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Article

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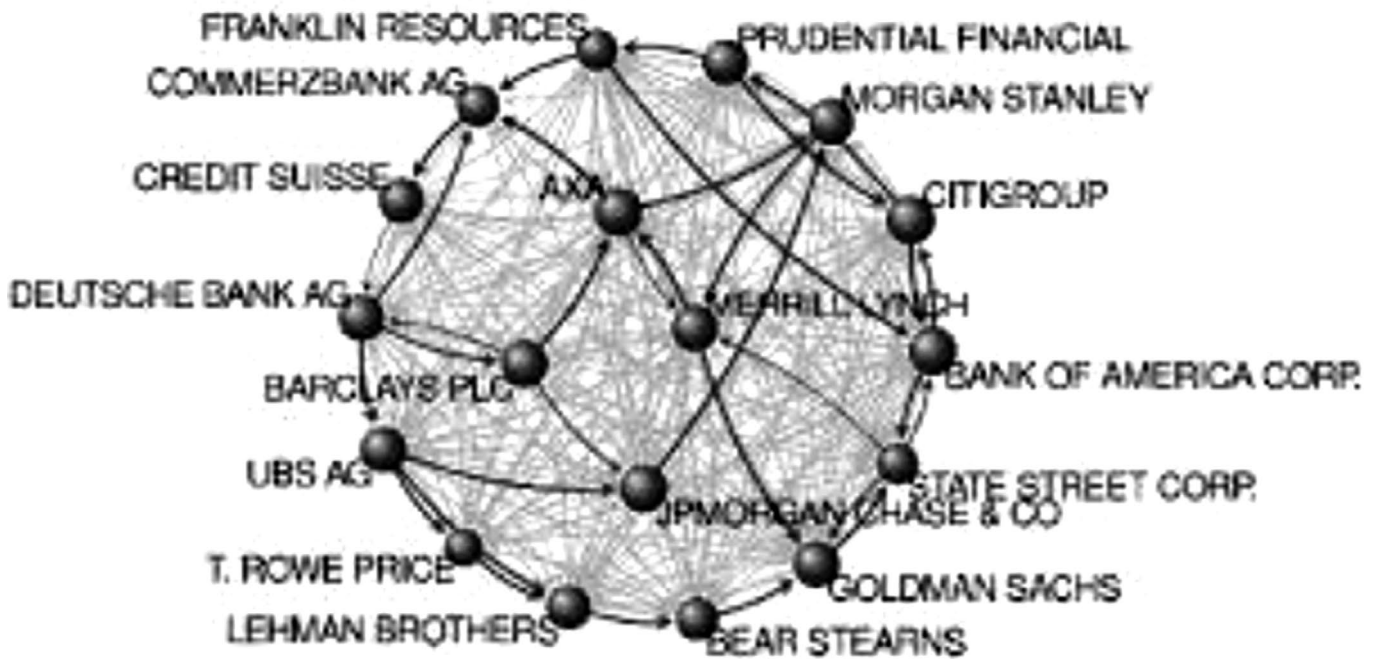
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BANKING & FINANCE | RESEARCH ARTICLE

Measuring systemic risk of Greek banks: New approach by using the epidemic model “SEIR”

Abdelkader Derbali^{1*} and Slaheddine Hallara²

Abstract: In the last decade of the financial crisis of 2007, the international financial system appeared to be on the brink of a major systemic crisis which leads to a failure of a systemically important European bank. This type of scenario highlights the need for identifying and measuring of the contribution of banks to systemic risk in the financial system. Then, the aim of this paper is to propose, for the first time, a new approach to measure systemic risk in the financial institutions. This approach is based on the epidemic model methodology. Then, we use the SEIR model with four compartments: Susceptible, Exposed, Infected, and Removed. We apply this model for a sample of 18 Greek banks listed in the Athens Exchange over the period from 2 January 2006 to 31 December 2012. Based on the empirical results, we find the existence of 12 times of default transmission during the study period and the transmission of default coincides with the number of Greek banks that have declared failure and then leaving the Athens Exchange. Also, we remark that the continuation of aid and recovery plans granted by international and national regulatory authorities did enough to save Greek banks.

Subjects: Banking; Corporate Finance; Risk Management

Keywords: systemic risk; epidemic model; SEIR; Greek banks; transmission

JEL classifications: D53; E02; E44; G21; G32; C52

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PUBLIC INTEREST STATEMENT

This paper analyzes the propagation of the default in the Greek financial system. This propagation justifies the presence of the systemic risk in Greece. So, this study is important because, after the outbreak of the financial crisis of 2007, the task of processing bank failures and its negative impact requires approaches to assess systemic risk and to determinate the role of Greek regulators. Thus, we find the existence of 12 transmissions of default during the period of study (02/01/2006–31/12/2012). Then, the role of the central bank is inadequate and even absent for the period of study. There is a deficiency in own regulations. Also, we find that the default probability, the recovery rate, the default correlation, the exposure at default, the frequency of default in the case of loss, the market capitalization, and the regulatory authorities are the main factors of the systemic risk in the financial system of Greece.

1. Introduction

The magnitude of the recent financial crisis has led to a redesign of the mechanisms' supervision of the financial sector. In particular, following the Larosière report (2009), the European Parliament voted to create a new instance of supervision: The European Systemic Risk Board (ESRB for European Systemic Risk Board). Part of the European policy response to the financial crisis, therefore, to have a dedicated instance for the systemic risk in addition to the usual trio of Financial Supervisory Authorities: the financial market authority (ESMA for European Securities and Market Authority), the bank authority (EBA to European Banking Authority), and the Insurance authority (EIOPA for European Insurance and Occupational Pensions Authority). According to Regulation EU (European Union) 1092/2010, the European Systemic Risk Board should have the task to monitor and to assess the systemic risk in normal times to mitigate the system's exposure to the risk of failure of systemic components and improve the resilience of the financial system to shocks. This mandate specifies both objectives and how to fill them. A key point is that the way—monitor and assess systemic risk—requires measurement tools.

The arrangement of systemic risk measurement tools is a new challenge in finance. New for this type of risk, and thus a part of the difficulty is in the subject of measurement. In financial literature, Acharya, Pedersen, Philippon, and Richardson (2009) examine the identification and the understanding of the systemic risk, Martínez-Jaramillo, Pérez, Embriz, and Dey (2010) and Amelia and Philip (2013) study the systemic risk and the phenomenon of financial contagion, Sanjiv and Raman (2004) and Silvan and Paolo (2007) learn an importance on the modeling of the systemic risk of a credit portfolios, and Mejra, Alenka, and Sebastijan (2011) investigate the macro-economic factors of systemic risk.

The financial crisis of 2007 proves to be the start of systemic events in most banking systems. The determination of these events is maintained using several models and approaches which find the existence of excessive propagation of banking failures. Greece is one among many countries which their banking system is strongly affected by the financial crisis of 2007. This gives rise to several questions which revolve around the following: the transmission date, the number of transmission, the transmission rate, the value or the size of bank assets in default and can pass this defect to other banks.

Even with the intervention of regulators, the state of uncertainty about the nature and causes of systemic risk is reflected in the potentially conflicting views on the relationship between financial network structure and the extent of financial contagion. Consequently, the presence of a more interconnected architecture improves the probability of systemic collapse events in the entire financial system and subsequently spread risk throughout the economy. This gives rise to the spread of financial contagion that promotes the increase in the scale and number of negative shocks to financial institutions, which in turn improves system instability. This view is also shared by Blume, David, Jon, Robert, and Eva (2011), Blume, Easley, Kleinberg, Kleinberg, and Tardos (2013) who considered the interbank contagion like an epidemic. This consideration has drawn our attention to develop a measure of systemic risk approach based on epidemic models.

This paper contributes to the systemic risk indicator building literature in several ways. First, we employ market data which reflect the real financial situation of Greek institution. Then, this paper expands the applicability of the measures proposed to assess the default transmission by the SEIR model. Also, we contribute to the determination of the systemic risk factors, as the default probability, the recovery rate, the default correlation, the exposure at default, the frequency of default in the case of loss, the market capitalization, and the regulatory authorities. Additionally, the proposed measure of the systemic risk explains the default transmission between Greek banks. Furthermore, we find that the presence of recovery plans decided by the international and the national regulatory authorities did enough to save Greek banks.

In this paper, we suggest a new approach to measure the systemic risk of the Greek banks. We will make use of an epidemic model to measure systemic risk. The epidemic models are used to model the spread of a disease in a population. These mathematical models of infectious diseases, initially purely theoretical tools, began to be practiced with the problem of infectious diseases in the 1980. The course of an epidemic in a population highly dependent on many parameters, mathematical models, have gradually established themselves as decision support tools for public policy. Our goal is to measure the systemic risk of Greek banks by adopting a biofinancial approach based on the use of an epidemic model “SEIR.”

We employ a sample composed of 18 Greek banks listed in the Athens Exchange from 2 January 2006 to 31 December 2012. The empirical results show the existence of 12 transmission fault of times during the study period. We remark that the failure of the transmission coincides with the failure of some Greek banks. The results presented in this paper are based on a set of assumptions that allow the validity of an epidemic model used to assess the systemic risk in the case of Greece. In addition, we show that the Greek financial system has a low exposure to the systemic events. Finally, we find that the aid programs and recovery plans implied by the international regulatory authorities did enough to save Greek banking system.

The rest of this paper is organized as follows: in Section 2, we develop a related literature concerning the measurement of systemic risk. Section 3 introduces the econometric approach and details the properties of the epidemic model used in this paper. Section 4 describes data. We explain the factors of systemic risk in section 5. Section 6 presents the main empirical results and analysis. Section 7 highlights the major conclusions of the different part of the present paper.

2. Literature review

Adrian and Brunnermeier (2008) used the approach of the Conditional VaR (CoVaR) to examine the effect of failure of a bank to other banks or to an entire banking system. To validate their approach, Adrian and Brunnermeier (2008) used stock prices and balance sheet data for a sample of 1224 institutions from 4 financial sectors and for a period of 25 years (1986–2010).

Based on Adrian and Brunnermeier (2008, 2009), Chan-Lau (2010) introduced an approach denoted CoRisk to study the risk of interdependence between the various financial institutions. Chan-Lau (2010) measured the default risk of transmission from one bank to other banks or to the entire financial system. The data employed to assess systemic risk are the implied default probabilities of CDS for 26 banks during the period from 2 May 2003 to 27 February 2009.

Segoviano and Goodhart (2009) propose a model for measuring systemic risk, the joint probability of default (JPod). This model was used to analyze conditional probabilities between institutions and the Banking Stability Index (BSI). The joint probability of default is the probability that the entire system fails at the same time. In addition, the index of banking stability is based on the measurement of conditional default probabilities. Their study is based on sample of 17 banks on Latin America, Eastern Europe, and Asia during the period from 1 January 2007 to 30 October 2008. Segoviano and Goodhart (2009) built their analysis on the distress or default dependency matrix between banks to determine the joint probability of default (JPod) and the index of banking stability (BIS).

Huang, Hao, and Zhu (2009, 2010) studied the phenomenon of systemic risk from 2001 to 2008. They propose a new measure of systemic risk denoted Distress Insurance Premium. Huang et al. (2009, 2010) gave two main indicators of systemic risk, the individual probability of default of each bank and the asset correlation. Besides, they found five indicators of systemic risk which are as follows: the values of CDS, the implied probability of default of CDS, the expected default frequency (EDF), the correlation of asset yields, and recovery rates. Their results show that all these indicators have a direct effect on systemic risk in Asian banks employed in their study.

Brownlees and Engle (2012) proposed an approach to determine the systemic risk. This approach is denoted SRISK measures which is used to identify the contribution of a financial institution to systemic risk on the whole financial system. Brownlees and Engle (2012) used a sample into four groups of US firms that have a market capitalization more than 5 billion dollars at the end of June 2007. The four groups are: repositories (29 institutions), brokers (32 institutions), companies insurance (10 institutions), and non-depository institutions (23 institutions). The period of study is from 3 June 2000 to 30 June 2010. Their results demonstrate that the companies with the highest SRISK have a strong contribution to the under-capitalization of the financial market crisis. These companies are considered to be the most systemically risky.

Acharya, Engle, and Richardson (2012), Acharya, Pedersen, Philippon, and Richardson (2010), and Acharya et al. (2009) proposed a model for measuring the systemic risk. This approach is named the Systemic Expected Shortfall (SES) or the expected systemic failure. Acharya et al. (2009, 2010, 2012) used a sample of 102 American financial institutions into 4 groups during a period of one year (June 2006–June 2007). They utilize the Expected Shortfall to estimate the systemic risk. Acharya et al. (2009, 2010, 2012) demonstrated the importance of the level of indebtedness of firms in their contributions to systemic risk.

Gray and Jobst (2010, 2011) developed a model called the systemic Contingent Claims Analysis (CCA). They used a sample of 36 largest institutions in the USA divided into 4 groups: investment banks, commercial banks, insurance companies, and specialized financial institutions. The period of study began on 1 January 2007 and ended on 31 January 2010. Their results show that the magnitude of systemic risk depends on the size of companies and on their interconnections in a multivariate system.

Derbali, Hallara, and Sy (2015) employed a conditional approach to estimate the systemic risk which allows decomposing the risk of the aggregate financial system of Greece. They employed the SRISK index to assess the systemic risk contribution of each Greek bank.

3. The modeling approach

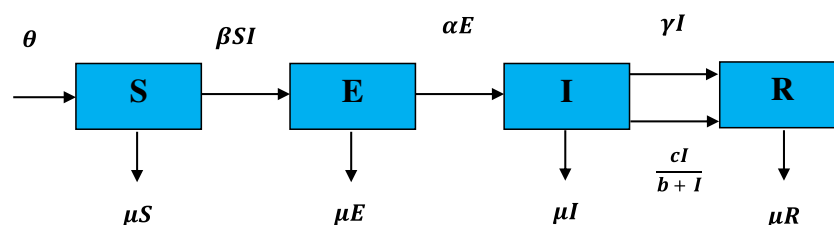
3.1. The initial forma of model “SEIR”

In this paper, we adopt the epidemic model “SEIR” for the measurement of the systemic risk. The SEIR model consists of four compartments (Figure 1). This model is presented in the form of differential equations which measures the transfers between the four compartments (S, E, I, and R) (Al-Sheikh, 2012; Zhou & Cui, 2011):

This is the fraction of initially defaulted banks. *E* is the value of banks exposed to default (Exposed). This is the fraction of the banks that are infected but not yet capable of transmitting the default to the infected banks. *I* is the value of the banks not exposed to default (Infected). This is the portion of the banks may become in default if they are in contact with the portfolios that initially are defaulted. *R* is the value of banks resistant or withdrawn (Removed). This is the portion of the credit portfolios immunized against default. These are honest portfolios that do not change regardless of the situation they may find themselves. γ is the mean recovery rate (RR). β is the mean default correlation (DC). μ is the mean probability of default (PD). α is the mean exposure at default (EAD). θ is the

Figure 1. The SEIR model.

Notes: *P* is the total value of banks ($P = S + E + I + R$), *S* is the value of susceptible banks (susceptible).



growth rate of the total value of market capitalization of all banks (GRMC). b is the frequency of default in case of Loss ($b = 1 - \text{Recovery Rate}$) (FDL). c is the maximum recovery rate at time (MAXRR). The total value of population (all banks) is measured as follow:

$$P = S + E + I + R \Rightarrow P(t) = S(t) + E(t) + I(t) + R(t) \tag{1}$$

So, we can see that $f(I, P)$ is the force of default transmission ($f(I, P) \geq 0$). In addition, the function f is increasing according to I and decreasing according to P and it can be written:

$$f(IP) \geq 0 \tag{2}$$

where $f(I, P) = \frac{\beta I}{P}$ if the population is not constant and $f(I, P) = \beta I$ if the population is constant.

$$\text{The proportion of banks in default} = \frac{I}{P} \tag{3}$$

The fundamental assumptions of standard SEIR model are:

Assumption 1: The total value of banks is assumed closed. Therefore, the effects related to changes in the total value of the banks are ignored and the P size is constant over time t , where: $S(t)$, $E(t)$, $I(t)$, and $R(t)$ are the fractions of four compartments at time t . $P(t) = S(t) + E(t) + I(t) + R(t)$.

Assumption 2: At $t = 0$, all banks are expected to be susceptible to default with the exception of the first banks that is in default.

Assumption 3: The model is assumed to be homogeneous. The total of banks is assumed to be homogeneous in terms of different types of financial institutions. Thus, the contact between the various portfolios (banks) is expressed by the mean of default correlations between the various portfolios. These contacts are homogeneous. Therefore, a portfolio is likely infected after a single random contact with infectious portfolio.

Moreover, the assumption of homogeneity implies that a bank (Infectious) transmits the failure to other portfolios which an independent and equiprobable manner with the same rate of infection.

Thus, the transmission process of the failure of a portfolio to other portfolios with a standard SEIR model is defined by the following non-linear system of differential equations (Al-Sheikh, 2012; Chowell et al., 2008; Zhou & Cui, 2011):

$$\begin{cases} \frac{dS(t)}{dt} = \theta - f(I, P)S(t) - \mu S(t) \\ \frac{dE(t)}{dt} = f(I, P)S(t) - \alpha E(t) - \mu E(t) \\ \frac{dI(t)}{dt} = \alpha E(t) - \gamma I(t) - \mu I(t) - \frac{cI(t)}{b+I(t)} \\ \frac{dR(t)}{dt} = \gamma I(t) - \mu R + \frac{cI(t)}{b+I(t)} \end{cases} \tag{4}$$

Then,

$$\begin{cases} \frac{dS(t)}{dt} = \theta - \beta I(t)S(t) - \mu S(t) \\ \frac{dE(t)}{dt} = \beta I(t)S(t) - (\alpha + \mu)E(t) \\ \frac{dI(t)}{dt} = \alpha E(t) - (\gamma + \mu)I(t) - \frac{cI(t)}{b+I(t)} \\ \frac{dR(t)}{dt} = \gamma I(t) - \mu R(t) + \frac{cI(t)}{b+I(t)} \end{cases} \tag{5}$$

where, $h(I) = \frac{cI(t)}{b+I(t)}$ is the recovery of infection implied by the regulatory authorities (mainly the Central Bank or other international authorities in the case of a portfolio of banks). The estimate of a

basic SEIR model is to estimate its various parameters in the case of a deterministic model or in the case of a stochastic model.

In this respect, the estimation method used is not unique but depends on the nature of the data used and observations on the contagion process.

Whatever the nature of deterministic or stochastic SEIR model, the standard version is the simplest version, since it assumes homogeneity of the structure of banks at two levels:

- The first level concerns the transmission of default, that is to say, each bank is lacking transmits this defect to another bank may become in default with the same transmission rate.
- The second level concerns the level of correlation between banks, that is to say, the transmission of default is due to defects equal to the correlations between default portfolios and portfolios may be in fault.

In this paper, we will try to model the different parameters following its stochastic nature. This model ensures the homogeneity of all portfolios of banks. The resolution of the system (S) used to calculate the rate of default transmission which will be adopted as a measure of systemic risk. The rate of default transmission between portfolios takes values that will be compared to 1 (Ducrot, 2010; Touzeau, 2010). Following this rate R_0 , the calculation results can be interpreted as follows:

- If $R_0 \leq 1$, then the DFE (disease-free equilibrium) is Locally Asymptotically Stable (LAS). The default will disappear and there is no transmission of the defect to other portfolios. In this case, we can observe a very low default correlation level or even non-existent between the portfolios.
- If $R_0 > 1$, R_0 , then the DFE is unstable and there is a transmission of default. So, we're talking at this point a fairly significant level of default correlation between portfolios.

In this alignment, the mathematical resolution of the system (S) is shown in the following. Moreover, we set X the vector of portfolios (E), (I), and (S). That is to say, $X = (E, I, S)$.

The theorem on the resolution of this type of system, assuming that the DFE is unstable, is presented as follows: Theorem 1 The disease-free equilibrium justifies the absence of infection. So, $E^* = I^* = R^* = 0$ and $S^* = P$. In our study, we speak of the absence of default is to say, a flawless state of equilibrium (DFE: Default Equilibrium Free).

In this case, we have $E^* = I^* = R^* = 0$ and $S^* = P$. Thus, $(S, E, I, R) = (S^*, 0, 0, 0) \leftrightarrow (S^*, 0, 0, 0) = \left(\frac{\theta}{\mu}, 0, 0, 0\right)$. $\mathcal{F}(X)$ and $\mathcal{V}(X)$ are functions of X .

In this context, the transmission rate R_0 , which measures the systemic risk equals to FV^{-1} . The DFE assume that R_0 is equal to the dominant eigenvalue of which FV^{-1} is the maximum value of FV^{-1} .

The dynamics of changes in the various compartments of the total portfolio of banks will be represented by the following equation:

$$\frac{dx_i}{dt} = \mathcal{F}(x) - \mathcal{V}(x) \tag{6}$$

where, x_i refers to all portfolios which form the total of banks ($i = 1, \dots, n$) and $\mathcal{F}(x)$ refers to the rate of appearance of new banks in a default state, that is to say what comes from other compartments of the total portfolio of banks in the defaulting bank compartment following a transmission failure and $\mathcal{V}(x)$ denotes the set of banks that go into default category of banks following the other causes that are beyond the compartment I.

In the case of a default-free state was $X_s = \{x | x_1 = \dots = x_m = 0\}$ with $m \leq n$. Theorem 2 The first three equations of the system (5) are independent of the compartment R . In this case, it is sufficient to use the new system (6) which is in the form of a system of differential equations.

$$\begin{cases} \frac{dS(t)}{dt} = \theta - \beta I(t)S(t) - \mu S(t) \\ \frac{dE(t)}{dt} = \beta I(t)S(t) - (\alpha + \mu)E(t) \\ \frac{dI(t)}{dt} = \alpha E(t) - (\gamma + \mu)I(t) - \frac{cI(t)}{b+I(t)} \end{cases} \quad (7)$$

In the absence of the default, we have $E^* = I^* = 0$ and $S^* = P$. In other words, $(S, E, I) = (S^*, 0, 0) \leftrightarrow (S^*, 0, 0) = \left(\frac{\theta}{\mu}, 0, 0\right)$.

We notes $X = (E, I, S)^T$ and $\frac{dX}{dt} = \mathcal{F}(X) - \mathcal{V}(X)$.

So we have,

$$\mathcal{F}(X) = \begin{pmatrix} \beta SI \\ 0 \\ 0 \end{pmatrix} \quad (8)$$

and,

$$\mathcal{V}(X) = \begin{pmatrix} (\alpha + \mu)E \\ -\alpha E + (\gamma + \mu)I + \frac{cI}{b+I} \\ -\theta + \beta IS + \mu S \end{pmatrix} \quad (9)$$

The Jacobean matrix $\mathcal{F}(X)$ and $\mathcal{V}(X)$ in the case of default transmission are shown, respectively, as follows:

$$D\mathcal{F}(X) = \begin{pmatrix} F & 0 \\ 0 & 0 \end{pmatrix} \quad (10)$$

$$D\mathcal{V}(X) = \begin{pmatrix} V & 0 \\ J_1 & J_2 \end{pmatrix} \quad (11)$$

Thereafter, we can write,

$$F = \begin{pmatrix} \frac{\partial F}{\partial E} & \frac{\partial F}{\partial I} \\ \frac{\partial F}{\partial E} & \frac{\partial F}{\partial I} \end{pmatrix} = \begin{pmatrix} 0 & \beta S \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} 0 & \frac{\beta\theta}{\mu} \\ 0 & 0 \end{pmatrix} \quad (12)$$

and,

$$V = \begin{pmatrix} \frac{\partial V}{\partial E} & \frac{\partial V}{\partial I} \\ \frac{\partial V}{\partial E} & \frac{\partial V}{\partial I} \end{pmatrix} = \begin{pmatrix} (\alpha + \mu) & 0 \\ -\alpha & \left(\gamma + \mu + \frac{c}{b}\right) \end{pmatrix} \quad (13)$$

So, we can calculate the matrix V^{-1} :

$$V^{-1} = \left(\begin{pmatrix} \frac{\partial V}{\partial E} & \frac{\partial V}{\partial I} \\ \frac{\partial V}{\partial E} & \frac{\partial V}{\partial I} \end{pmatrix} \right)^{-1} = \begin{pmatrix} (\alpha + \mu) & 0 \\ -\alpha & \left(\gamma + \mu + \frac{c}{b}\right) \end{pmatrix}^{-1} \quad (14)$$

First of all, we calculate the determinant of the matrix V :

$$\det(V) = \left((\alpha + \mu) * \left(\gamma + \mu + \frac{c}{b}\right) \right) - (0 * (-\alpha)) = (\alpha + \mu) * \left(\gamma + \mu + \frac{c}{b}\right) = (\alpha + \mu)(\gamma + \mu) \quad (15)$$

Then,

$$V^{-1} = \frac{1}{\det(V)} V^{ct} \tag{16}$$

with,

$$V^{ct} = \begin{pmatrix} (\gamma + \mu + \frac{c}{b}) & 0 \\ \alpha & (\alpha + \mu) \end{pmatrix} \tag{17}$$

and

$$\begin{aligned} V^{-1} &= \frac{1}{\det(V)} V^{ct} = \frac{1}{\det(V)} \begin{pmatrix} (\gamma + \mu + \frac{c}{b}) & 0 \\ \alpha & (\alpha + \mu) \end{pmatrix} \\ &= \frac{1}{(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} \begin{pmatrix} (\gamma + \mu + \frac{c}{b}) & 0 \\ \alpha & (\alpha + \mu) \end{pmatrix} \end{aligned} \tag{18}$$

$$V^{-1} = \begin{pmatrix} \frac{(\gamma + \mu + \frac{c}{b})}{(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} & \frac{0}{(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} \\ \frac{\alpha}{(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} & \frac{(\alpha + \mu)}{(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} \end{pmatrix} = \begin{pmatrix} \frac{1}{(\alpha + \mu)} & 0 \\ \frac{\alpha}{(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} & \frac{1}{(\gamma + \mu + \frac{c}{b})} \end{pmatrix} \tag{19}$$

Finally, we can calculate the value of FV^{-1} which is written as follows:

$$\begin{aligned} FV^{-1} &= \begin{pmatrix} 0 & \frac{\beta\theta}{\mu} \\ 0 & 0 \end{pmatrix} \begin{pmatrix} \frac{1}{(\alpha + \mu)} & 0 \\ \frac{\alpha}{(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} & \frac{1}{(\gamma + \mu + \frac{c}{b})} \end{pmatrix} = \begin{pmatrix} \frac{\beta\theta}{\mu} \frac{\alpha}{(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} & \frac{\beta\theta}{\mu} \frac{1}{(\gamma + \mu + \frac{c}{b})} \\ 0 & 0 \end{pmatrix} \\ &= \begin{pmatrix} \frac{\beta\theta\alpha}{\mu(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} & \frac{\beta\theta}{\mu(\gamma + \mu + \frac{c}{b})} \\ 0 & 0 \end{pmatrix} \end{aligned} \tag{20}$$

Then,

$$FV^{-1} = \frac{1}{\mu(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} \begin{pmatrix} \beta\theta\alpha & \beta\theta \\ 0 & 0 \end{pmatrix} \tag{21}$$

$$R_0 = FV^{-1} = \frac{\beta\theta\alpha}{\mu(\alpha + \mu)(\gamma + \mu + \frac{c}{b})} = \frac{1}{\mu} \left(\frac{\alpha}{(\alpha + \mu)} \right) \left(\frac{\beta\theta}{(\gamma + \mu + \frac{c}{b})} \right) \tag{22}$$

The rate of default transmission rate is calculated based on the basis property, such as:

$$(S(0), E(0), I(0), R(0)) \in \left\{ (S, E, I, R) \in [0, P]^4 : S + E + I + R = P \right\} \tag{23}$$

After obtaining the value of R_0 , so we can therefore interpret the result of this rate by comparing it to 1. The interpretation of the result is done by the following analysis (Porter, 2012):

- If $R_0 \leq 1$, then the DFE (disease-free equilibrium) is Locally Asymptotically Stable (LAS). The default will disappear and there is no transmission of the default to other portfolios. One speaks in this case, a very low default correlation level or even non-existent between credit portfolios. Therefore, we can assume that $R_0 = SR \leq 1 \Rightarrow \lim_{t \rightarrow +\infty} (S(t), E(t), I(t), R(t)) = DFE = (P, 0, 0, 0)$

- Where $R_0 > 1$, then the DFE is unstable and there is a transmission failure. So we're talking at this point a fairly significant level of default correlation between credit portfolios. The calculation of R_0 is to prove the stability of the DFE. So systemic risk or failure of the transmission rate justifies the following equations:

$$R_0 = SR > 1, I(0) > 0 \Rightarrow \lim_{t \rightarrow +\infty} (S(t), E(t), I(t), R(t)) = (S^*, E^*, I^*, R^*)$$

THEOREM 3 For a value of transmission rate (systemic risk) greater than 1, the system of differential equations (6) admits one positive solution $X^* = (S^*, E^*, I^*)$:

$$\begin{aligned} S^* &= \frac{\theta}{\beta I^* + \mu} = \frac{\theta}{\mu R_0} \\ E^* &= \frac{I^*(\gamma + \mu)}{\alpha} = \frac{\mu(\gamma + \mu)}{\alpha \beta} (R_0 - 1) \\ I^* &= \frac{\mu}{\beta} (R_0 - 1) \end{aligned} \tag{24}$$

Thus, to determine the equilibrium values of the various compartments S^* , E^* , R^* , and I^* , we will try to solve the system (24).

$$\begin{cases} \theta - \beta I^* S^* - \mu S^* = 0 \text{ (i)} \\ \beta I^* S^* - (\alpha + \mu) E^* = 0 \text{ (ii)} \\ \alpha E^* - (\gamma + \mu) I^* + \frac{cI^*}{b+I^*} = 0 \text{ (iii)} \end{cases} \tag{25}$$

According to this system, one can deduce the following equations:

$$S^* = \frac{\theta}{\beta I^* + \mu} \tag{26}$$

$$E^* = \frac{\beta I^* S^*}{(\alpha + \mu)} = \frac{(\beta I^*) \left(\frac{\theta}{\beta I^* + \mu} \right)}{(\alpha + \mu)} = \frac{\beta I^* \theta}{(\alpha + \mu)(\beta I^* + \mu)} = \frac{\beta I^* \theta}{\mu^2 + \alpha \mu + (\beta \alpha + \beta \mu) I^*} \tag{27}$$

In this case, we use the value of E^* and integrating in the equation (iii). Therefore:

$$\begin{aligned}
 E^* - (\gamma + \mu)I^* + \frac{cI^*}{b + I^*} &= \frac{\alpha\beta I^* \theta}{\mu^2 + \alpha\mu + (\beta\alpha + \beta\mu)I^*} - (\gamma + \mu)I^* + \frac{cI^*}{b + I^*} = \frac{[(\alpha\beta I^* \theta) * (b + I^*)] - [(\mu^2 + \alpha\mu + (\beta\alpha + \beta\mu)I^*) * (\gamma + \mu)I^* * (b + I^*)] + [cI^* * (\mu^2 + \alpha\mu + (\beta\alpha + \beta\mu)I^*)]}{[\mu^2 + \alpha\mu + (\beta\alpha + \beta\mu)I^*] * [b + I^*]} \\
 \alpha b \beta \theta I^* + \alpha \beta \theta I^{*2} - \left(\left[(\mu^2 + \alpha\mu)(\gamma + \mu) * b \right] I^* + \left[(\beta\alpha + \beta\mu)(\gamma + \mu) * b I^{*2} \right] + \left[(\mu^2 + \alpha\mu)(\gamma + \mu) \right] I^{*2} + [(\beta\alpha + \beta\mu)(\gamma + \mu)] I^{*3} + c(\mu^2 + \alpha\mu) I^* + c(\beta\alpha + \beta\mu) I^{*2} \right) &= \\
 \alpha b \beta \theta I^* + \alpha \beta \theta I^{*2} - \left[(\mu^2 + \alpha\mu + (\beta\alpha + \beta\mu)I^*) * [b + I^*] \right] &= \\
 \alpha b \beta \theta I^* + \alpha \beta \theta I^{*2} - \left[(\mu^2 + \alpha\mu)(\gamma + \mu) * b \right] I^* - \left[(\beta\alpha + \beta\mu)(\gamma + \mu) * b I^{*2} \right] - \left[(\mu^2 + \alpha\mu)(\gamma + \mu) \right] I^{*2} - [(\beta\alpha + \beta\mu)(\gamma + \mu)] I^{*3} + c(\mu^2 + \alpha\mu) I^* + c(\beta\alpha + \beta\mu) I^{*2} &= \\
 I^* \left[\alpha b \beta \theta + \alpha \beta \theta I^* - \left[(\mu^2 + \alpha\mu)(\gamma + \mu) * b \right] - [(\beta\alpha + \beta\mu)(\gamma + \mu)] I^* - \left[(\mu^2 + \alpha\mu) \right] I^2 - [(\beta\alpha + \beta\mu)(\gamma + \mu)] I^3 + c(\mu^2 + \alpha\mu) + c(\beta\alpha + \beta\mu) I^* \right] &= 0 \\
 \left[\mu^2 + \alpha\mu + (\beta\alpha + \beta\mu)I^* \right] * [b + I^*] &= 0
 \end{aligned}$$

(28)

To solve this equation, we must have two possible cases:

1st case: $I^* = 0$

For this case, the solution obtained I^* is rejected.

2nd case:

$$[\alpha b \beta \theta + \alpha \beta \theta I^* - [(\mu^2 + \alpha \mu)(\gamma + \mu)^* b] - [(\beta \alpha + \beta \mu)(\gamma + \mu)^* b] I^* - [(\mu^2 + \alpha \mu)(\gamma + \mu)] I^* - [(\beta \alpha + \beta \mu)(\gamma + \mu)] I^{*2} + c(\mu^2 + \alpha \mu) + c(\beta \alpha + \beta \mu) I^*] - [(\beta \alpha + \beta \mu)(\gamma + \mu)] I^{*2} + [\alpha \beta \theta - [(\mu^2 + \alpha \mu)(\gamma + \mu)]] I^* = 0 \quad (29)$$

Thus,

$$\alpha b \beta \theta - (\mu b(\alpha + \mu)(\gamma + \mu) + \mu c(\alpha + \mu) - [\beta(\alpha + \mu)(\gamma + \mu)] I^{*2} + [\alpha \beta \theta - \beta b(\alpha + \mu)(\gamma + \mu) - \mu b(\alpha + \mu)(\gamma + \mu) + c \beta(\alpha + \mu)] I^* = 0 \quad (30)$$

This equation is in the form of a second-degree equation $ax^2 + bx + c = 0$. To solve this equation, we must calculate the value of Δ which is equal to $[b^2 - 4ac]$. So, Δ can have three possible values:

- If $\Delta < 0$: then this equation has no solution.
- If $\Delta = 0$ then this equation has two equal solutions, $x_1 = x_2 = \frac{-b}{2a}$
- If $\Delta > 0$ then this equation has two solutions x_1 and x_2 . With the value of $x_1 = \frac{-b - \sqrt{\Delta}}{2a}$ and the value of $x_2 = \frac{-b + \sqrt{\Delta}}{2a}$.

So we will try to solve the equation:

$$\alpha b \beta \theta - (\mu b(\alpha + \mu)(\gamma + \mu) + \mu c(\alpha + \mu) - [\beta(\alpha + \mu)(\gamma + \mu)] I^{*2} + [\alpha \beta \theta - b(\beta + \mu)(\alpha + \mu)(\gamma + \mu) + c \beta(\alpha + \mu)] I^* = 0 \quad (31)$$

Thus, it has

$$\begin{cases} a = -\beta(\alpha + \mu)(\gamma + \mu) \\ b = \alpha \beta \theta - (\alpha + \mu)(b(\beta + \mu)(\gamma + \mu) - c \beta) \\ c = \alpha b \beta \theta - (\alpha + \mu)(\mu b(\gamma + \mu) - \mu c) \\ x = I^* \end{cases} \quad (32)$$

So now,

$$\Delta = b^2 - 4ac = [\alpha \beta \theta - (\alpha + \mu)(b(\beta + \mu)(\gamma + \mu) - c \beta)]^2 - 4 * (-\beta(\alpha + \mu)(\gamma + \mu)) * (\alpha b \beta \theta - (\alpha + \mu)(\mu b(\gamma + \mu) - \mu c)) \quad (33)$$

Subsequently, there may be three possible cases:

- If $\Delta < 0$, then Equation (32) has no solution.
- If $\Delta = 0$, then Equation (32) has two equal solutions $I_1^* = I_2^* = \frac{-b}{2a}$. I_1^* and I_2^* must be positive. Thus, to obtain a positive sign of I_1^* and I_2^* we should a and b have different signs. If a and b have the same sign, therefore the solutions obtained will be rejected.
- If $\Delta > 0$, then Equation (32) has two solutions x_1 and x_2 . With the value of $I_1^* = \frac{-b - \sqrt{\Delta}}{2a}$ and the value of $I_2^* = \frac{-b + \sqrt{\Delta}}{2a}$. Similarly, we should taken the positive value of I_1^* or I_2^* . So, four cases are observed:

- If $a < 0$ and $b > 0$, then, $I_1^* > 0$ and $I_2^* = 0$. In this case, it takes the value of $I_1^* = I^*$ and we can be calculated the values of S^* , E^* and R^* .
- If $a < 0$ and $b < 0$, so, $I_1^* < 0$ and $I_2^* = 0$. In this case, we must reject the two solutions I_1^* and I_2^* .
- If $a > 0$ and $b > 0$, then, $I_1^* < 0$ and $I_2^* = 0$. In this case, we must reject the two solutions I_1^* and I_2^* .
- If $a > 0$ and $b < 0$, then $I_1^* > 0$ and $I_2^* = 0$. In this case, we can takes the value of $I_1^* = I^*$ which used to obtain the value of S^* , E^* , and R^* .

Thus, for both possibilities ($a < 0$ and $b > 0$) and ($a > 0$ and $b < 0$), the value of $I_1^* = I^*$ can be written as follows:

$$I_1^* = I^* = \frac{-b - \sqrt{\Delta}}{2a} \tag{34}$$

Furthermore, the resolution of the system at equilibrium will be as follows:

$$\begin{cases} S^* = \frac{\theta}{\beta I^* + \mu} = \frac{\theta}{\beta \left(\frac{-b - \sqrt{\Delta}}{2a} \right) + \mu} \\ E^* = \frac{I^*(\gamma + \mu)}{\alpha} = \frac{\left(\frac{-b - \sqrt{\Delta}}{2a} \right)(\gamma + \mu)}{\alpha} \\ I^* = \frac{-b - \sqrt{\Delta}}{2a} \\ R^* = \frac{\gamma I^*}{\mu} = \frac{\gamma \left(\frac{-b - \sqrt{\Delta}}{2a} \right)}{\mu} \end{cases} \tag{35}$$

3.2. The final form of model “SEIR”

In this part, we present in Figure 2 the final form of the SEIR model which used to quantify the systemic risk between financial institutions (portfolio of banks).

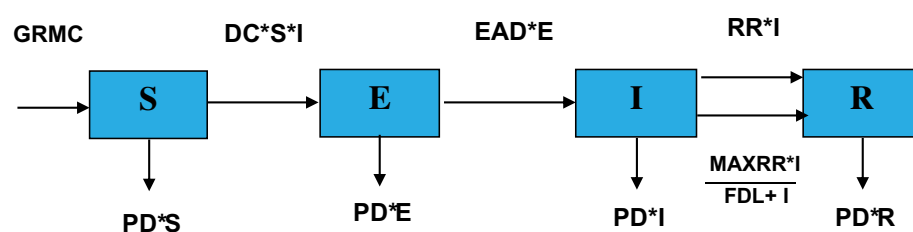
This model will be transformed into a system (36) which presented in the form of stochastic differential equations:

$$\begin{cases} \frac{dS(t)}{dt} = GRMC - DC * I(t)S(t) - PD * S(t) \\ \frac{dE(t)}{dt} = DC * I(t)S(t) - (EAD + PD)E(t) \\ \frac{dI(t)}{dt} = EAD * E(t) - (RR + PD)I(t) - \frac{MAXRR * I(t)}{FDL + I(t)} \\ \frac{dR(t)}{dt} = RR * I(t) - PD * R(t) + \frac{MAXRR * I(t)}{FDL + I(t)} \end{cases} \tag{36}$$

We note that the term $h(t) = \frac{MAXRR * I(t)}{FDL + I(t)}$ represent the role of regulatory authorities to save banks with default risk. Primarily, the regulatory authorities come from the central bank that organizes, directs, and supervises the banking system. The central bank is to guarantee the healthy situation of the banking system.

The resolution of this system has allowed us to measure systemic risk (SR) of a portfolio of banks. That is to say, we will determine a measure of systemic risk to verify the existence of a transmission of default of a portfolio to other portfolios. Thus, systemic risk will be measured by the following formula:

Figure 2. The final form of systemic risk.



$$R_0 = FV^{-1} = \frac{\beta\theta\alpha}{\mu(\alpha + \mu)\left(\gamma + \mu + \frac{c}{b}\right)} = \frac{1}{\mu} \left(\frac{\alpha}{(\alpha + \mu)} \right) \left(\frac{\beta\theta}{\left(\gamma + \mu + \frac{c}{b}\right)} \right) \quad (37)$$

Then,

$$SR = \frac{DC * EAD * GRMC}{PD(EAD + PD)\left(RR + PD + \frac{MAXRR}{FDL}\right)} = \frac{1}{PD} \left(\frac{EAD}{(EAD + PD)} \right) \left(\frac{DC * GRMC}{\left(RR + PD + \frac{MAXRR}{FDL}\right)} \right) \quad (38)$$

We can also determine the fractions of the four categories of the banks. These fractions are calculated based on the value of systemic risk:

$$\left\{ \begin{array}{l} S^* = \frac{GRMC}{DC\left(\frac{-b-\sqrt{\Delta}}{2a}\right) + PD} \\ E^* = \frac{\left(\frac{-b-\sqrt{\Delta}}{2a}\right)(RR + PD)}{EAD} \\ I^* = \frac{-b-\sqrt{\Delta}}{2a} \\ R^* = \frac{RR\left(\frac{-b-\sqrt{\Delta}}{2a}\right)}{PD} \end{array} \right. \quad (39)$$

4. Data

The data used in this paper composed of 18 Greek banks listed in the Athens Exchange from 02 January 2006 to 31 December 2012. Then, daily prices are transformed to daily logarithmic returns

Table 1. List of Greek banks

Name of bank	The period of study
ALPHA BANK	02/01/2006-31/12/2012
ASPIS BANK	02/01/2006-30/06/2010
ATE	02/01/2006-31/12/2012
ATTICA BANK	02/01/2006-31/12/2012
BANK OF CYPRUS	02/01/2006-31/12/2012
BANK OF GREECE	02/01/2006-31/12/2012
EGNATIA BANK (KO)	02/01/2006-20/09/2007
EGNATIA BANK (ΠΟ)	02/01/2006-20/08/2007
EMPORIKI BANK	02/01/2006-29/04/2011
EUROBANK EFG	02/01/2006-31/12/2012
GENIKI BANK	02/01/2006-31/12/2012
MARFIN EGNATIA BANK	02/01/2008-31/03/2011
MARFIN FINANCIAL GROUP	02/01/2006-30/03/2007
MARFIN POPULAR BANK	02/01/2008-11/04/2012
NATIONAL BANK	02/01/2006-31/12/2012
PIRAEUS BANK	02/01/2006-31/12/2012
PROTON BANK	02/01/2006-30/12/2011
TT HELLENIC POSTBANK	02/01/2008-31/12/2012

which used to calculate the fundamental factors of systemic risk. Table 1 reports the list of all Greek banks used in this paper. In this table, we present the name of the bank. So, we remark that the period of existing in the Athens Exchange of each banks is not identical to other banks during the period of study. This is justified by the default situation of these banks which accomplished by their leave for the Athens Exchange before the final date of study (31/12/2012).

5. The determinants of systemic risk

In this section, we present the potential indicators of systemic risk. These indicators are the parameters used for modeling systemic risk through the development of a biofinancial approach. Determining the different systemic risk parameters is based on the assumptions of epidemic models. The parameters to be determined are mainly the probability of default, default correlation, recovery rate, the frequency of default in case of loss, the growth rate of the value of the market capitalization, and exposure to default now.

In this paper, we used a SEIR epidemic model type that is based on assumptions is mainly justified by the assumption regarding the characteristics of the portfolios of banks that will be used in our sample. The development of the SEIR model assumes that the study population is homogeneous.

In addition, we used a sample of 18 banks that are homogeneous (Zhou & Cui, 2011). Here, the basic assumption is verified that the population is characterizing by the homogeneity (Liu, Ruan, & Zhang, 2015).

For the transmission of the default, it is assumed that a default in the bank passes the default immediately when he went into failure.

The exchange between portfolios initially defaulted and portfolios may become in default is in proportion to the statistical average of default correlations (CD). The exchange between portfolios initially defaulted and portfolios exposed to the default are in proportion to the statistical average exposures default time (EAD). The relationship between portfolios initially defaulted and portfolios immunized to default are in proportion to the statistical average recovery rate (RR). The other parameters used are: the frequency of default for loss (FDL), the maximum average of recovery rate (MAXRR), and the growth rate of the value of market capitalization of portfolio of banks (GRMC).

5.1. The probability of default and the recovery rate

The probability of default was estimated using the analysis developed by Merton (1974). The basic assumption of the model is that the value of the assets of a company V follows a stochastic process and that failure is realized if V crosses the default barrier. The latter may be regarded as the recovery value for failure. It measures the amount $TR * D$. With TR means the recovery rate at date t and D debt per share of the company that varies in time.

The firm is said to be in default if at time t the value of its assets is less than its nominal value, i.e. though $V_t < F_t$. The recovery rate is then written as follows:

$$TR = \frac{F_t}{V_t} \tag{40}$$

And loss given default (P_t) is:

$$P_t = 1 - TR = \frac{F_t - V_t}{F_t} \tag{41}$$

The value of assets is assumed to follow a geometric Brownian process given by the following equation:

$$dV_t = \mu V_t dt + \sigma V_t dW_t \tag{42}$$

In other words,

$$\frac{dV_t}{V_t} = \mu dt + \sigma dW_t \tag{43}$$

which, is μ the drift of the value of the assets of the firm, σ is the asset volatility and W_t is a standard Brownian process. It is assumed that $\mu = 0$.

According to the development of the KMV model, the fault distance is defined as follows (Crosbie & Bohn, 2003):

$$DD = \frac{V_A - X}{\sigma_A V_A} \tag{44}$$

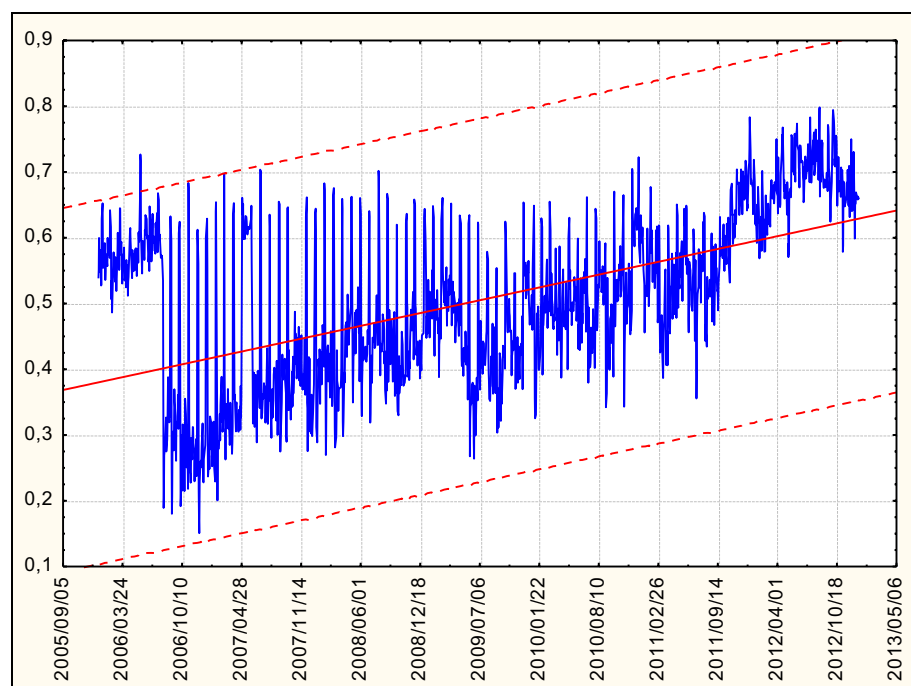
From the fault distance, one can deduce the value of the probability of default as follows (Schäfer & Koivusalo, 2013):

$$P_{KMV} = Prob\{V_A(T) < X\} = N\left(-\frac{\ln\left(\frac{V_A}{X}\right) + \left(\mu - \frac{1}{2}\sigma_A^2\right)T}{\sigma_A \sqrt{T}}\right) = N(-DD) \tag{45}$$

In the biofinancial approach to the measurement of systemic risk, we referred to the estimate of the average probability of default of individual banks used in our paper at each time t . According to the results found in the first chapter, we can deduce the average default probability of the different banks in our sample. Figure 3 shows the dispersion of the average probability of default during the study period in the case of banks in Greece. According to this figure, we found that the probability of default is characterized by an increasing rate.

Figure 3. The average default probability of Greek banks.

Note: This figure report the average probability of default of 18 banks used in this paper for the study period from January 02, 2006 to December 31, 2012.



The level of the Greek bank default is increasing during the study period, mainly following the declaration of bankruptcy of Greece in 2009. The accumulation level of sovereign debt in the euro area has an impact on the economy Economic Greece and especially its banking system.

The effect of the subprime crisis was transmitted from the USA to the euro zone. The impact of this crisis manifests itself in the bankruptcy of several banks, the excess of the level of unemployment, the imbalance in the balance of payments of these countries, and the increase in external debt.

Greece is one of the most affected countries by the financial crisis even in the presence of stimulus plans against the risk of loss. The failure of banks to Greece was passed from one bank to other banks. This was the objective of our paper, in which we try to model the systemic risk of a loan portfolio. This model aims to verify the existence of a communication failure in the banking system of Greece.

The default accumulation is justified by the low recovery rate charged by banks. What justifies the lack of effective management in banks and also the absence of control and supervision by the central bank and banks too.

Figure 4 shows the ineffectiveness of the recovery rate of the banks in Greece. According to this figure, we noticed that after the third quarter of 2011 the average recovery rate was fairly high levels to cover bank losses. Increasing the level of the recovery rate is verified by the stimulus packages and aid granted by the Member States of the European Union. Greece has benefited from aid granted by the EU to support its economy in general and it's banking system in particular.

In Figure 5, we presented the distribution of the maximum recovery rate (MAXRR). This parameter is directly related to the function $h(t)$ in the SEIR model that measures the intervention of regulatory authorities in the fight against bank failure propagation in Greece during the study period. The intervention of the national and international regulatory authorities did not ensure the soundness of the banking system of Greece.

Descriptive statistics of average recovery rate and maximum recovery rate for all banks used in our study and for each date t are presented in Table 2.

Figure 4. The average recovery rate of banks in Greece.

Note: This figure summarizes the average recovery rate of 18 banks used in our research for the study period from January 02, 2006 to December 31, 2012.

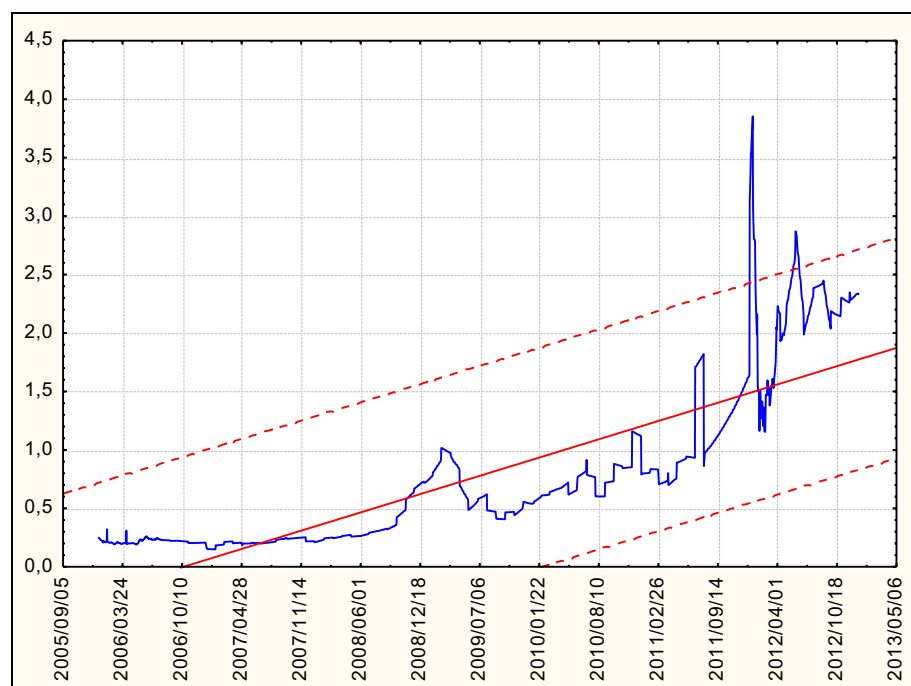


Figure 5. The maximum recovery rate (MAXRR) bank of Greece.

Note: This figure report the maximum recovery rate of 18 banks used in our research for the study period from January 02, 2006 to December 31, 2012.

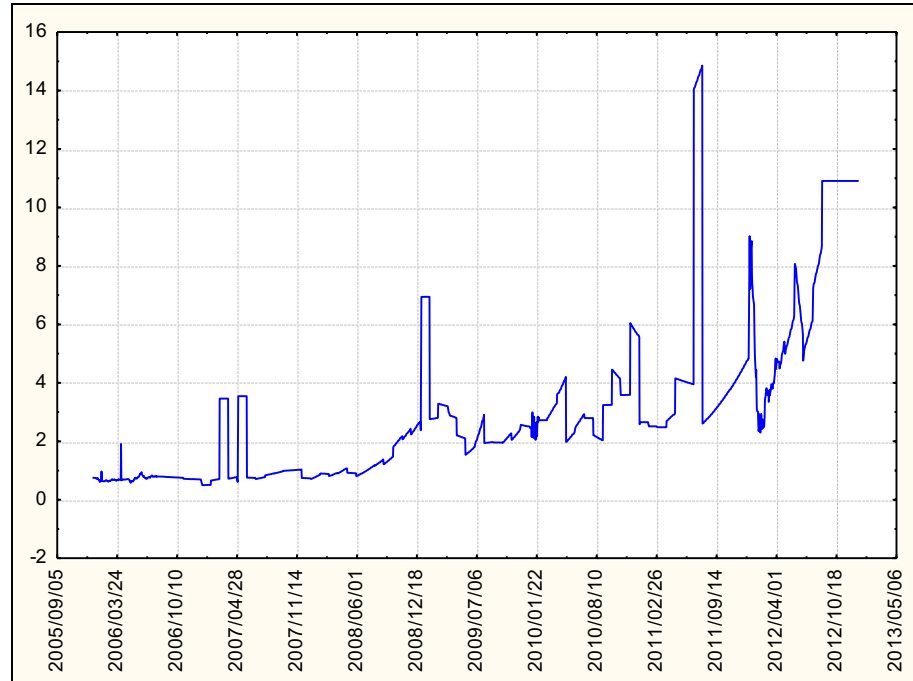
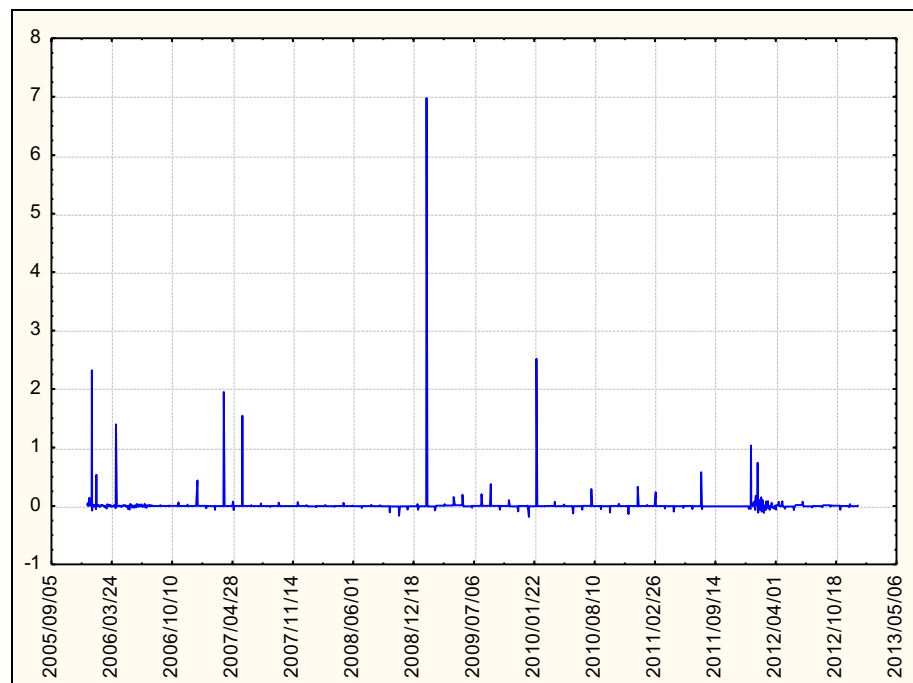


Table 2. Descriptive statistics

	Obs.	Mean	Min	Max	Variance	Std. dev	Skewness	Kurtosis
RR	1,748	0.775939	0.149549	3.85324	0.467068	0.683424	1.449630	1.353938
MAXRR	1,748	2.973614	0.498459	14.85419	7.698507	2.774618	2.016648	4.223239

Figure 6. The growth rate of the market capitalization (GRMC) of Greek banks.



Similarly, in Figure 6, we represented the growth rate of the value of the loan portfolio. In epidemic models, the growth rate measures the rate of increase in the size of the study population. In our work, we used the KMV model to measure the probability of default of banks in Greece. KMV model is based on the use of historical price action of the studied companies. In this case, we determined the growth rate of the total market capitalization of 18 banks that make up the sample of our study. Table 3 summarizes the descriptive statistics of the growth rate of the value of studying portfolio.

5.2. Exposure to default time and default frequency for loss

The other parameters used for the measurement of systemic risk of a credit portfolio are the exposure to the default time (EAD) and the default frequency for loss (FDP) (Bellotti & Crook, 2012; Leow & Mues, 2012). The FDP is often considered to be constant but it is sometimes regarded as a random variable. As for EAD, it is often defined as the amount of capital to be paid at the time of default by borrowers, but in some cases, it may include lost interest (Basel Committee on Banking Supervision, 2006).

Exposure to the default time (EAD) is calculated as follows:

$$EAD = \frac{PA}{PD * FDP} \tag{46}$$

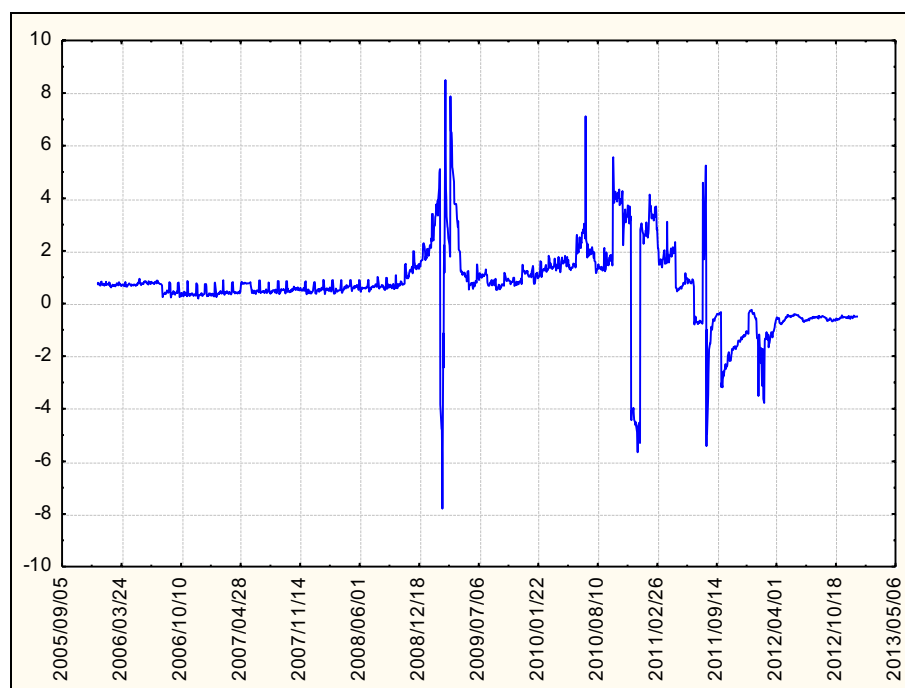
where, *PD* is the probability of default, *FDL* is the frequency of default in case of loss and *EL* is the expected loss ($PA = 1 - \frac{V_t}{F_t}$) (Giovanni, Levchenko, & Mejean, 2012; Schäfer & Koivusalo, 2013).

In Figure 7, we present the volatility of the average exposure at default of Greek banks.

Table 3. Descriptive statistics								
	Obs.	Mean	Min	Max	Variance	Std. dev	Skewness	Kurtosis
GRMC	1,748	0.010817	-0.188745	6.979145	0.041150	0.202855	26.22219	828.3062

Figure 7. Average exposure at default (EAD).

Note: This figure report the average exposure at default of 18 banks used in this paper for the study period from 02 January 2006 until 31 December 2012.



The default frequency for loss is the amount of money that is lost by a financial institution or a bank when a borrower defaults on a loan. Hartmann-Wendels, Miller, and Töws (2014) suggest that there are several methods to calculate the loss given default, but the most frequently used method is the comparison between the actual total loss and total potential exposure at default. Most banks have experienced difficulties in calculating the value of the FDL for a loan. Faced with this difficulty, the banks examine their overall portfolios by determining the FDL based on cumulative losses and exposure.

Thus, the FDL is calculated as follows:

$$FDP = \frac{Perted\ unportefeulle}{EAD} \tag{47}$$

According Schäfer and Koivusalo (2013), the loss of a portfolio is calculated as follows:

$$Perted\ unportefeulle = PD * PA \tag{48}$$

In this case, the default frequency in the event of loss is measured by the following relationship:

$$FDP = \frac{PD * PA}{EAD} \tag{49}$$

Figure 8 summarizes the evolution of the default frequency in the event of average loss of banks in Greece during the study period going from 2 January 2006 to 31 December 2012.

Table 4 summarizes the descriptive statistics of the two parameters; EAD and FDL. These statistics relate to exposure to average default time and default frequency in the event of average loss.

5.3. The default correlation

The default correlation of the measurement problem is well-developed in the financial literature. Thus, different approaches have been proposed for the modeling of the default correlation. Wang, Shan, and Geng (2015) proposed a scoring model of the transition probabilities of default, which are driven by economic factors. This model is explained by a dynamic process.

Figure 8. The average frequency of default in the case of loss (FDL).

Note: This figure report is the average frequency of default for the case of loss of 18 banks used in this paper for the study period from 02 January 2006 until 31 December 2012.

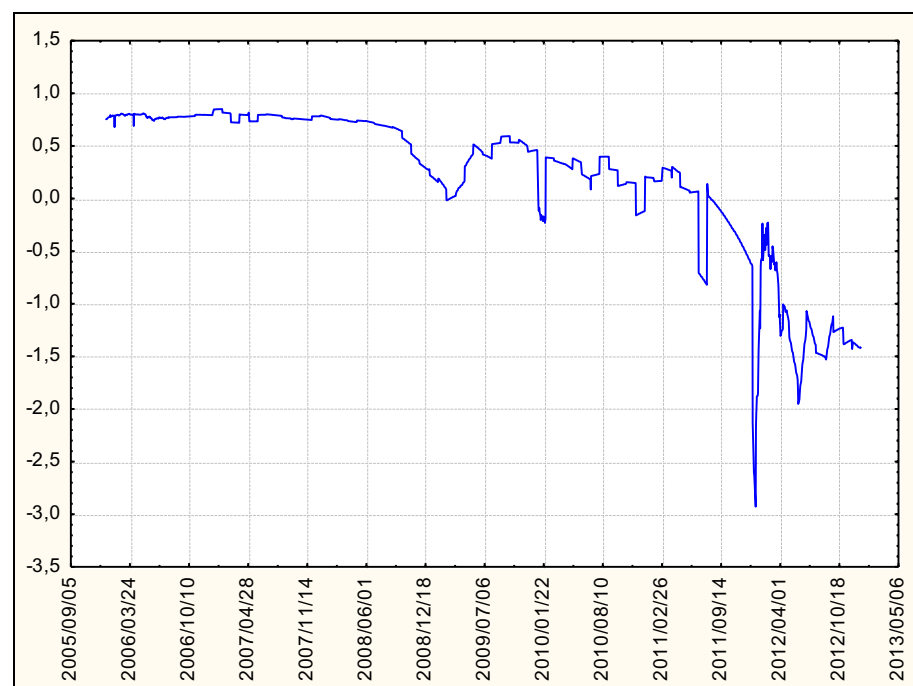


Table 4. Descriptive statistics

	Obs.	Mean	Min	Max	Variance	Std. dev	Skewness	Kurtosis
FDL	1,748	0.204368	-2.92824	0.850451	0.499190	0.706534	-1.45359	1.333923
EAD	1,748	0.620046	-7.79659	8.498492	2.126643	1.458301	-0.24817	4.605794

In this paper, we use a model based on KMV model to estimate default correlation between the Greek banks. KMV model calculated the default correlation between two borrowers. The default correlation between two banks A and B is written as follows:

$$\rho_{AB}^D = \frac{(JDF_t)_{AB} - (PD_t)_A * (PD_t)_B}{\sqrt{[(PD_t)_A(1 - (PD_t)_A)] * [(PD_t)_B(1 - (PD_t)_B)]}} \quad (50)$$

where, ρ_{AB}^D is the default correlation between the two banks A and B, $(PD_t)_A$ is the probability of default of bank A at time t, $(PD_t)_B$ is the probability of default of bank B at time t, and $(JDF_t)_{AB}$ is the joint default probability between the two banks A and B at time t. In this case, the joint default probability between the two banks A and B at time t will be expressed as follows:

$$(JDF_t)_{AB} = (PD_t)_{AB} = \Phi_2(\Phi^{-1}((PD_t)_A), \Phi^{-1}((PD_t)_B), \rho_{AB}) \quad (51)$$

where, $\Phi_2(\cdot)$ is the function of bivariate normal cumulative distribution, $\Phi^{-1}(\cdot)$ is the inverse function of univariate cumulative normal distribution, and ρ_{AB} is the correlation between the asset returns of the two banks A and B.

$$\rho_{AB} = \frac{\sigma_{AB}}{\sigma_A \sigma_B} = \frac{cov(R_A, R_B)}{\sigma_{R_A} \sigma_{R_B}} \quad (52)$$

$$cov(R_A, R_B) = \sigma_{AB} = \sum_{i=1}^2 P_i (R_{Ai} - E(R_A))(R_{Bi} - E(R_B)) \quad (53)$$

where, $cov(R_A, R_B)$: is the covariance between asset returns of banks A and B, σ_A is the standard deviation of the asset returns of bank A, σ_B is the standard deviation of the asset returns of bank B, R_{Ai} is the asset returns of portfolio A, R_{Bi} is the asset returns of portfolio B, $E(R_A)$ is the expected asset returns of bank A, and $E(R_B)$ is the expected asset returns of bank B.

We calculated the average default correlation value for the different years (2006–2012) for a daily frequency. Table 5 summarizes the various statistics on the distribution of the average default correlation (DC).

Figure 9 reports the evolution of the average default correlation. We can observe that the default correlation is highly and positive during the period of study.

However, the number of default correlations varies with the number of existing banks in the Athens Exchange. Table 6 summarizes the number of default correlations based on the number of banks and date, as the number of banks listed in the Athens Exchange is not the same for each time t.

Table 5. Descriptive statistics

	Obs.	Mean	Min	Max	Variance	Std. dev	Skewness	Kurtosis
DC	1,748	0.276925	-0.115776	0.864569	0.047681	0.218359	0.490966	-0.365925

Figure 9. The evolution of default correlation (DC).

Note: This figure summarizes the mean of default correlation between 18 Greek banks used in this paper for the study period from 02 January 2006 to 31 December 2012.

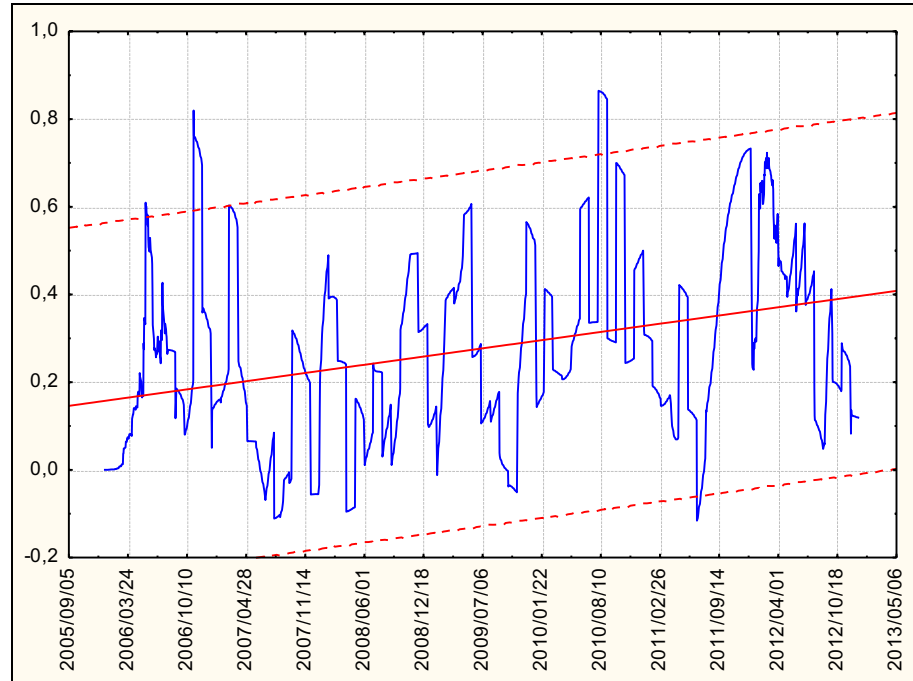


Table 6. The number of default correlations

Period	Number of days	Number of existing banks in the Athens exchange	Number of default correlation
02/01/2006 to 30/03/2007	312	15	32,448
02/04/2007 to 20/08/2007	97	14	8,730
21/08/2007 to 20/09/2007	23	13	1,771
21/09/2007 to 31/12/2007	70	12	4,550
02/01/2008 to 30/06/2010	616	15	64,064
01/07/2010 to 31/03/2011	191	14	17,190
01/04/2011 to 29/04/2011	19	13	1,463
02/05/2011 to 30/12/2011	171	12	11,115
02/01/2012 to 11/04/2012	70	11	3,780
12/04/2012 to 31/12/2012	179	10	7,876

6. Empirical results

According to the empirical results, we found that there are 12 dates of transmission of default in the case of banks in Greece:

- One transmission in 2006.
- Two transmissions in 2007.
- Five transmissions in 2009.
- Two transmissions in 2010.
- One transmission in 2011.
- One transmission in 2012.

Figure 10 reports the volatility of systemic risk during the period from 2 January 2006 to 31 December 2012.

Generally, the main transmission dates are deducted immediately after the declaration of failure of Greece in 2009 except for three dates in 2006 and 2007. The different results of the estimation of systemic risk are shown in Table 7.

Table 8 reports the descriptive statistics of systemic risk and of the different compartments of SEIR model. From this table, we note that systemic risk has a higher level of volatility. For the four compartments of systemic risk, we remark that the Susceptible portfolios are likely to become more volatile than Exposed, Infected, and Removed portfolios.

Figure 11 reports the volatility of four compartments of systemic risk measured by epidemic model 'SEIR' during the period from 2 January 2006 to 31 December 2012.

In epidemic models, the default correlation is very important in the assessment of systemic risk and in solving the system of differential equations. In addition, the default correlation justifies the level of dependence between different Greek banks that constitute the study population used in this paper. During the period of study, the number of default correlation number varies according to the number of existing banks on the Athens Exchange and depending on the time of transmission of default. Table 9 summarizes the volatility of default correlation on default transmission periods.

From Table 9, we tried to determine the number of declared default after each transmission of default. In Table 10, we presented the different dates transmission of default dates accomplished by the number of bank which had declared failure and left the Athens Stock Exchange.

Based on the results presented in Table 10, we decomposed the study period into five subperiods based on the failure dates, the number of banks that had declared failure and left the Athens Exchange. Table 11 summarizes all the subperiods and their dates and the number of transmission combine them.

Figure 10. Systemic risk (SR).

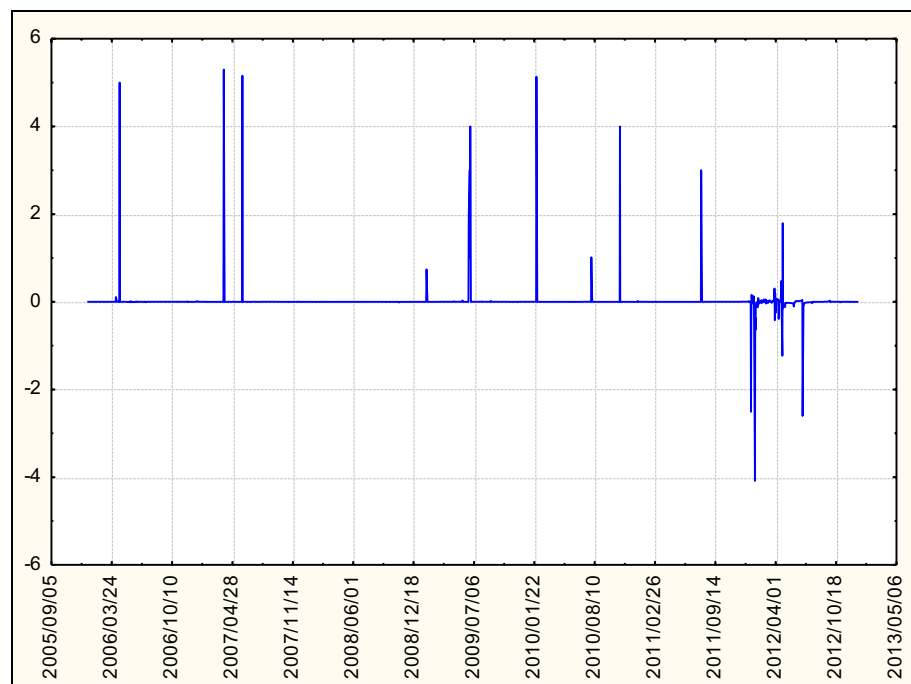


Table 7. The different dates of default transmission

The default transmission date (SR > 1)	SR value	The value of S*	The value of E*	The value of I*	The value of R*
19/04/2006	5.0006153	0.44488648	0.41960956	0.13531776	0.0001862
30/03/2007	5.2970103	0.99984395	6,9385E-05	6,5959E-05	2,0703E-05
31/05/2007	5.1573438	0.99901469	0.00043651	0.00041721	0.00013159
19/06/2009	2.0006752	0.41217565	0.31751271	0.27023112	8,0517E-05
22/06/2009	3.0007966	0.4397149	0.31579495	0.24442201	6,81481E-05
23/06/2009	1.0007579	0.43504867	0.3140503	0.25082958	7,14472E-05
24/06/2009	4.0006830	0.42201318	0.31228201	0.26562574	7,90646E-05
25/06/2009	2.0006179	0.40917982	0.31049095	0.28024218	8,70542E-05
29/01/2010	5.1349557	0.989464612	0.00296003	0.00384998	0.00372538
30/07/2010	1.0159414	0.34178886	0.28082659	0.36526491	0.012119647
29/07/2011	3.0010208	0.50264181	0.1214959	0.37242186	0.003440431
24/04/2012	1.7918449	0.49982389	0.12799133	0.37195427	0.000230502

Table 8. Descriptive statistics

	Obs.	Mean	Min	Max	Variance	Std. dev	Skewness	Kurtosis
SR	1,748	0.017843	-0.000003	-4.08346	5.297010	0.340306	9.2759	162.085
S	1,748	0.997080	1.000000	0.34179	1.000000	0.040644	-13.9783	194.938
E	1,748	0.001444	0.000000	0.00000	0.419610	0.021070	15.4041	244.403
I	1,748	0.001465	0.000000	0.00000	0.372422	0.020992	14.9805	230.959
R	1,748	0.000012	0.000000	0.00000	0.012120	0.000314	34.4760	1282.523

Figure 11. The volatility of the four compartments of SEIR model (S, E, I, and R).

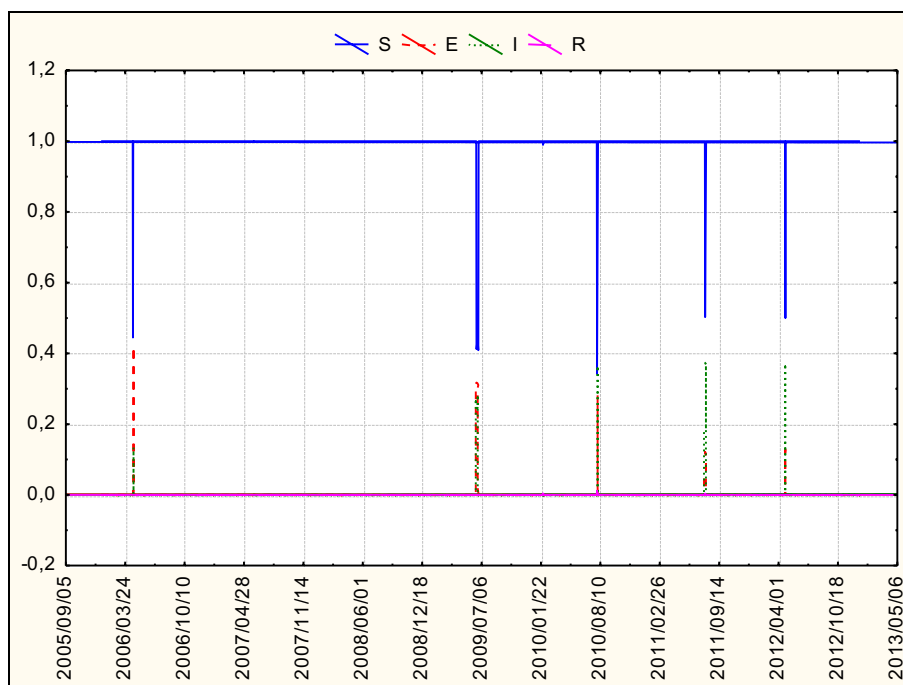


Table 9. The volatility of default correlation

Date of transmission of default	Study period	Number of days	Number of existing banks in the Athens Exchange	Number of default correlation
19/04/2006	02/01/2006 to 19/04/2006	74	15	7,696
30/03/2007	20/04/2006 to 30/03/2007	238	15	24,752
31/05/2007	02/04/2007 to 31/05/2007	41	14	3,690
19/06/2009	01/06/2007 to 20/08/2007	56	14	5,040
	21/08/2007 to 20/09/2007	23	13	1,771
	21/09/2007 to 31/12/2007	70	12	4,550
	02/01/2008 to 19/06/2009	358	15	37,232
22/06/2009	19/06/2009 to 22/06/2009	1	15	104
23/06/2009	22/06/2009 to 23/06/2009	1	15	104
24/06/2009	23/06/2009 to 24/06/2009	1	15	104
25/06/2009	24/06/2009 to 25/06/2009	1	15	104
29/01/2010	26/06/2009 to 29/01/2010	151	15	15,704
30/07/2010	01/02/2010 to 30/06/2010	103	15	10,712
	01/07/2010 to 30/07/2010	22	14	1,980
29/07/2011	02/08/2010 to 31/03/2011	169	14	15,210
	01/04/2011 to 29/04/2011	19	13	1,463
	02/05/2011 to 29/07/2011	64	12	4,160
24/04/2012	01/08/2011 to 30/12/2011	107	12	6,955
	02/01/2012 to 11/04/2012	70	11	3,780
	12/04/2012 to 31/12/2012	179	10	7,876

According to Table 10, we found that there are seven banks that have left the Athens Exchange after their failure and after the high depreciation of their values in the stock market of Greece.

The transmission of default is based on the application of a SEIR epidemic model. The advantage of these models is the determination of the date of transmission of default and the number of default for a population consisting of a set of banks in this paper.

The SEIR model is composed of four compartments that we have determined based on the assumptions of epidemic models. The evolutions of the different compartments (*S*, *E*, *I*, and *R*) are shown in Figures 12–16. This representation is based on the distribution of the different subperiods that we have chosen.

This paper is based on the development of biofinancial approach for measuring systemic risk of a portfolio of banks. This approach is based on the selected sample (18 Greek banks), the assumptions of our empirical evidence, and the econometric techniques used to test this approach. In addition, we used an epidemic model (SEIR) from which we tested the transmission of default in banks in Greece during the study period (02/01/2006–31/12/2012).

Note that, even in the presence of an intervention by the central bank and other regulatory authorities, we noticed that there are banks that have declared failure. We can say that the role of the central bank of Greece is not enough to save bank on default and to prevent the propagation of the default from one bank to another, or to the entire banking system.

Table 10. The presentation of different transmission fault dates

The date of transmission of default (SR > 1)	The date of default of a bank and its exit from the Athens Exchange	Banks that had declared failure
19/04/2006		
30/03/2007	30/03/2007	MARFIN FINANCIAL GROUP
31/05/2007	20/08/2007	ΕΓΝΑΤΙΑ BANK (ΚΟ)
	20/09/2007	ΕΓΝΑΤΙΑ BANK (ΠΟ)
19/06/2009		
22/06/2009		
23/06/2009		
24/06/2009		
25/06/2009		
29/01/2010	30/06/2010	ASPIS BANK
30/07/2010	31/03/2011	MARFIN EGNATIA BANK
	29/04/2011	EMPORIKI BANK
29/07/2011	11/04/2012	MARFIN POPULAR BANK
24/04/2012		

Table 11. The representation of the different subperiods

Period	Date	Number of transmissions of default	Number of banks leaving the Athens exchange
1	02/01/2006 to 30/05/2007	2	1
2	31/05/2007 to 18/06/2009	1	2
3	19/09/2009 to 29/07/2010	6	1
4	30/07/2010 to 28/07/2011	2	2
5	29/07/2011 to 31/12/2012	1	1

The variable measuring the role of Greece regulatory authorities is less than 1 until the end of the first half of 2008. During this period, we noticed that there were only three banks that have left the Athens Exchange. The role of regulators is insufficient because the variable $h(t)$ exceeded 1 (Liu, Yu, & Zhu, 2015). Following the period of 2008, we note that there are four banks that had declared failure and left the Athens Exchange. This is justified by the high level of the variable $h(t)$ since it reaches a very important value equal to 11. In addition, during the second period, just after the first half of 2008 until 31 December 2012, the Greece declared its failure and several help have granted by the member countries of the European Union. Even these plans have not stopped the propagation of the failure of banks in Greece. The intervention of the International Monetary Fund, the European Central Bank, the Government of Greece and the Greek central bank is insufficient to save Greece and to prevent systemic risk in the Greek banking system. Figure 17 reports the volatility of $h(t)$.

Then, since the financial crisis of 2007, successive plans succeed aid to Greece with a lot of absurd demands to save them and also save his creditors. We note that at the end of 2014 Greece have a total of debts that are equal to 300 billion dollars. Figure 18 summarizes the main creditors of Greece.

The results found in this paper are consistent with the assumptions of the model used and therefore, we validated the use of this model. The SEIR model used allowed us to determine the different

Figure 12. The presentation of the first period.

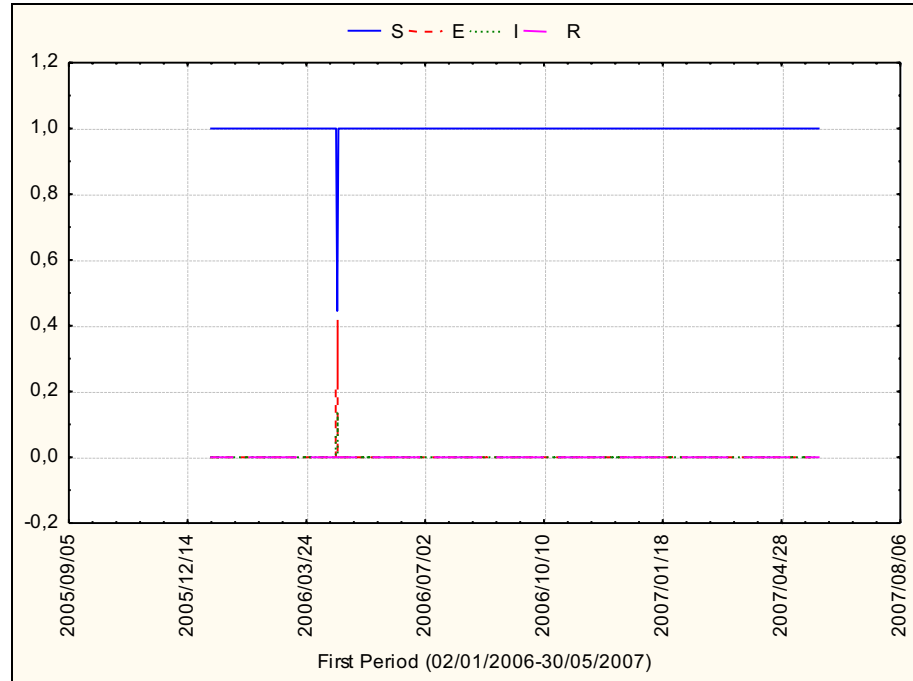
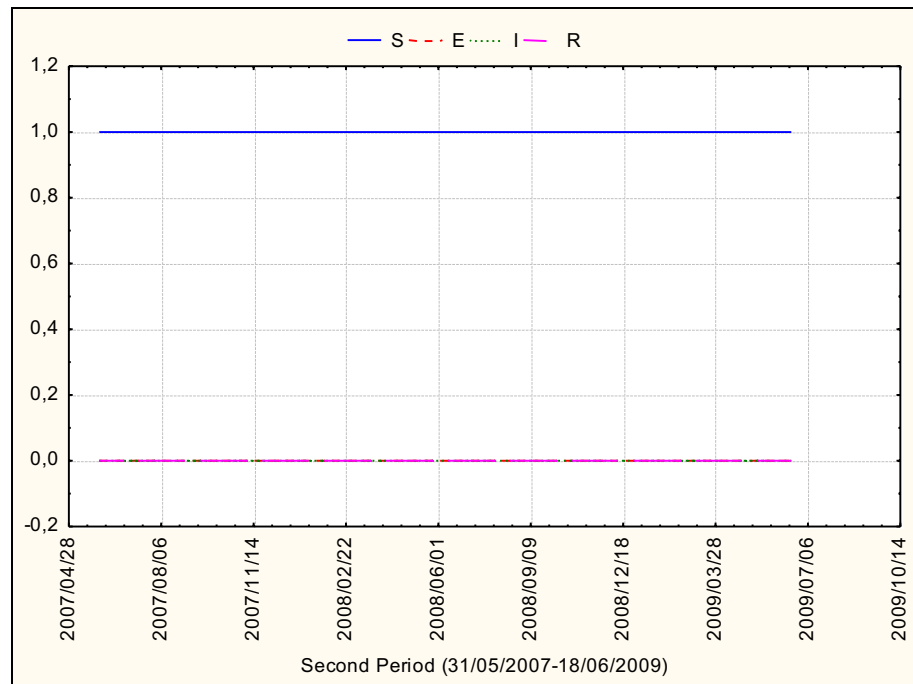


Figure 13. The presentation of the second period.



dates of transmission of default between banks in Greece. In addition, following this transmission there are seven banks that have declared their failure and left the Athens Exchange.

7. Conclusion

Measurement of risk is considered to be one of the most interesting issues in the recent literature in finance, especially after the outbreak of the financial crisis of 2007. This concept is developed recently by several authors, while the measures discussed systemic risk are different from one author

Figure 14. The presentation of the third period.

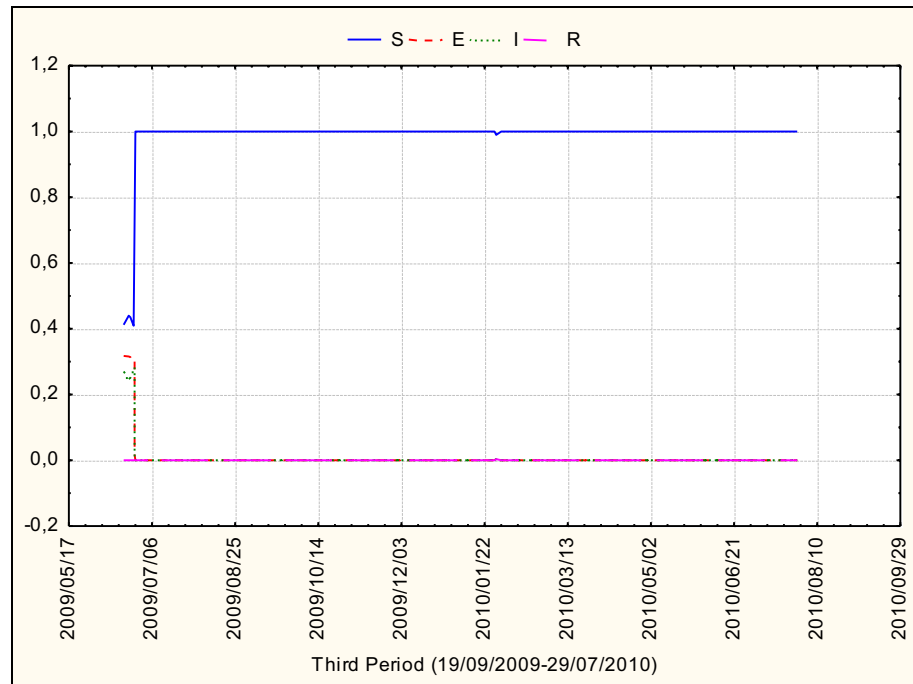
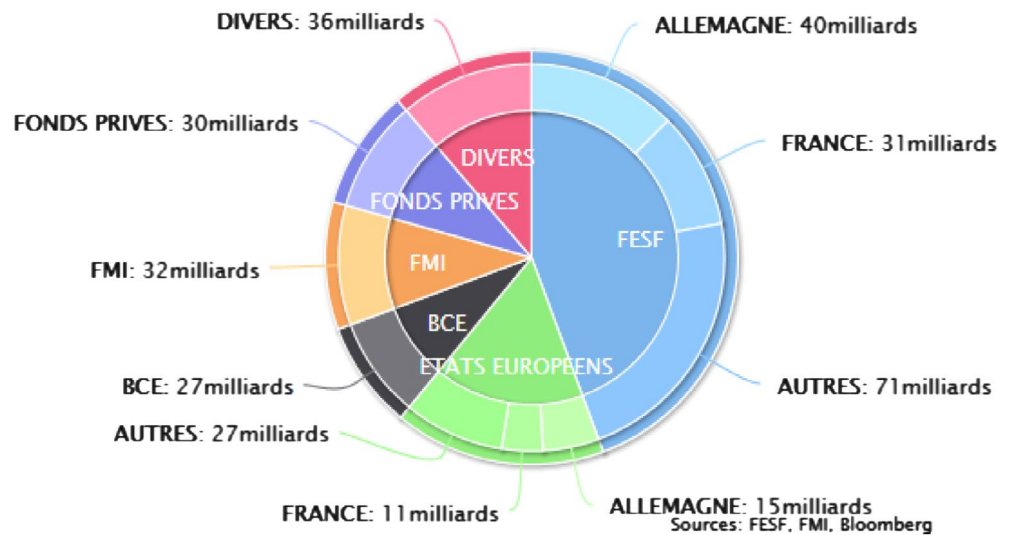


Figure 15. The presentation of the fourth period.



to another. In this paper, we present a biofinancial approach adopted for the modeling of systemic risk. We estimated the potential indicators of systemic risk as measured by the SEIR epidemic model. This model has four categories of portfolios. In addition, this model can measure the rate of transmission of default from portfolio to other portfolios. However, the transmission is conditioned by the value of systemic risk found in every moment. This value is compared to a threshold equal to 1. If the value of the systemic risk is less or equal to 1, there is no default transmission and if it is greater than 1, therefore there is a transmission of default.

We use a sample of 18 Greek banks listed in the Athens Exchange from 02 January 2006 to 31 December 2012. By observing the empirical results found in this paper, we found the existence of 12 transmissions of default during the period of study (02/01/2006–31/12/2012). The transmission of default coincides with the default of Greek banks that have declared failure then leaving the Athens

Figure 16. The presentation of the fifth period.

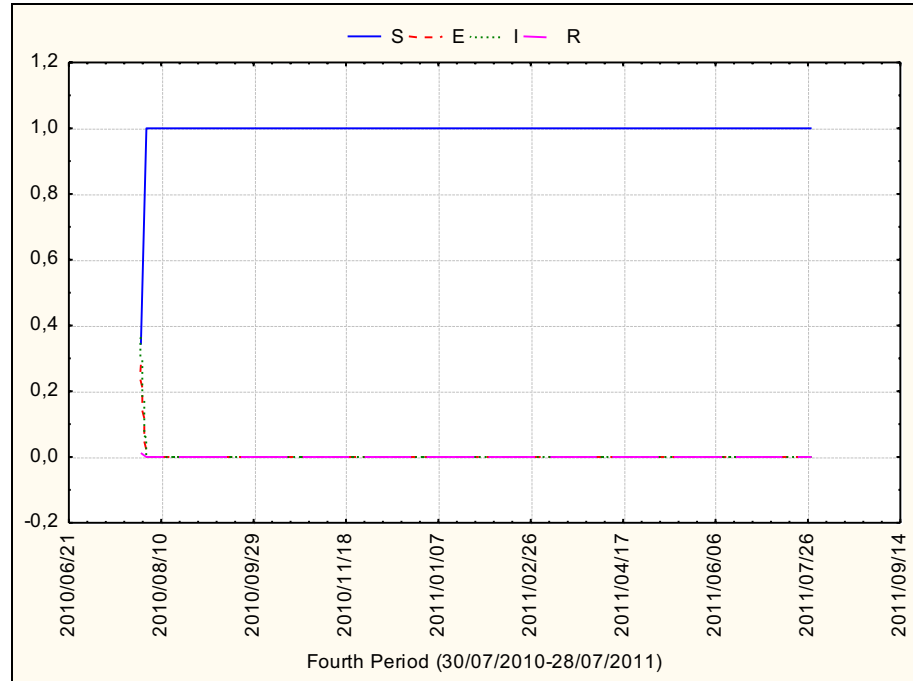
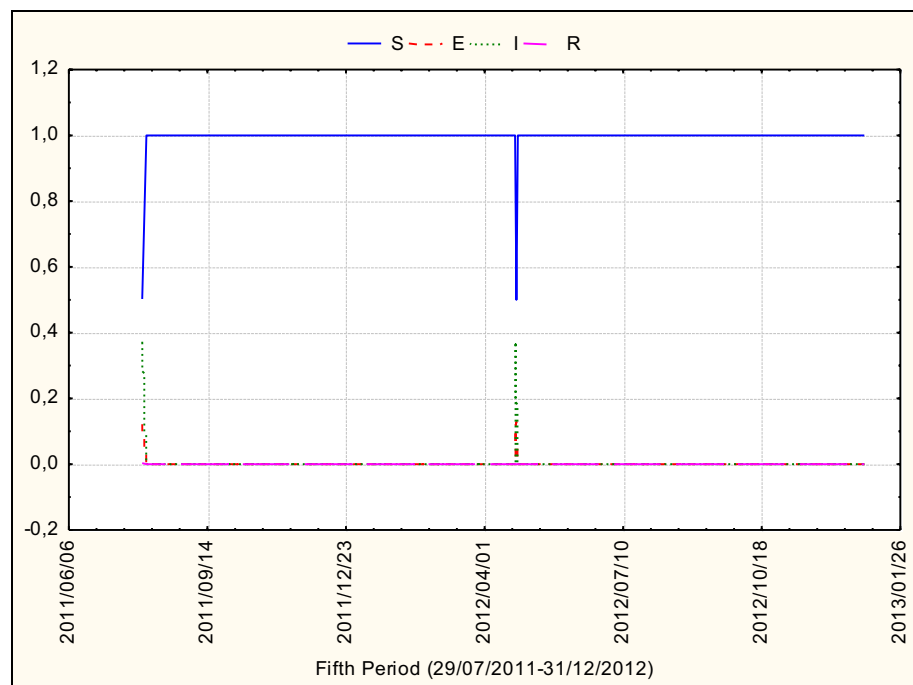


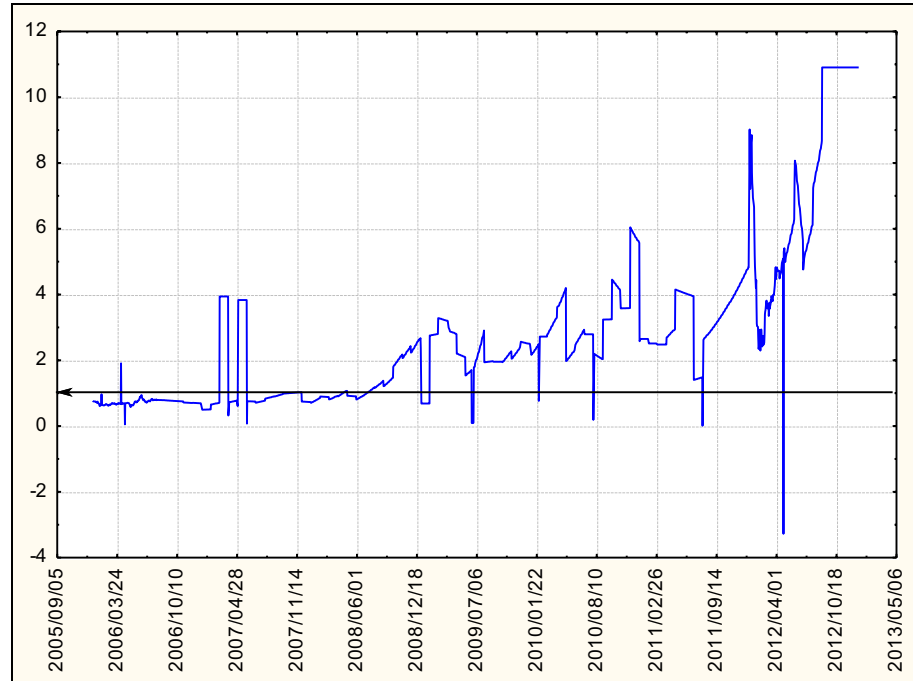
Figure 17. The evolution of the function $h(t)$.



Exchange. The results presented in this paper are based on a set of assumptions that allow the validity of “SEIR” model of systemic risk. We have shown that the Greek banking system is in recession. The continuation of aid plans employed by regulatory authorities did enough to help Greece.

We find that the main factors of the systemic risk are the default probability, the recovery rate, the default correlation, the exposure at default, the frequency of default in the case of loss, the market capitalization, and the regulatory authorities.

Figure 18. The Greek debt.



The role of the central bank is inadequate and even absent for the period of study. There is a deficiency in own regulations. We note that seven years are sufficient for 40% of the sample (7 banks) that declared their failure and left the stock market in Greece. Thus, two major observations are necessary: strong regulation is not always synonymous with financial stability and improving the transparency of information should be at the heart of any regulatory reform to prevent systemic risks that may arise from the traditional banking industry. The regulatory authorities are required to restore the new micro-prudential and macro-prudential reforms to control and to manage the systemic risk.

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