however, rises entry barriers. We found that a visible, prestigious elite is likely to attract potential entrants to the population. It is likely that mimetic behavior on behalf of potential entrants occurs as it may reduce ‘searching costs’ when making an entry decision (Haveman, 1993).

Our findings are limited to an emergent population, where the legitimation process is likely to be the dominant force. It would be interesting to replicate this study in more mature populations, where the competition phase will be more important than in this study. We expect that network structures will have even more impact in more mature populations, as competition for resources is likely to be fiercer.

Due to the emergent nature of the industry in our study, the number of disbandings is low. It would be interesting to study the influence of the population network structure, together with the organization level network structure, on disbanding rates in general and on the probability of the disbanding of a specific organization. Do prestigious organizations, with many links to other organizations in the same industry, have lower rates of disbandings ? How does the disbanding of a prestigious organization influences foundings and disbandings ?

We think that adding network arguments to the study of vital rates in populations will enhance our understanding of fundamental organizational processes. Our findings are just a small step towards this goal.

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Table 1 : Description of the variables (N=104)
Panel A : Basic Statistics

| | Mean | St. dev. | Minimum | Maximum |
|---|---|---|---|---|
| *Control variables* | | | | |
| Stock market index | 16.201 | 16.527 | -19.231 | 44.000 |
| Long term interest rate | 5.115 | 2.214 | -3.652 | 7.393 |
| Growth of GNP | 1.845 | 1.538 | -1.000 | 5.900 |
| 2nd stock market | 0.790 | 0.409 | 0.000 | 1.000 |
| *Density dependence* | | | | |
| Density | 53.933 | 27.815 | 4.000 | 93.000 |
| Density$^2$/1000 | 36.751 | 29.310 | 0.160 | 86.490 |
| *Hypothesis 1* | | | | |
| # co-investments | 58.667 | 61.230 | 2.000 | 205.000 |
| % isolates | 50.366 | 20.255 | 15.190 | 80.000 |
| *Hypothesis 2* | | | | |
| Avg. clique duration | 4.195 | 3.451 | 1.390 | 12.000 |
| Var. clique duration | 3.546 | 3.847 | 0.756 | 10.000 |
| *Hypothesis 3* | | | | |
| Avg. prestige | 4.370 | 2.062 | 1.780 | 16.000 |
| Var. prestige | 66.934 | 14.796 | 44.949 | 95.618 |

Panel B : Correlation between variables

| | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Stock market index (1) | .90* | -.03 | .50* | .49* | .42* | .31* | -.27* | -.67* | -.66* | .25* | .26* |
| Long term interest rate (2) | | -.56* | .56* | .57* | .47* | .37* | -.37* | -.20* | -.49* | -.15 | .25* |
| Growth of GNP (3) | | | -.46* | -.05 | .07 | .22* | -.07 | -.05 | -.32* | .37* | .12 |
| 2nd stock market (4) | | | | .73* | .60* | .48* | -.54* | -.64* | -.87* | .14 | .47* |
| Density (5) | | | | | .98* | .89* | -.88* | -.76* | -.71* | .46* | .70* |
| Density$^2$/1000 (6) | | | | | | .95* | -.91* | -.73* | -.58* | .56* | .72* |
| # co-investments (7) | | | | | | | -.88* | .75* | .50* | .58* | .66* |
| % isolates (8) | | | | | | | | -.41* | -.74* | -.74* | -.88* |
| Avg. clique duration (9) | | | | | | | | | .81* | -.67* | -.83* |
| Var. clique duration (10) | | | | | | | | | | -.19* | -.54* |
| Avg. prestige (11) | | | | | | | | | | | .81* |
| Variation of prestige (12) | | | | | | | | | | | |

Significance levels : * : $p<0.05$ ; 2-sided test

Table 2 : Estimates of maximum likelihood models

| Model | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|---|---|
| Maximum likelihood | -189.865 | -175.318 | -174.834 | -172.490 | -173.718 | -174.966 | -172.814 | -173.795 |
| Maximum density | | 66 | 74 | 77 | 69 | 66 | 73 | 68 |
| Constant | -5.234*** | -6.226*** | -6.244*** | -8.771*** | -7.121*** | -7.072*** | -5.071*** | -5.343*** |
| | (0.289) | (0.545) | (0.545) | (1.471) | (0.765) | (1.102) | (1.059) | (0.897) |
| *Control variables* | | | | | | | | |
| Stock market index | 0.016* | -0.182 | -0.003 | -0.010 | 0.005 | 0.002 | -0.001 | -0.004 |
| | (0.006) | (0.009) | (0.009) | (0.010) | (0.009) | (0.010) | (0.009) | (0.009) |
| Long term interest rate | 0.060 | -0.202* | -0.171 | -0.256** | -0.245* | -0.194* | -0.283** | -0.211* |
| | (0.059) | (0.117) | (0.126) | (0.125) | (0.114) | (0.115) | (0.009) | (0.111) |
| Growth of GNP | -0.108* | -0.219** | -0.157 | -0.249** | -0.212* | -0.194* | -0.214* | -0.199* |
| | (0.057) | (0.111) | (0.262) | (0.115) | (0.109) | (0.114) | (0.112) | (0.112) |
| 2nd stock market | 1.154*** | -1.830* | -1.543* | -1.931** | -1.693** | -1.562* | -1.758** | -1.776** |
| | (0.243) | (0.797) | (0.917) | (0.796) | (0.755) | (0.828) | (0.819) | (0.798) |
| *Density dependence* | | | | | | | | |
| Density | | 0.202*** | 0.181*** | 0.221*** | 0.210*** | 0.214*** | 0.191*** | 0.208*** |
| | | (0.041) | (0.051) | (0.047) | (0.042) | (0.044) | (0.044) | (0.043) |
| Density$^2$/1000 | | -1.539*** | -1.230*** | -1.442*** | -1.531*** | -1.624*** | -1.307*** | -1.520*** |
| | | (0.300) | (0.308) | (0.324) | (0.302) | (0.319) | (0.347) | (0.318) |
| *Hypothesis 1* | | | | | | | | |
| # co-investments | | | -0.007 | | | | | |
| | | | (0.008) | | | | | |
| % isolates | | | | 0.035** | | | | |
| | | | | (0.018) | | | | |
| *Hypothesis 2* | | | | | | | | |
| Avg. clique duration | | | | | 0.108* | | | |
| | | | | | (0.066) | | | |
| Var. clique duration | | | | | | -0.000 | | |
| | | | | | | (0.000) | | |
| *Hypothesis 3* | | | | | | | | |
| Avg. prestige | | | | | | | -0.235* | |
| | | | | | | | (0.190) | |
| Var. prestige | | | | | | | | -0.019* |
| | | | | | | | | (0.017) |

Significance levels : *** : p<0.01 ; ** : p<0.05 ; * : p<0.1 ; 2-sided test for control variables, 1-sided test for density and network variables.