Business, Management and Economics Engineering
ISSN: 2669-2481 / eISSN: 2669-249X
2021 Volume 19 Issue 1: 24–33
https://doi.org/10.3846/bmee.2021.12708

ON THE FAILURE AND SYSTEMIC RISK OF INNOVATION CLUSTER: COPULA APPROACH

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Received 12 May 2020; accepted 04 September 2020

Abstract. In order to assess and parameterize the risk of innovation activity implemented by innovation clusters, it is necessary to determine the reliable tools of measuring of systemic risk.

Purpose – to propose an adequate approach to evaluate the systemic risk with regard to the impact of interlinkages between cluster entities and other external factors.

Research methodology – general overview of research papers and documents presenting concepts and methodologies of evaluation of systemic risk and performance of networked structures as approach to evaluate the systemic risk with regard to the impact of interlinkages between cluster entities and other external factors, applied research.

Findings – it is suggested to develop the further parameterization of intensity.

Modelling of the tail dependence and asymmetric dependence between pairs of networked positions remains an important task.

Research limitations – the lack of information concerning the structure and types of interactions and relationship between the members of innovation cluster. There are made some additional assumptions related to reduced-form approach of credit risk modelling.

Practical implications – proposed conceptual model of evaluation of systemic risk should be useful for understanding and further treatment of measuring risk in a case of innovation management.

Originality/Value – the concept of the measuring the systemic risk in innovation cluster as a joint probability of correlated failure of commercialization of innovative activity results is proposed and analysed in this paper.

Keywords: correlation, dependence structure, systemic risk, failure.

JEL Classification: D85.

Introduction

The innovation cluster is an entity that unifies different entities to achieve the same goal – usually successful commercialization of innovations. The meaning of establishing and operating of business clusters creating innovations is based on the synergy effect (for more details, see e.g., Valuzis & Gudelyte, 2017).

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During the assessment of cluster performance and innovative activity it is important to figure out how and whether the right is the result of activity (its compliance to set purposes), and the need to more accurately quantify the level of measurable parameters and to set qualitative settings of creation and deployment of innovations by expert evaluation. On the other hand, the concentration of business entities and production in a certain location per se is not sufficient condition to determine high rates of innovative activity (Beaudry & Breschi, 2000).

The success of commercialization of innovation is impacted by many various factors, some of which are not even observable or known, i.e. a large and unknown complex of uncertainties. As a result, the activities of an innovation cluster are inherently riskier than in a usual business plan. What are the factors that cause problems in the innovation cluster? What is the probability of an innovation cluster collapsing? These issues are important for the analysis of the activities of the individual innovation cluster as well as for the policy of promoting innovation at national level. Therefore, quantitative analysis and mathematical methods must be developed, which enable the objects in question to give a specific meaning and produce unambiguous, uniformly understandable and comparable results. A major cause of innovation risk and cluster risk management is the unusually high uncertainty and occurrence of many failures of different business entities, a risk which is linked to the structure of networking and the dependence between failures.

Innovation cluster as entities that face with high uncertainty as a whole tend toward instability and leads to the concerns of investors about the stability of financial system and risk contagion among cluster, This is due to the fragile nature of their entities (also see, e.g., Kleinow & Moreira, 2016), complex transfer of technology, inevitably accompanied by information asymmetry, numerous additional risks associated with the demand for the commercialized product, technologies, etc., technological risks (potential competitors create more advanced technology or applied new technologies can be pirated, etc.).

In networked structure with intensive collaboration of business entities individual lifetime distributions are affected by the defaults of other entities. The channels of contagion within networked structure create and maintain systemic risk, meaning the danger that an initial shock can be amplified and spread when innovation cluster entities react and further transfer it to other entities within the cluster, so that the total effect proliferates largely from the initial default or another unfavorable shock. These contagion phenomena rely on complex network effects since collaborating entities of innovation cluster are interlinked by their diverse claims with business partners within the cluster and with external entities. On the other hand, the default of one entity puts more stress on the other entities (see also, e.g., Guzmics & Pflug, 2019). Specific sources of systemic crisis within the cluster are failures of separate entities, liquidity crisis and contagion due to interrelationship and collaboration. Dependence between failures stems from at least two nonexclusive sources. The financial state of a business entity and individual failure in commercialization of innovations varies with randomly fluctuating macroeconomic factors. Dependence between the failures of commercialization of innovation exists because different business entities are affected by common macroeconomic factors. Correlation of failures with respect to multiple counterparties is highly relevant for the efficiency of performance of innovation cluster and for commercialization of innovation. In addition, management of innovation risk can only be successful if an adequate risk model is in place that can quantify the relevant risk factors. In this paper, the correlation of failures means that all stochastic processes, describing the value of firm's asset and risky investment value are correlated. The networked structure of innovation cluster implies that dependence between failures is caused by direct and non-direct economic relations between business entities that can lead to cascade of defaults. The impact of the failure of some entity on the conditional failure probability of other cluster entities can arise via different channels (Gersbach & Lipponer, 2003). In addition, the synergy effect is influenced by the individual links between members of the cluster type. On the other hand, uncertainty implying business risk is not easily explained, it makes sense to apply an intensity function that summarizes the effect of all sheer forces on the innovation cluster.

Measuring methods based on the elements of graph theory are not sufficient to fully describe the distribution of risk and loss in an innovation cluster. The copula function helps to measure the common level of riskiness of whole innovation cluster and also to characterize the dependence structure of multivariate cases. In this paper, the generalized conceptual framework of the evaluation of innovation cluster performance and ways of assessment of relations within network is proposed. In the first part of the paper, the concept of failure of commercialization of innovation performed by innovation cluster is established, in the second part, the general approach based on copula techniques to describe the joint probability of failure of innovative activity is introduced.

1. Concept of the failure of cluster innovative activity

One of the most pervasive aspects of the contemporary networked structures is the rich network of interconnections among entities. Although the financial liabilities owed by one entity to another one are usually modeled as unidirectional obligations de-pendent on the financial health only, in reality, the liability structure of corporate obligations is invariably much more intricate. Assumption that innovation clustering allows intense resource sharing in order to realize complementarity and achieve positive synergy in innovation cluster mean a flexible manufacturing and design of business ideas. Usually improvement of quality and sharpened ability to utilize many advantageous conditions of cluster with change of market and appearance of new added value chain become a competitive power and optimal allocation of resource. Improving resource utilization efficiency is possible when fully realizing complementarities within cluster. Development and coordination among cluster entities, strengthening of complementarities of each company and effective information dissemination and communication can ensure optimal resource sharing, zero inventory and quality management in an all-round way, making more full use of social resource. The other is outsourcing. After comparing internal production and organization expense with market trading cost, guidance of cluster development and division and coordination benefit urge enterprise to outsource part of its own activity to other enterprise and enlarge production scale or lower cost by use of social resource through outsourcing and in such way fully exploit the potential of partners within innovation cluster. In addition, a strong specialization of cluster entity also means that the company assumes a significant risk, because if technology or specialization suddenly becomes unnecessary, then it would either the collapse of that company or the active entities of the cluster.

Assume that the project of innovation commercialization of *i*th cluster entity matures at time $T_i > 0$, $i = 1,...,n$ and is $T = \min(T_1,...,T_n)$ the maturity of commercialization of innovation. The behavior of the gap between the value of commercialized innovation and financial liabilities and the risks arising from it can be treated as an option. In this case, the exercise price of an option is understood as the volume of investment. The same benefit structure is typical for European put option at the time of exercise, which is equal to the difference between the market value of the underlying asset and the pre-agreed price, whichever is lower, or zero otherwise:

$$f(T) = \max(V(T) - D(T), 0) = \begin{cases} 0, & V(T) \le D(T); \\ V(T) - D(T), & V(T) > D(T). \end{cases} \tag{1}$$

The processes of the value of commercialized innovations and attracted investments are stochastic. The commercialization of innovation is considered unsuccessful if the value of the innovation falls below a certain threshold, e.g., the value of invested capital. This threshold can be set in various ways. For example, it is often treated as a measure of the balance sheet liability of a given business enterprise, and the failure corresponds to a state in which the value of the innovation created by the cluster entities becomes less than the capital invested in its creation and commercialization.

Without losing the generality, assume that the maturity of innovation project is *T*. If these terms for each business entity were different, they would be correlated to the lowest maturity, and if the borrowing entity repaid it on time, the liabilities of other ones will be executed after the first repayment would be treated as uncorrelated loan. Also, if the borrowing business entity were to become insolvent, it would not completely change the nature of the task. In the case of innovation cluster, interest is concentrated on a networked structure of individual companies for each of which there is defined a point event, occurring after some random period. Let us introduce a random variable called the time-until-default, to denote this length of time:

$$\tau = \begin{cases} \inf\{t : V(t) = D(t)\} \\ +\infty, \quad V(t) \ne D(t). \end{cases}, \quad \tau_i = \begin{cases} \inf\{t : V_i(t) = D_i(t)\} \\ +\infty, \quad V_i(t) \ne D_i(t) \end{cases}, \tag{2}$$

where $D(t) = \sum_{i=1}^{n} D_i(t)$ is the amount of investment to the project of commercialization of innovation, $V(t) = \sum_{i=1}^{n} V_i(t)$ – the created value of innovation project (respectively $D_i(t)$ and $V_i(t)$ are the same parameters for *i*th cluster entity, $i = 1,...,n$) that can be characterized by respective geometric Wiener processes. This random variable is the basic for the valuation of cash flows subject to failure. The substance of this exercise is to understand the structure of failure of commercialization of innovation. This task can be transformed into an exercise for finding the distribution function of equivalents (in the sense of stopping moments), i.e., the time when the amount of financial liabilities first falls below the value of the business entity's assets.

High stability of networking may be favourable for mutual trust and efficiency of exploitation, but it is not favourable for exploration. It is necessary to maintain variety in order of exploration. Wasserman and Faust (1994) stated that the performance of enterprises, capture of resources and other actions can be treated as the function where the enterprises lie in the innovation network. Following Xihong et al. (2010), different network positions represent different opportunities to acquire new knowledge and resources. Owen-Smith and Powell (2004) also stated that enterprises occupying preponderant network positions can link different network nodes through their positions to acquire resources and control resources. Such relevance of business entity in networked structure treated in graph theory terms as centrality in some literature reflects the level of opportunities within cluster and coordination of cooperation.

2. Modelling of the probability of failure of cluster innovative activity

A suitable risk measure for systemic risk should capture many different facets that describe the importance of a given entity on networked structure (Benoit et al., 2013; Adrian & Brunnermeier, 2011). The suitability of modeling the dependence structures between financial variables using copula models have been recognized by previous studies on several types of dependence such as serial dependence, cross-dependence and cross-interdependence in stock markets (Ab Razak & Noriszura, 2019).

Systemic risk can occur as a consequence of an aggregate negative shock affecting all entities in the network such as a common exposure to a macroeconomic factor: economic output, unemployment, inflation; or a common exposure to fluctuations in interest rates, foreign exchange rates, drop in market prices, etc. Another source of systemic risk is the contagion of financial distress in the system (Moussa, 2011).

Hirshleifer et al. (1994) state that the sequential nature of information arrival has a significant impact on trading decisions. They revealed that investors who receive common and private information before others do, become short-term "profit-takers" and have a tendency to trade the same group of stocks. In addition, On the other hand, analysing another networked structure -banking sector and financial markets, Acharya and Yorulmazer (2007, 2008) argue that banks have a strong incentive to herd in order to maximize their probability of bail out. This type of behaviour increases the likelihood of a crisis due to systemic risk.

Contagion and systemic risks provide a natural field for applications of copulas because such topics involve joint and conditional distributions. In a certain sense, contagion is a particular way of analysing dependence (Fermanian, 2017). Segoviano and Goodhart (2009) propose a methodology to capture inter-linkages effects between banks, which is based on a copula formula and it is a non-parametric method, which extracts the link between events rather than predetermining laws of motion. The objective of this methodology is to find the joint distribution, which best fits a prior joint distribution according to the information criteria and is consistent with the probability of distress for each bank.

It is possible to treat the activity of an innovation cluster and its value as an investment portfolio behaviour. In this case, similar tasks remain to describe, as closely as possible, the likelihood of success or failure and the relationship between the level of risk and rate of return and, finally, the interactions and influence of the components on the final valuation results. Which means that the business of a company is affected by business cycles and so on. These models are useful for assessing the credit risk of a loan portfolio – changing the intensity of corporate insolvency cases makes it easier to model uneven changes in the value of a loan portfolio. Reduced models require less information on a firm's assets and its financial liabilities because they use data available to all market participants, if available in the market. In addition, the reduction model assumes that the structure of financial liabilities is not a continuous process, although debt repayment is an observable process (Elizalde, 2006).

An important feature of reduced credit risk models is that, in the case of a company's insolvency, the intensity parameters can change over time, which means that the company's performance is affected by business cycles and so on. These models are useful for assessing the credit risk of a loan portfolio – changing the intensity of corporate insolvency cases makes it easier to model uneven changes in the value of a loan portfolio. Reduced models require less information on a firm's assets and its financial liabilities because they use data available to all market participants, if available in the market. In addition, reduced models assume that the structure of financial liabilities is not a continuous process, although debt repayment is an observable process.

One of the most important reasons for the application of default models to describe the probability of failure of innovation cluster is the fact that the specification of full joint default probabilities is too complex (Schönbucher, 2000). In analysis of the probability of single default the time of default in reduced form models is not determined via the value of the company firm, but it is the first jump of an exogenously given jump process. Describing the failure of innovation commercialization aims to establish a generalized parameter for measuring cluster success, i.e. the likelihood that the cluster's overall commercialization of innovation will reach a certain level (in line with investor expectations) or not. The changes of this indicator could provide more information about innovation cluster performance and its recent developments and probability of default. In that case, it makes sense to run a copula technique. Copulas offer economic agents facing uncertainty a powerful and flexible tool to model dependence between random variables and are preferable to the traditional, correlation-based approach (for more details, see Giesecke, 2004; Kole et al., 2005). Copulas are needed to determine the impact of internal and external factors, characterized by a common intensity function, on the overall performance of an innovation cluster. This attempts to establish a generalized parameter for measuring the success of a cluster, i.e. the likelihood that the cluster's overall commercialization of innovation will reach a certain level (in line with investor expectations) or not.

Consider the innovation failure times of each cluster member $\tau_1,\ldots,\tau_n$ as the marginal random variables whose joint distribution function is determined by a copula function. Assume that Y is a random variable with distribution function F. Then $U = F(Y)$ is a uniform [0,1] random variable. The probability of failure would be the probability of an event that the random variable τ is less than the investment maturity T: $P(\tau \le T)$. Also, there exists an n-dimensional copula C such that

$$P(\tau \le T) = F(T) = C(F_1(T_1), F_2(T_2),\ldots, F_n(T_n)),\ (y_1, y_2,\ldots, y_n) \in R^n . \tag{3}$$

To estimate a joint probability distribution of failure times, one can start by estimating the marginal probability distributions of individual defaults, and then transform these marginal estimates into the joint distribution using a copula function (Neftci, 2001). In addition, if each distribution function F_i, $i = 1,\dots, n$ is continuous, then the copula C is unique (Nelsen, 1999). On the other hand, the marginal distribution of the individual failure time τ_i can be given by following formula:

$$\begin{aligned} &F_i(T_i) = F(\infty,,\dots,\tau_i \le T_i,\dots,\infty) = \\ &P(\tau_1 \le \infty,,\dots,\tau_i \le T_i,\dots,\tau_i \le \infty) = \\ &C(1,\dots,F_i(T_i),..,1), \quad i = 1,\dots,n. \end{aligned} \tag{4}$$

The structure of dependence between the marginal distributions related by copula is characterized by the choice of the copula. If one applies the normal copula function, then

$$P(\tau \le T) = \Phi_n(\Phi^{-1}(F_1(T_1)),\Phi^{-1}(F_2(T_2)),\dots,\Phi^{-1}(F_n(T_n))), \tag{5}$$

where Φ_n is the n – dimensional normal cumulative distribution function with the respective matrix of correlation coefficients Σ and Φ^{-1} is inverse of one-dimensional standard normal distribution.

The copula function provides the level of dependence and dependence structure of multivariate cases. Also, copulas are invariant to transformations of data (Ning, 2010). In addition, copulas ensure the scale-free measures of dependence and the flexibility that it offers in modeling multivariate data allows to separately model the marginal distribution of each variable and the dependence structure. On addition, the copula function can provide tail dependence index and captures the asymmetric dependence which are often created from the fat tail problems in multivariate cases (Ab Razak & Noriszura, 2019).

The reduced-form approach models the conditional failure arrival rate per unit time and do not consider the relation between the failure and business entity's value in an explicit manner. In this class of models the impact of defaults on the default intensities of surviving firms is exogenously specified; the joint distribution of the default times is then endogenously derived. This leads to intuitive parameterization of dependence between defaults (Frey & Backhaus, 2004). Intensity approach introduces correlation in the failures intensities making them dependent on a set of common variables and on a entity-specific factor.

The Gaussian copula model has been extensively criticized mainly for its inability to generate scenarios with simultaneous failures or failure cluster. Several alternatives to the Gaussian copula have been suggested in the financial literature: Gumbel, Clayton, Cauchy or t-copula models (Moussa, 2011).

Besides the well-known risk structure determined by the regulators financial sector, there exist additional sources of risk in the innovation industry, namely, higher than usual uncertainty and volatility in an innovative case. This is namely what determines the involvement of venture capitalists and the attitude towards the business they create as a high-risk and fast-growing investment opportunity. All of these risks can, to an appropriate extent, lead to systemic risk in the innovation cluster. On the other hand, common market shocks to balance sheets may exacerbate contagion, thus takes into account common and independent market shocks to balance sheets as well as counterparty risk through mutual exposures. In such cases a copula with tail dependence can be applied to determine the joint distribution of market shocks, which allows to generate clusters of large magnitude market shocks. Dependence of failures using copulas can be implemented by applying the approach of Schönbucher and Schubert (2001). Their general idea is to link the failure thresholds expressed as uniform [0,1] random variables $U_1,..., U_n$ with a copula. Technically it is implemented by combining the pseudo default intensities based on simulation of respective marginal distributions of individuals failures and the copula function with real intensities which links the default thresholds. The difference between pseudo and real intensities means that real intensities, in addition to all the information considered by pseudo intensities, include information about the failure status of all related business entities. The pseudo intensity includes information about the state variables and the failure situation of *i*th business entity, and only coincides with the "real" intensity in cases of independent failure or when the information of the market is restricted. It is possible to characterize "real" intensity of *i*th business entity using the techniques of logistic regression (or other discrete choice approach):

$$h_i(x) = \frac{\exp\{w(x^i)\}}{1+\exp\{w(x^i)\}}, \tag{6}$$

where h_i is the intensity function defined for *i*th cluster entity, $w(x^i) = \beta' x^i(t) = \beta_0^i + \beta_1^i x_1^i(t) + ... + \beta_m^i x_m^i(t) + \varepsilon_i(t)$, $\beta' = (\beta_0, \beta_1, \beta_2, ..., \beta_m)$ are parameters of regression, $x^i{}'(t) = (1, x_1^i(t), x_2^i(t), ..., x_m^i(t))'$ – factors of *i*th cluster entity's innovative performance, $\varepsilon_i(t) \sim \Phi_i(0, \sigma_i^2)$. The parameters governing this hazard rate are inferred from market data.

In addition, reduced-form models can incorporate correlations between failures by allowing hazard rates to be stochastic and correlated with macroeconomic variables. To introduce correlation between defaults, one would typically introduce correlation between the intensity processes. However, the problems begin when one attempts to estimate them. These problems are due, in part, to the lack of adequate respective data from which to extract information about the dependence structure of the credit risk of the firms under consideration. Within the reduced-form approach, it is possible to define failure dependence applying copulas. Following Schönbucher and Schubert (2001), applying reduced form approach the failure of innovation cluster can be treated as a jump process with an exogenous intensity. Various reduced-form models differ from each other in their choices of the state variables and the processes they follow.

On the other hand, there are some disadvantages of applying correlation approach: in some situations this is appropriate, however, more often correlation is used in a manner which is inconsistent with its actual meaning. Correlation as a measure of dependence does not necessarily uniquely define the joint distribution and can be distorted by outliers and nonlinearities (Staudt, 2010). In addition, despite that the correlation coefficient has developed as the most natural measure of dependence and its widespread use, the correlation fails to capture the important tails behaviour of the joint probability distribution (see, e.g., Embrechts et al., 2002; Bernardi & Catania, 2015).

Conclusions

This paper proposes to treat the activity of an innovation cluster and its value as an investment portfolio behavior with respective measuring of risk. The proposed model of assessment of systemic risk is in theoretical exploration stage. The stochastic variable time-until-failure to define strictly the concept of the failure of innovative activity of innovation cluster is introduced. Also, some additional assumptions related to reduced-form approach of credit risk modeling are made. It is possible to characterize intensity functions defining the individual failure by discrete choice approach. On the other hand, the limitations of this analysis may be the object of further research and further improvement (for example, when incorporating the jumps in the value processes). The lack of information concerning the structure and types of interactions and relationship between the members of innovation cluster means that it is necessary to search efficient statistical methods to evaluate parameters of unobservable process. In addition, the proposal to introduce a more general approach of evaluation system of innovation clusters performance and its applications need additional information (in particular – on the cluster of mutual assistance and liabilities).

Due to the lack of real data, there is no possibility for exhaustive empirical research.

The opportunities of parameterization of systemic risk and to create and to generalize compatible dependence structure between innovation cluster entities defining the impact of cooperation relations in networked structure are analyzed in this paper.

In the future, it is necessary to develop the further parameterization of intensity. Also, due to the problems that cannot be eliminated by application of correlations, modeling of the tail dependence and asymmetric dependence between pairs of networked positions remains an important task.

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