Intelligent Systems with Applications 12 (2021) 200055

Contents lists available at ScienceDirect

Intelligent Systems with Applications

journal homepage: www.elsevier.com/locate/iswa

Re-constructing the interbank links using machine learning techniques. An application to the Greek interbank market ☆

Anastasios Petropoulos[a], Vasilis Siakoulis[b,*], Panagiotis Lazaris[b], Sotirios Chatzis[c]

[a] Bank of Greece, 21 El. Venizelosg, Greece
[b] Bank of Greece, Greece
[c] Cyprus University of Technology, Archiepiskopou Adrianou 30, Limassol 3036, Cyprus

ARTICLE INFO

Article history:
Received 19 April 2021
Revised 18 September 2021
Accepted 13 October 2021
Available online 26 October 2021

JEL:
G01
G21
C53

Keywords:
Machine learning
Networks
Sentiment
Analysis
Text mining
Crises forecasting

ABSTRACT

We propose an innovative approach to model the probability of interlinkages in an interbank network with the use of Machine Learning techniques. More precisely we forecast the probability of a pair of banks entering into an interbank market borrower - lender relationship considering their financial characteristics and their past observed behavior. In this framework we examine a new method that employs machine learning in order to increase the accuracy of agnostic algorithms in reconstructing a financial network. The XGBOOST method is combined with both Maximum Entropy (MAXE) and Minimum Density (ANAN). The main contribution of this paper is that we enrich the information generally available for financial networks with variables that are available for the publication of banks financial statements (ensemble method). A set of agnostic models, i.e. models that the exposure allocation algorithm does not include prior information, are used as a benchmark to measure the additional benefit for applying machine learning in estimating prior network probabilities. By comparing the results between the agnostic algorithms and the ensemble method we see an increase in the accuracy and a decrease in the MAE of the financial networks on average. Our purpose is to depart from agnostic assumptions usually employed in interbank matrix allocation algorithms and take into account the financial features of the banks when assigning prior link probabilities. Our main finding is that machine learning algorithms outperforms the benchmark Logistic Regression model in interbank link forecasting and this is also reflected in the enhanced performance when overall network similarity measures are performed.

1. Introduction – motivation

System wide stress testing is one of the most challenging tasks for supervisory authorities across the world. Addressing in a proper manner the secondary contagion effects caused by an initial perturbation in a financial system through the network of institutions pipeline is an important goal for banking supervisors and central banks responsible for micro- and macro-prudential policy. However, this attempt is often (when not always) limited by the partial information about the structure of the underlying networks. Especially in the case of financial networks the information on the interconnections among institutions is privacy-protected, dramatically reducing the possibility of correctly estimating crucial systemic properties such as the resilience to the propagation of shocks. The need to compensate for the scarcity of data, while optimally employing the available information, has led to the birth of a research field known as network reconstruction.

This paper presents an innovative approach to model the probability of interlinkages in an interbank network with the use of machine learning techniques. More specifically we employ an Extreme Gradient Boosting algorithm (XGBOOST) to forecast the probability of 2 banks entering into an interbank market borrower-lender relationship taking into account their financial characteristics and their past observed behavior. In this way we depart from past studies of random generation of interbank networks which are either agnostic in the way probabilities of bilateral relationships are calculated or make ad-hoc assumptions i.e. small banks are more probable to be borrowed from large banks.

We propose a new method that employs machine learning in order to increase the accuracy of agnostic algorithms in reconstructing a financial network. The XGBOOST method is com-

☆ The views expressed in this paper are those of the authors and not necessarily those of Bank of Greece.

* Corresponding author.
E-mail addresses: apetropoulos@bankofgreece.gr (A. Petropoulos), vsiakoulis@bankofgreece.gr (V. Siakoulis), plazaris@bankofgreece.gr (P. Lazaris), sotirios.chatzis@cut.ac.cy (S. Chatzis).

https://doi.org/10.1016/j.iswa.2021.200055

bined with both Maximum Entropy (MAXE) and Minimum Density (ANAN). The main contribution of this paper is that we enrich the information generally available for financial networks with variables that are available for the publication of banks financial statements (ensemble method). A set of agnostic models, i.e. models that the exposure allocation algorithm does not include prior information, are used as a benchmark to measure the additional benefit for applying machine learning in estimating prior network probabilities. By comparing the results between the agnostic algorithms and the ensemble method we see an increase in the accuracy and a decrease in the MAE of the financial networks on average.

The main point of the paper is not to provide an alternative in the literature to the agnostic network construction algorithms. The purpose of the paper is to show the value of developing a formalized method for estimating the prior linkage probabilities based on the particular characteristics of the agents involved in the network in a similar way to Musmeci et al. (2013). It is recognizable that agnostic algorithms employ a different information set, as it is also evident that the inclusion of extra information can improve the utility of agnostic models especially in stressed situations and large interbank networks. In total, the accuracy increase is more sizable in periods where a shock hits the network making it more useful for quantification of risk. In addition, the improvement will be more sizable as the number of participants increases since agnostic measures will lose their forecasting ability

In order to allocate the bilateral exposures amounts and reconstruct the matrix, estimated probabilities are fed as priors in the Minimum Density algorithm developed by Anand et al. (2015) whereas we benchmark our results with a variate of allocation algorithms provided in the literature. We employ the Minimum Density algorithm instead of the equally well known in the literature Maximum Entropy algorithm (Upper and Worms, 2014) because the latter has the shortcoming that tends to create complete networks which obscure the true structure of linkages in the original network. We calibrate our model in the Greek banking system which is far from a complete network and the interbank activity is based on long term relationships where smaller banks tend to use a limited set of money center banks as intermediaries. Indeed, most banks would find it prohibitively costly in terms of information processing and risk management to lend funds to every active bank in the system.

Our model can be used to simulate and assess interbank contagion effects on banking sector soundness and resilience. The approach furthermore enables to rank the institutions belonging in the network, considering which bank failure would have the most detrimental contagion effects on the system. In this sense the correct representation of the network is crucial for the outcome of a system wide stress test. When someone overestimates the number of links in an interbank system, the results may underestimate the extent of contagion. For instance, if a default takes place, to a network that spreads the exposures widely, then the impact will be allocated to a greater number of institutions with limited exposures whereas in the opposite case the same aggregated impact will be allocated to a limited number of institutions with a significantly greater amount of exposures. .

The remainder of the paper is structured as follows. In Section 2, we focus on the related literature review on interbank matrix allocation algorithms and applications to banking systems across the world. Section 3, describes the data collection and processing. In Section 4, we provide details regarding the estimation process of the various alternative models developed. In Section 5, we compare the employed methodologies whereas in the concluding Section 6, we summarize our findings, we identify any potential weaknesses and limitations, while we also discuss areas for future research extensions.

2. Literature review

There is large number of network reconstruction algorithms in the current literature. These algorithms take as input the aggregated assets and liabilities of the participating banks in the interbank market and allocate them on bilateral exposures either through an iterative process where from an initial “guess” of the network entries are re-scaled until aggregate positions satisfy the asset – liabilities constraints or through a Monte-Carlo sampling process. Anand et al. (2018) conduct a horse race of network reconstruction methods using network data obtained from 25 different markets spanning 13 jurisdictions and ranked the methods in terms of their ability to reconstruct the structures of links and exposures in networks.

Upper and Worms (2004) developed a Maximum Entropy algorithm so as to estimate the matrix of bilateral credit relationships for the German banking system. The method entails maximizing an entropy function subject to a set of constraints (usually the bank’s total asset and liabilities to counterparties). In the initial guess network, institution i’s exposure to institution j is the product of i’s aggregate interbank asset position and institution j’s aggregate interbank liability position. This network is subsequently re-scaled by the aggregate positions, first along the rows and then the columns, until the aggregate position constraints are satisfied.

Baral and Fique (2012) enrich the Maximum Entropy method with a bivariate copula to estimate adjacency matrices. Since a copula is a cumulative distribution function, it generates the probabilities of bilateral connections, which can then be used to simulate stochastic matrices or adjacency matrices by imposition of a cut-off rule. Those probabilities of bilateral connections are fed into the Maximum Entropy method to produce the interbank network. Drehmann and Tarashev (2013) propose an alternative method that generates a series of high-concentration networks by perturbing the network produced by the Maximum Entropy method. The Maximum Entropy based algorithms performs well when large fraction of the links are of an equal size and the average link size is roughly similar to the aggregate exposure divided by the number of financial institutions.

Anand et al. (2015) propose the Minimum Density method (anan) that combines information-theoretic arguments with economic incentives to produce more realistic interbank networks that preserve important characteristics of the original interbank market. The method is an iterative algorithm that loads the most probable links with the largest exposures consistent with the total lending and borrowing of each bank, yielding networks with minimum density. This algorithm performs well when the interbank network is sparse.

Halaj and Kok (2013) introduce an additional iterative algorithm to simulate and assess interbank contagion effects on banking sector soundness and resilience. Through and iterative assignment process links are drawn at random with an equal probability, so the stock of interbank liabilities and assets reduces as the volume of the assigned (matched) placements increases. The procedure is repeated until no more interbank liabilities are left to be assigned as placements from one bank to another.

Musmeci et al. (2013) present a method to reconstruct complex network from partial information. They assume to know the links only for a subset of the nodes and to know some non-topological quantity (fitness) characterizing every node. The missing links are generated on the basis of the latter quantity according to a fitness model calibrated on the subset of nodes for which links are known. Cimini et al. (2015) also employ a fitness model that determines the likelihood both of directed linkages and exposures. Their model is similar to the Musmeci et al. (2013), with the difference that for the latter matrices are undirected and the assignment algorithm is

Maximum Entropy whereas the Cimini et al. (2015) has directed linkages and the exposure assignment also follows a fitness model.

Interbank market structure is a very important topic for regulators and academics since it is the cornerstone in the building up of system wide stress testing framework. Therefore a large relevant empirical literature has been developed across many countries and banking systems.

Duarte and Jones (2017) constructed an empirical measure of expected network spillovers that arise through default cascades for the U.S. financial system for the period 2002–16 including a large cross section of U.S. financial firms that comprises all bank holding companies, all broker-dealers, and all insurance companies, and consider their entire empirical balance sheet exposures. They find negligible expected spillovers from 2002 to 2007 and from 2013 to 2016. However, between 2008 and 2012, they find that default spillovers can amplify expected losses by up to 25 percent, a significantly higher estimate than previously found in the literature.

Mistrulli (2011) analyze how contagion propagates within the Italian interbank market using a unique data set including actual bilateral exposures. Based on the availability of information on actual bilateral exposures for all Italian banks, the results obtained by assuming the maximum entropy are compared with those reflecting the observed structure of interbank claims. Bargigli et al. (2016) also focus on the Italian interbank market investigating two different centrality measures in multiplex networks and finding that there are several medium sized banks which are central in some links and peripheral in others.

Van Lelyveld and Liedorp (2006) investigate interlinkages and contagion risks in the Dutch interbank market. Based on several data sources, including survey data, they estimate the exposures in the interbank market at bank level and perform a scenario analysis to measure contagion risks. We find that the bankruptcy of one of the large banks will put a considerable burden on the other banks but will not lead to a complete collapse of the interbank market. Finally Amundsen and Arnt (2012) used records of payments in the Danish large value payment system to compute a unique, high-frequency data set on bilateral exposures between banks and they found that the risk of contagion in the Danish interbank market due to an unexpected failure of a major bank is very limited.

Luitgard (2020) developed a new model for solvency contagion that it allows for the spread of contagion already before the point of default and hence can account for contagion due to distress and mark-to-market losses. Cinelli et al. (2021) developed a model of financial contagion set up to estimate the width and length of the cascades in the interbank markets, incorporating incomplete information by considering a worst-case scenario in which unobserved links were assumed to be present. Cao et al. (2021) measure systemic risk capturing spillovers arising from deleveraging and price impact in financial systems and calculate the amplification of losses during the contagion process. Maringer et al. (2021) develop a new network reconstruction algorithm inspired by the transportation planning literature and research in stochastic search heuristics.

3. Data collection

The international interbank market is a global network used by financial institutions in order to exchange funds in various currencies. The aforementioned transfer of funds is among others related to the institutions' "needs". One typical example is when an institution A has an excess in funds and at the same time an institution B has an increase need to cover its deficit. The two institutions through the network of interbank markets are able to exchange an amount of funds by matching their excess and deficit related liquidity. Another category of interbank transactions is the one related to the Over the Counter Derivative markets. For example, swap rate receivers are transacting with swap rate borrowers or institutions exchange United States Dollars for Euros.

The transfer of liquidity can occur by using secured or unsecured transactions. In a secured transaction the lender requests collateral to guarantee the loan provided. The collateral is usually a liquid financial instrument (e.g. bond or stock). At the other end of the spectrum, when institutions lend each other via unsecured transactions, no exchange of collateral is required. In our analysis, we focus on transactions entail transfer of liquidity via a borrower - lender relationship, covering both secured and unsecured transactions. More specifically we concentrate our interest in the Greek Banking network and we include in our analysis unsecured loan and deposit transactions regardless of their seniority, repurchase and reverse repurchase transactions as well as sell by back and buy sell back transactions.

The Greek Banking network is composed by Other Systemic Institutions, Less Systemic Commercial Banks and Less Systemic Cooperative Banks. Although the number of institution became limited (around 20) due to the Greek Sovereign crisis, the Greek banking institutions carry different characteristics in terms of business models, balance sheet size and liquidity capacity.

The network constitutes the exchange of liquidity funds between different institutions operating in Greece from 2014Q3 to 2019Q3 on a weekly basis. Transactions conducted with institutions not operating in Greece are excluded. The interbank network as well as the liquidity and solvency metrics are derived directly from Bank of Greece Regulatory Database. The time period covers a few different instances of liquidity conditions in Greece such as political uncertainty that ended up to a referendum and the introduction of capital controls in 2015 as well as political stable periods in which institutions were able to operate normally and build high liquidity buffers. For each data point two institutions are consider connected if and only if at that date they have at least one open interbank transaction.

The dataset consist of a series of matrices with open interbank transaction between institutions operating in Greece in specific reference dates. Each matrix, referring to a specific reference date and the frequency of the selected dates, is weekly covering the whole time span. For each reference date (each matrix) two institutions are consider connected if and only if at that date they have at least one open interbank transaction. In order to analyze the network in a coherent econometric way interbank matrices are transposed to data format as illustrated in Table 1. In t1 Bank A has lent to Bank B (amount 10), Bank B has lent to Bank C (amount 20) and Bank C has lent to Bank A (amount 5). In this case, the dependent variable takes the value of 1 (irrespectively from the lent amount) whereas in the rest of the relations between the 3 banks the dependent variable takes the value zero. The matrices in the sample are end of week point in time data, so the next week ($t+1$) the same allocation of interbank link presence ($y=1$) and non-presence ($y=0$) is performed. Finally, for each reference date we retrieve the most recent lagged independent variable value. For instance, capital adequacy ratios are updated every month, thus for all weekly observation within the whole month this independent variable remains constant.

In this way one can easily apply an econometric approach by matching each time stamp with Lender Borrower characteristics and predict either the exposure measures or the link indicator. In our case we focus on the link indicator setting up a classification problem with a binary dependent variable taking the value of 1 if a bilateral interbank relationship is observed between bank L (lender)) and bank B (borrower). Our initial matrix dataset consists of weekly observations from 2/8/2013 to 20/9/2019 and the size of the matrix is 16×16 including 16 banks which were fully operative during that period. Taking out the diagonal elements our transposed matrix has around 70.000 observations.

Table 1
Illustrative example of bilateral interbank exposure matrix transposition.

Initial Matrix

t1	Bank A	Bank B	Bank C
Bank A		10	
Bank B			20
Bank C	5		

t2	Bank A	Bank B	Bank C
Bank A		5	
Bank B			10
Bank C			

t3	Bank A	Bank B	Bank C
Bank A		20	
Bank B			15
Bank C		50	

Transposed Matrix

Time	Lender to Borrower	Exposure	Link
t1	A lends to B	10	1
t1	A lends to C	0	0
t1	B lends to A	0	0
t1	B lends to C	20	1
t1	C lends to A	5	1
t1	C lends to B	0	0
t2	A lends to B	5	1
t2	A lends to C	0	0
t2	B lends to A	0	0
t2	B lends to C	10	1
t2	C lends to A	0	0
t2	C lends to B	0	0
t3	A lends to B	20	1
t3	A lends to C	0	0
t3	B lends to A	0	0
t3	B lends to C	15	1
t3	C lends to A	0	0
t3	C lends to B	50	1

The structure of the Greek Interbank Market has taken different forms before, during and after the crisis years.

We acknowledge the limitation paused by a small network of banks similar to the Greek banking system but on the other hand, the time series of the interbank matrices investigated in this study is long and includes both Crisis and Non-Crisis periods. During non-crisis periods Greek Interbank market is one of the alternatives through which banks manage their liquidity deficits and surpluses. When the crisis peaked in 2015 and with the imposition of capital controls in June 2015 the interbank market shrunk to a significant degree since questions relevant to the viability of the banking system increased substantially the risk profile of the counterparties involved. In addition the deposit drain eroded the funding surpluses which could be lent whereas banks resorted to the Emergency Liquidity Assistance of the European Central Bank in order to cover their funding needs. The different structure and size of the interbank market during crisis and non-crisis times is evident in Fig. 1 from which we observe that both size of exposures and complexity of linkages are very different when compare a crisis date (22/1/2016)) with a non - crisis one (23/11/2018).

4. Model development

We depart from previous studies which usually employ agnostic approaches in the specification of prior for the probability of bilateral relationships across banks i.e. small banks are more probable to be borrowed from large banks so large banks exhibit higher probability of entering the market as lenders and small banks have lower probability to enter the market as borrowers. We base the estimation of prior interconnected probability to a set of indicators that reflect the liquidity and capital solvency of the banks as well as their size. The indicators we are using are the Loan to Deposit ratios of lenders and borrowers (LTD_L and LTD_B) to capture liquidity solvency (lower LTD means better liquidity capacity) and the respective Capital Adequacy ratios (CAR_L and CAR_B) to cover for capital solvency. We additionally include the yield on deposits of lenders and borrower (YIELD_L and YIELD_B), calculated as interest expense to deposits, along with a dummy variable taking value of 1 if the bank is classified as significant institution based on the assessment of the single supervisory mechanism (SSM). Finally we include as covariate the spread of the Greek 10 year bond over the German bond in order to account for the Greek macroeconomic status as perceived by the market.

A lot has changed in the banking regulation (with the adoption of Basel III); capital adequacy and liquidity are measured in a standardized way and investors (including banks themselves) look at indicators like LCR, CET1 ratio and ratings. We focus only on LTD and CAR ratio as some regulatory ratios have been introduced later in the time span we cover (such as LCR) whereas others have changed due to redesigning of regulatory framework (such as CET1 composition).

From Fig. 2 we notice that no multi-collinearity effects exist among the dependent variables, as the pairwise correlation does not surpass 35% in the more extreme cases. In addition based on Augmented Dickey Fuller test (Table 2) the null of no stationarity is rejected for all the dependent variables implying no significant changes in trend during the observation period.

The abovementioned factors are used as independent variables whereas the dependent variable is a binary factor taking the value of 1 if a bilateral interbank relationship is observed between bank L (lender)) and bank B (borrower) based on the observed interbank

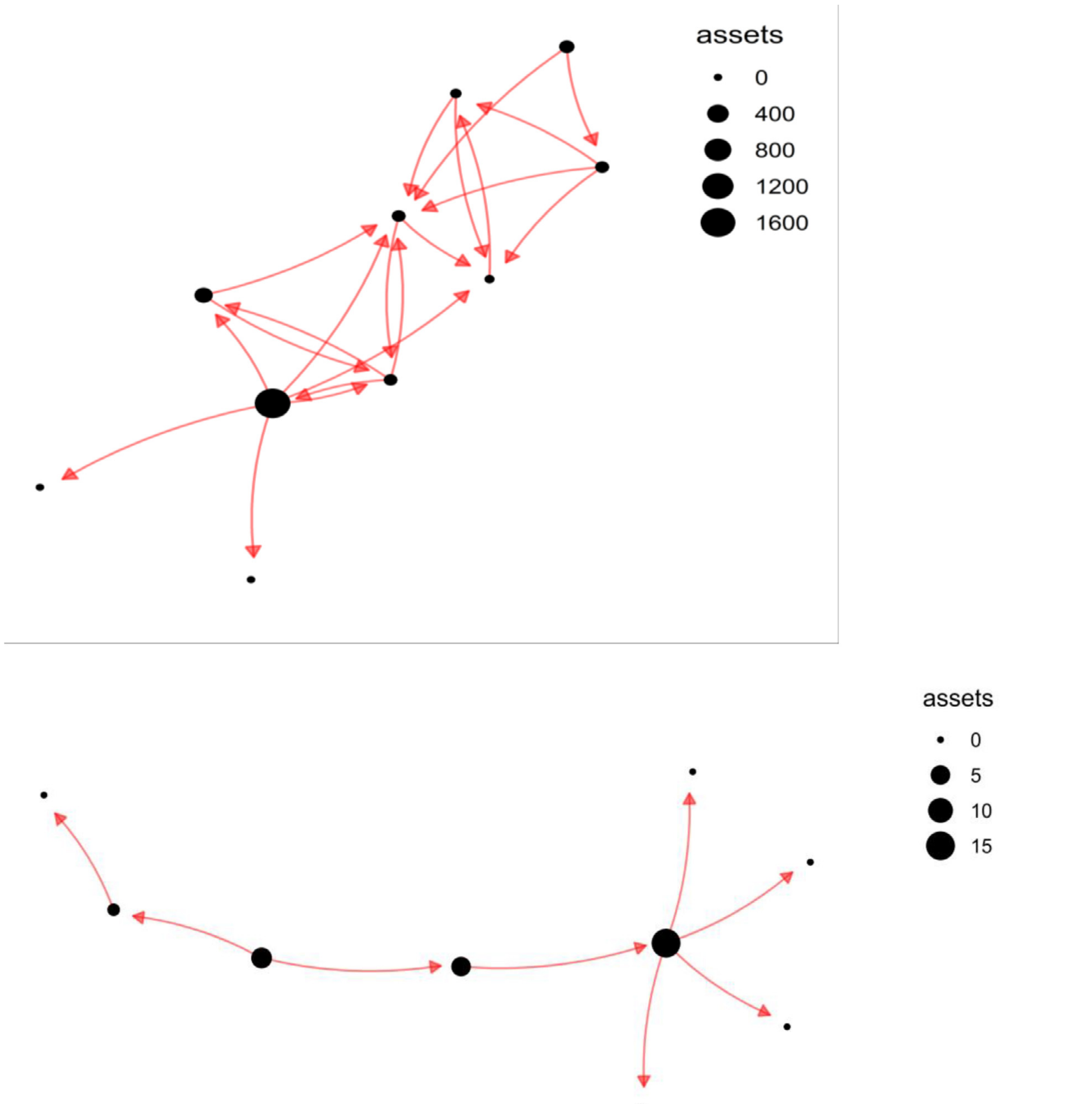

Fig. 1. Greek interbank market structure during non-crisis (upper chart) and crisis period (lower chart). Assets refer to lending in the market (amounts in millions).

Table 2
Augmented Dickey Fuller stationarity test of the independent variates included in the XGBOOST and Logit model probability specifications.

	ADF	P-VALUE%
LTD_L	−5.14	0.00
CAR_L	−9.74	0.00
YIELD_L	−5.43	0.00
LTD_B	−29.56	0.00
CAR_B	−28.97	0.00
YIELD_B	−28.94	0.00
Gr_Spread	−3.69	2.369

matrix and zero otherwise. In order to assess the relevance and the effect of the factors employed we estimate a Logistic Regression model the relevant estimates of which are shown in Table 2 using the formula $P(Y_i = 1) = \frac{exp(\beta_i{}' x_i)}{1+exp(\beta_i{}' x_i)}$. Betas are provided in Table 3 in column estimate. In particular, we define the following vectors

$$\beta = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \dots \\ \beta_{p-1} \end{bmatrix}_{p\times 1} \quad X = \begin{bmatrix} 1 \\ X_1 \\ \dots \\ X_{p-1} \end{bmatrix}_{P\times 1} \quad X_i = \begin{bmatrix} 1 \\ x_{i1} \\ \dots \\ x_{i,p-1} \end{bmatrix}_{p\times 1}$$

$$X_i{}'\beta = \beta_0 + \beta_1 x_{i1} + \dots + \beta_{p-1} x_{i,p-1}$$

So the interbank link probability between lender and borrower bank is defined as

$$\mathrm{SoE}\{Y_i\} = \pi_i = \frac{exp\left(X_i{}'\beta\right)}{1 + exp(X_i{}'\beta)}$$

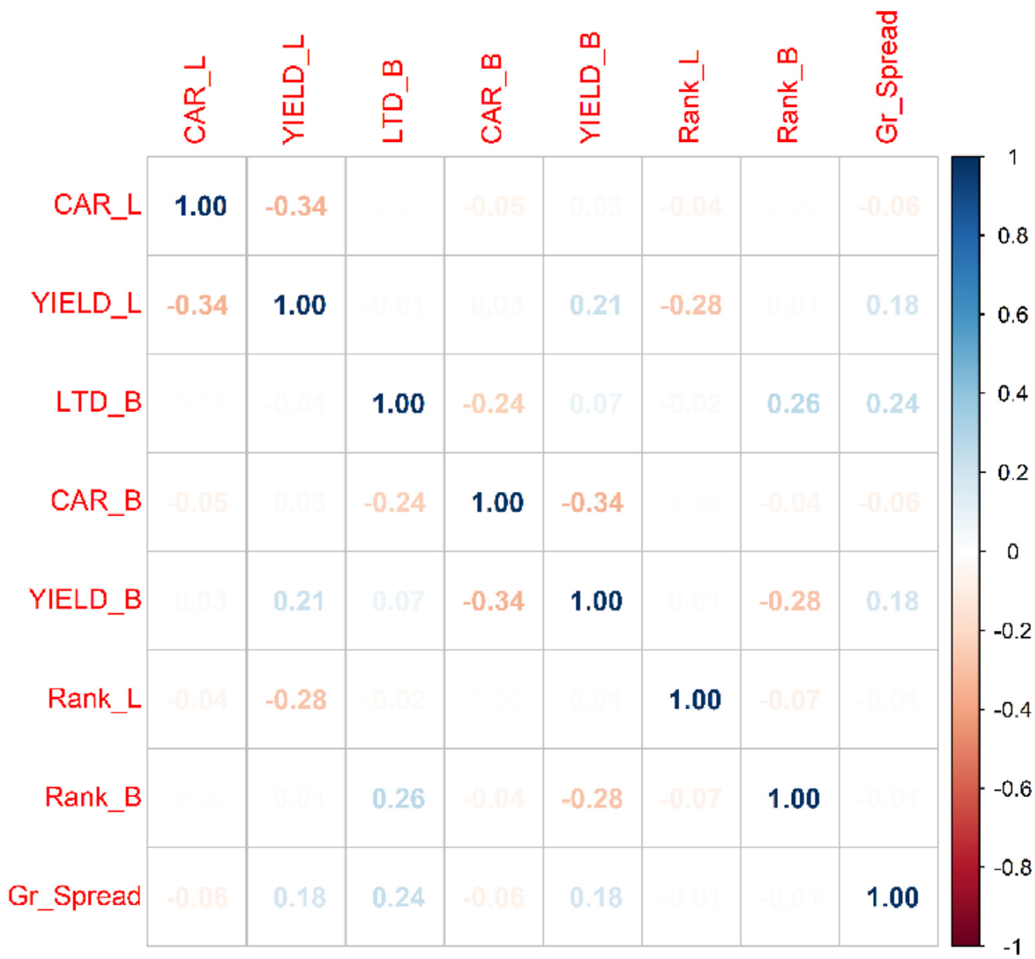

Fig. 2. Correlation matrix of independent variates included in the XGBOOST and Logit model probability specifications.

Table 3
Logistic Regression estimates for the probability of bilateral relationship.

Coefficients:	Estimate	Std.Error	z-value	Pr(>|z|)	
LTD_L	−0.016	0.001	−15.897	< 2e-16	***
CAR_L	0.002	0.002	0.810	0.418	
YIELD_L	−0.551	0.043	−12.747	< 2e-16	***
LTD_B	−0.018	0.001	−15.597	< 2e-16	***
CAR_B	−0.056	0.003	−17.149	< 2e-16	***
YIELD_B	−0.092	0.031	−2.943	0.003	**
Rank_L	2.435	0.057	42.674	< 2e-16	***
Rank_B	2.171	0.055	39.321	< 2e-16	***
Gr_Spread	0.016	0.010	1.627	0.104	
–					
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1					
AIC:	17,695				

In our case based on the covariates employed, the form of Logistic regression employed is

$$\log\left(\frac{p}{1-p}\right) = \mathrm{LTD_L} + \mathrm{CAR_L} + \mathrm{YIELD_L} + \mathrm{LTD_B} + \mathrm{CAR_B} + \mathrm{YIELD_B} + \mathrm{Rank_L} + \mathrm{Rank_B} + \mathrm{Gr\_Spread}$$

From the Logit model we deduce that significant institutions have higher probability of using the interbank market either as lenders (RANK-L) or as borrowers (RANK_B). This partially justifies the ad-hoc assumption that many allocation algorithms use assuming that larger institutions are more active in the interbank market. In addition banks with a solvent liquidity status, as expressed by low Loan to Deposit ratios (LTD_L and LTD_B), have an increased probability to engage into an interbank transaction. In a similar vein banks with lower deposit yields enter more probably in an interbank transaction both as lenders and borrowers (YIELD_L and YIELD_B). The behavior observed in Loan to Deposit and Yield ratios is more pronounced in the Greek case where during the sovereign crisis banks suffered from deposit outflows and increased cost of funding accompanied by a shrunk in the Greek interbank market. Also the negative sign in the capital adequacy of the borrower (CAR_B) may seem as counterintuitive given that capital solvent banks are usually treated as sovereign counterparties, but in the Greek case during the crisis and the narrowing of the interbank market, banks had proceed in share capital increases strengthening their capital ratios. Finally, the sovereign status of the Greek economy expressed via the spread of Greek government bond vs the German Bond may was relevant on the size of the interbank market but it does not seems to affect significantly the bilateral relationships among Greek banks. For each reference date we retrieve the most recent lagged independent variable value. For instance, capital adequacy ratios are updated every month, thus for all weekly observation within the same the whole month this independent variable remains constant.

In the current study we depart from the traditional econometric techniques, such as Logistic regression, and we apply a methodology from the general domain of Machine Learning techniques called Extreme Gradient Boosting (XGBoost). The supervisory motivation for employing such types of methodologies rests on the availability of large scale supervisory data upon which the capability of pattern detection by traditional statistical methodologies is limited due to multicollinearity, dimensionality and convergence issues. In particular interbank systems have many interrelations and participants whereas the collection of high frequency data on the transactions from supervisory authorities produces large size datasets where non – linear relationships are prominent. In this domain Machine Learning techniques may provide value added in comparison to classical econometric techniques which cannot capture complicated non-linear structures.

Extreme Gradient Boosting has been proposed by Friedman (1999) and has the advantage of reducing both variance and bias. It reduces variance because multiple models are used and it additionally reduces bias in training the subsequent model by informing it what errors the previous models made. The algorithm supports the fitting of various types of objective functions, including regression, classification, and ranking whereas it offers increased flexibility, since optimization is performed on an extended set of hyper-parameters. We implemented XGBOOST in our study by utilizing the XGBOOST R package.

We employed in the classification algorithm the variables shown in Table 1 along with 3 additional variables defined as the ratio of Loan to Deposit, Capital Adequacy and deposit yield between Borrower and Lender (LTD_R, CAR_R and Yield_R) which allow us to account for the inter-relationship effects between counterparties. We also tried inserting those variables in the Logistic Regression but they led to singular fitted probabilities. An advantage of the bagging and boosting techniques is that they built multiple models based on subsamples of variables and average among them. In this way they do not suffer from frequent issues in traditional econometrics such as singularities and multicollinearity.

In the Logit case the parameters are estimated via the maximization of the associated, standard in literature, likelihood function. The XGBOOST is an algorithm where random subsets of the sample are drawn from which a set of models are estimated which in turn are combined into a boosted estimator. The information space required under both methods (Logit - XGBOOST) is the same whereas they are used to determine solely the link prior probability. This estimated linkage prior probability filters the exposure allocations of agnostic methods such as MAXE and ANAN (ensemble method). For example, the Logit-ANAN (Logit-MD) and XGBOOST-ANAN (XGBOOST-MD) use the Logit/XGBOOST estimated interbank link probability as a prior linkage probability and employ the Anan (MD) reconstruction algorithm for exposure allocation. By comparing the results between the agnostic algorithms and the ensemble methods, we see an increase in the accuracy and a decrease in the MAE of the financial networks on average. The agnostic models are used, as a benchmark to measure the additional benefit for applying machine learning in estimating prior network probabilities.

The actual network is not usually available because it involves ad hoc data collection form regulatory authorities to monitor in more closely the financial system. The models developed can be used for other future periods when the actual network is not available. Another use of this analysis is that we describe variables that influence the a priori probabilities of two banks engaging in a transaction. The variables are generally available to the public and can be used along with the MAXE or Anan (MD) algorithms. Alternatively, only publicly available accounting information such as Loan to Deposit ratios of the two banks can also be used standalone in order to adjust the probabilities in case where other variables are not accessible.

Boosting algorithms have the relative advantage that they are not "black boxes" regarding the factors affecting the final result, since they provide a module for calculating variable importance measures through reshuffling. Randomizing means randomly reshuffling the values of the independent variable. If the independent variable has significant explanatory power, this will be gone when the reshuffled variable is imported back into the estimation process leading to loss in model predictive power. If the variable does not have explanatory power the loss of predictive power will be marginal. By comparing, the loss of predictive power on can generate an importance ranking of the employed variables. We run the variable importance algorithm and we show in Fig. 3 the ranked list of more important variables

We notice that the size of the Borrower and the relationship in the liquidity status between lender and borrower determine significantly as expected the probability of a bilateral relationship among them. In addition the variables which were not statistically significant in the Logistic Regression receive lower risk weight in the XGBoost estimation. In all it seems that the variables describing the economic solvency of the borrower rank higher, as expected, in the decision of whether to engage in a bilateral interbank relationship.

In addition in order to verify the added value of using Machine Learning Technique vs a traditional statistical technique in modeling interconnectedness we benchmark our results, besides current methods described in the relevant literature, with the results obtained based on the estimated probability of interconnectedness as calculated from the Logistic regression estimates of Table 1 and employ in the same vein as XGBoost the Minimum Density algorithm of Anand et al. (2015) in order to allocate the exposures in the interbank matrix.

5. Model validation

In order to assess the robustness of our approach we perform a thorough validation procedure. More precisely, we report the performance results obtained from the experimental evaluation of our method, in terms of out-of-sample performance. The in sample and out of sample periods refer to stress and non-stress periods. i.e. 5 year of data 2014–2019 broken down to non-crisis 3.5 years (70%) and crisis 1.5 years (30%). The crisis period is from March 2015 (Grexit fears peaked) to September 2016 (Greek banks recapitalized). In the case of ensemble models, the in-sample information on prior probability determining factors is used to predict prior probabilities in the out of sample. In the case of agnostic models no prior information of the in-sample is used in the out of sample projection.

Note that in order to train the machine learning algorithm in the current study the 70% in-sample dataset is further split randomly in train and validation set using 55–15 rule. The validation dataset is used to find the best set of hyper-parameters of the models and select the best candidate model for performing out of sample evaluation.

Classification accuracy, is the main criterion to assess the efficacy of XGBoost against the Logistic regression model in correctly predicting the bilateral links in the interbank market, in terms of discriminatory power and performance misinterpretation. We tested a series of metrics that are broadly used for quantitatively estimating the discriminatory power of each scoring model, such as the Area under the ROC curve metric, as well as the Kolmogorov Smirnov (KS) statistic as performance measures.

In addition we estimate a Probability of Interbank relationship cut-off point according to which we distinguish the forecasted interbank. After thoroughly examining different values for this parameter, and based on the performance of the classification in the in-sample dataset used for model development, we set the cut off criterion with a cost profile function where we penalize a false positive 5 times against a false negative. This means that we allocate more importance when predict correctly the interbank links. The penalization rate affects the results in Table 5, which includes the metrics comparing Logit and XGBOOST model. This number was set as initial value close to the ratio of a fully connected network versus the actual networks. In addition, after running a sen-

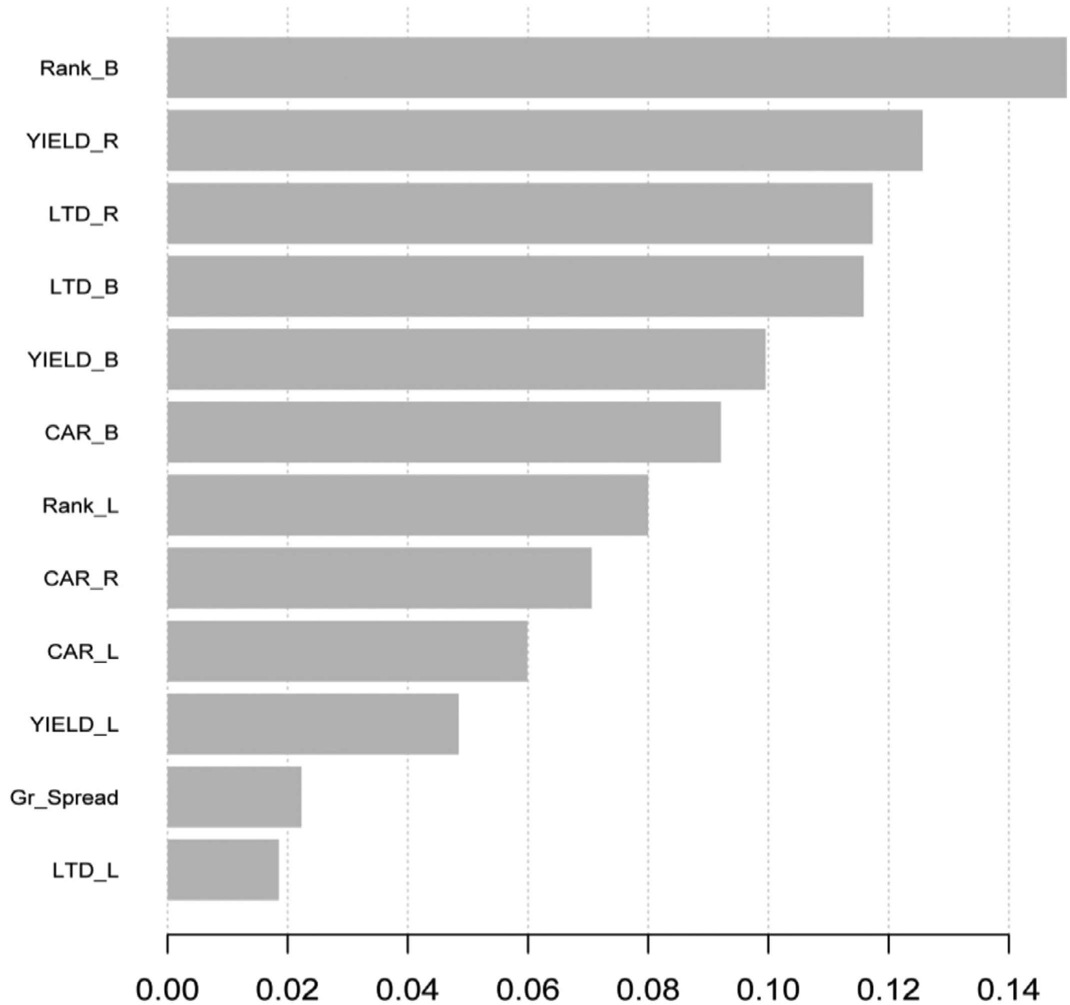

Fig. 3. Extreme Gradient Boosting Variable Importance plot.

sitivity analysis on the results after perturbing this number (3 to 7) the outcome does not change so the XGBOOST continue to outperform Logit model. In terms of out of sample classification accuracy of the XGBoost model clearly outperforms Logit model taking into account comparable false alarm rates (Table 3).

The penalization of false positive vs false negatives is directly related with the focus of the analyst. In particular from a supervisory perspective it is more important to detect efficiently the factors that affect the probability of occurrence of true positive interbank links i.e. penalize the false positive outcomes. This penalization ration is not taken into account in Table 6 but it is taken into account in Table 5 metrics G-Mean, LR, Youden, and BA measures which are cut-off dependent i.e. one has to define a probability threshold above which the bank linkage event is expected to occur or not.

For comparing the classification accuracy between Logistic Regression and XGBOOST algorithm we employ a set of standard measures for imbalanced datasets proposed by Bekkar et al. (2013) (Table 4) and described analytically in the Appendix. The class imbalance in the Greek interbank system lies in the fact that out of 16 banks only 5–6 of them have significant interbank activity leading to an interbank matrix with a preponderance of zeros corresponding to the cases of not existent relationships. From the density of the network (graphically illustrated in Fig. 1) we deduce that even in the non-crisis period the interbank relationships were limited among large banks and a restricted number of small financial institutions so the network exhibits low density. The class imbalance problem is translated in our case as sparse (low-density) network issue, which complicates the correct prediction of positive outcomes.

Table 4
Classification tables of candidate models.

Logit	pred			
TRUE	**0**	**1**	**Signal**	**Rate**
0	15.084	2.466	False Alarm	14%
1	217	573	Hit Rate	73%
XGBoost	**pred**			
TRUE	**0**	**1**	**Signal**	**Rate**
0	14.379	3.171	False Alarm	18%
1	6	784	Hit Rate	99%

We also employ a series of metrics that are broadly used for quantitatively estimating the discriminatory power of each scoring model, such as the Area under the ROC curve metric, as well as the Kolmogorov Smirnov (KS) statistic.

Furthermore, we present in Fig. 3 the ROC curves corresponding to the methodologies analysed. This curve is created by plotting the true positive rate against the false positive rate at various threshold settings. As such, we illustrate the obtained trade-offs between sensitivity and specificity, as any increase in sensitivity will be accompanied by a decrease in specificity. The closer the curve follows the left-hand border and then the top border of the ROC space, the more accurate the modeling approach. The cor-

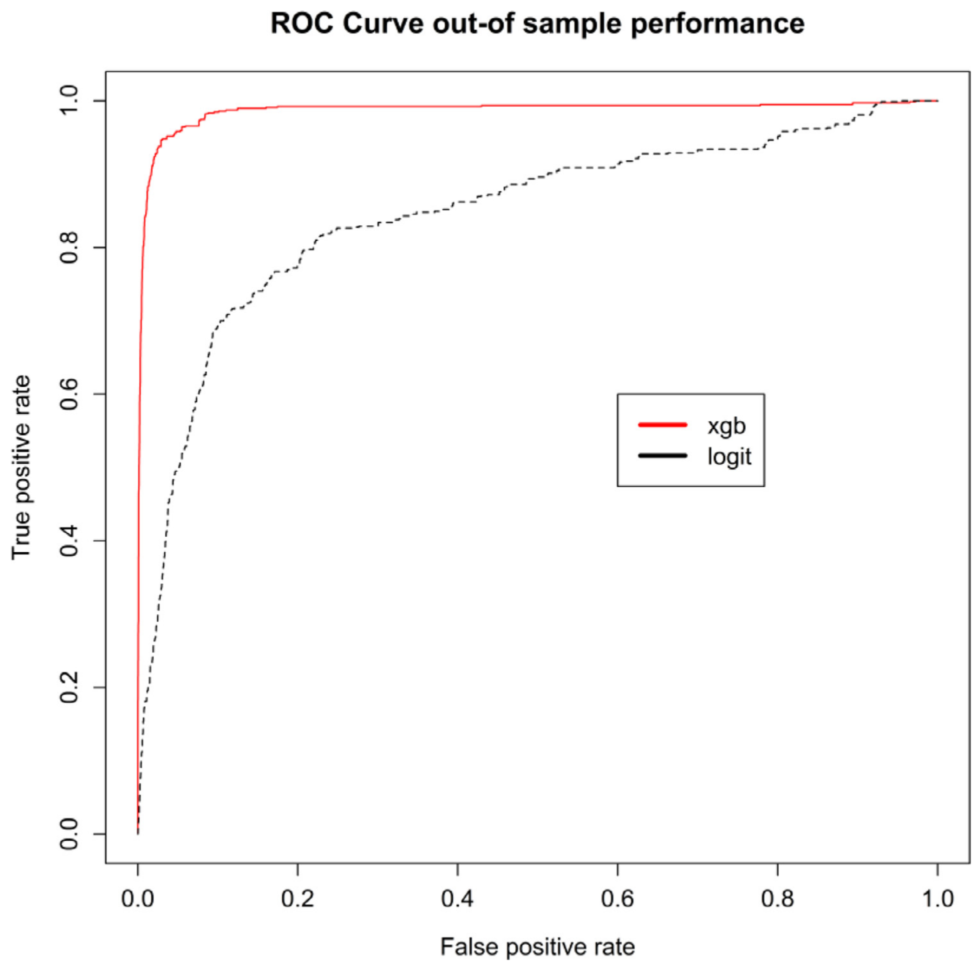

Fig. 4. ROC curve for classifying the existence of interbank links (xgb: XGBoost, logit: Logistic regression).

responding ROC curve of extreme gradient boosting (XGBoost) is higher over all the considered competitors supporting the high degree of efficacy and generalization capacity of the proposed employed machine learning system.

These measures are used to derive a full spectrum conclusion regarding the classification power of each model relative to the others. Even though there could be an amount of correlation between metrics, we incorporate them all, in order to classify correctly the employed techniques based on their predictive performance. Based on the results (Table 4, Fig. 3) we note that XGBoost outperforms the benchmark Logit model, along almost all measures.

In order to assess our method based on a widespread spectrum of different interbank matrix allocation techniques we benchmark our results vs six different techniques[1] namely

- Maximum Entropy (MAXE) algorithm of Upper and Worms (2004)
- Minimum Density (MD) algorithm of Anand et al. (2015)
- Baral and Fique (2012) algorithm (BARA)
- Halaj and Kok (2013) algorithm (HALA)
- Drehmann and Tarashev (2013) algorithm (DREH)
- Cimini et al. (2015) algorithm (CIMI)

We additionally employ for benchmarking purposes the approach of estimating the prior probability of interconnectedness through a Logistic regression model and then employ the Minimum Density algorithm of Anand et al. (2015) in order to allocate the exposures in the interbank matrix. For comparing realized vs forecasted matrix accuracy we employ a set of similarity measures described in Anand et al. (2018) plus a Mean Absolute percentage error (MAE). The first 2 measures (Hamming and Accuracy) focus on the capability of the methodology to allocate correctly the interbank links whereas the Jensen and Cosine measures assess the proper allocation of exposures in each detected link. The Mean Absolute Error measures both the Link and Exposure allocation capacity.

More precisely in Hamming distance we sum over all links the difference between the original and reconstructed networks and in accuracy measure the percentage of true-positive and true-negatives links in the reconstructed network are compared relative to the original network. In the Jensen–Shannon divergence we measure the divergence between original and reconstructed networks, normalizing all entries in the networks to sum up to one and in the Cosine similarity we compare the Cosine of the angle between the original and reconstructed networks.

The Link measures (Hamming and Accuracy) are bounded by 0 and 1 with a value of 1 signifying perfect accuracy, whereas for Jensen–Shannon divergence the metric is bounded by 0 and 1 with a value of 0 signifying non divergence between actual and estimated matrix. For Cosine similarity the metric is bounded by 0 and 1 with a value of 1 signifying non divergence between actual and estimated matrix.

The similarity measures results (shown in Table 6) confirm that the Machine Learning based approach (XGBOOST-MD) has the low-

[1] The relevant matlab code for estimating the interbank matrix based on different techniques is available by Anand et al (2018) in https://www.sciencedirect.com/science/article/pii/S1572308917303649

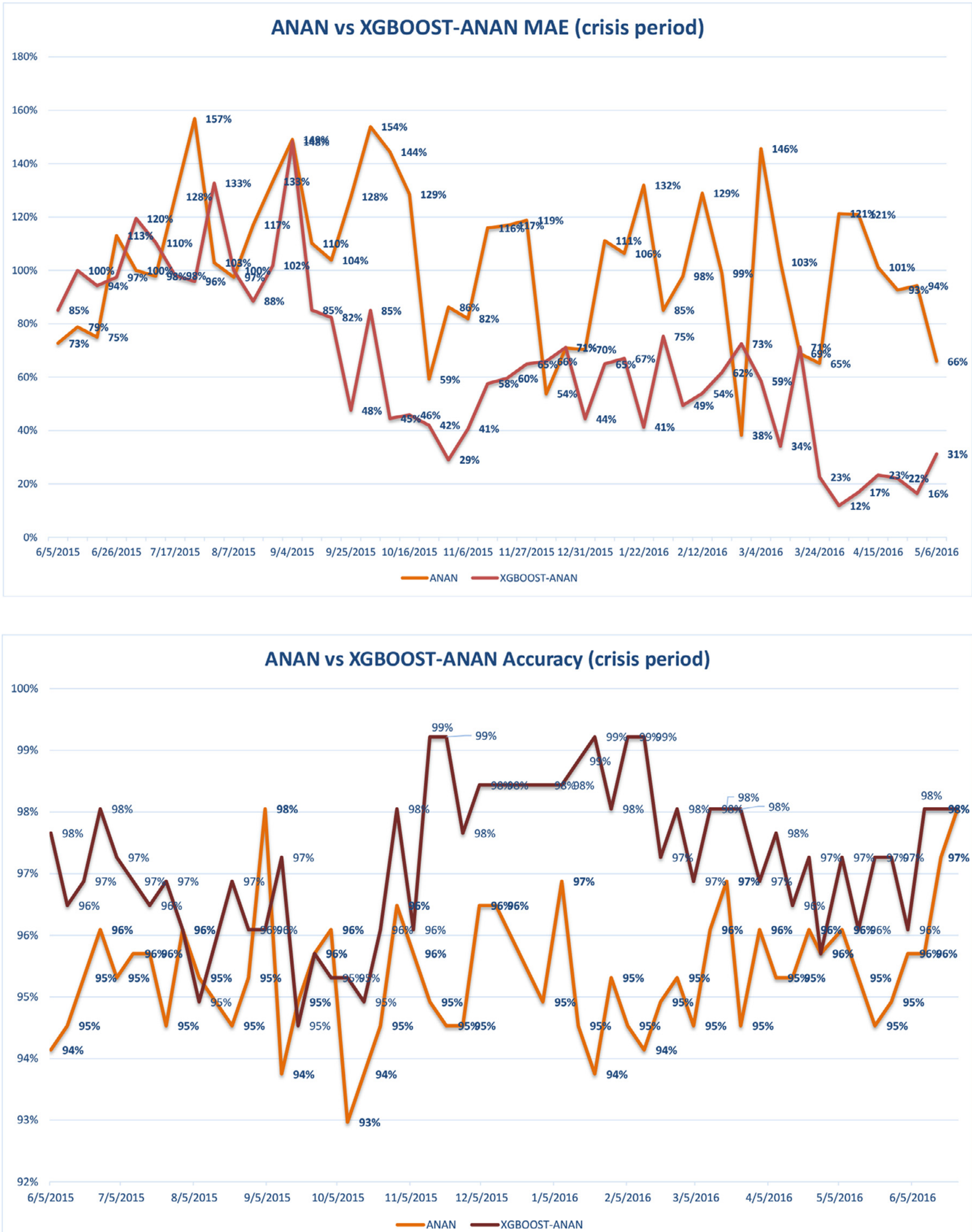

Fig. 5. Similarity measures assessment between actual and estimated interbank matrix based on the Maximum Entropy (MAXE) and Minimum Density (ANAN) algorithms, with and without the inclusion of an XGBOOST prior, during crisis and non-crisis period.

est Mean Absolute error which is the measure that captures both the proper allocation of exposures and accuracy of the interbank links. In addition XGBOOST-MD performs better in Hamming and Accuracy measures which focus on the accuracy of bilateral link estimation. More importantly when focusing on the classification accuracy of interbank links XGBOOST exhibits better distance metrics than the Logistic Regression approach signifying the value added of future application of machine learning techniques in interbank network construction. On the other hand in measures that concentrate on the proper allocation of the exposure amounts (Jensen and Cosine), the Maximum Entropy Algorithm (Upper & Worms, 2004) and Baral and Fique (2012) algorithm which is basically and enriched Maximum Entropy version over-perform.

Based on Anand et al. (2018) CIMI methodology is a clear winner among probabilistic methods (DREH, CIMI) but not among all the methods (both probabilistic and deterministic). Overall based on the “horse race” performed in Anand et al. (2018) no clear winner exists among the agnostic algorithms as the results are depen-

Table 5
Results of the metrics for the out of sample performance of all candidate models.

	Logit	XGBOOST
AUROC	0.845	0.987
KS	0.599	0.918
G-mean	0.789	0.902
LR	0.320	0.009
Youden	0.585	0.811
BA	0.792	0.906

dent on the structure and density of the actual network. In particular, as Anand et al. (2018) also points, in dense networks the algorithms of Bara, DREH and MAXE over-perform compared to other methods because they build complete networks. On the other hand, in low-density networks the algorithms of Anan (stated otherwise as Maximum Density - MD), CIMI, HALA and MUSM over-perform since they correctly identify which links are absenting the original networks. This stems from the fact that these three methods tend to produce sparse networks. The class imbalance problem in the case of the Greek banking system is equivalent in having a low-density network so among a large set of banks only a relative small part of them has interbank relations.

The main contribution of this paper is that we enrich the information generally available for financial networks with variables that are available for the publication of banks financial statements. The agnostic models are used as a benchmark to measure the additional benefit for applying machine learning in estimating prior network probabilities. By comparing the results between the agnostic algorithms and the ensemble methods we see an increase in the accuracy and a decrease in the MAE of the financial networks on average.

In order to complement our XGBOOST-Anan (XGBOOST-MD) we also combine the MAXE entropy model with the XGBOOST model by filtering the MAXE matrix through a binary matrix deriving from interbank linkages probability estimates (based on XGBOOST) using bootstrapping. In particular, at the core of our method is a 'fitness' model, which postulates that the probability of a bank acquiring links with counterparties in the interbank market. First, from the banks characteristics, the lending – borrowing relation is estimated. Second, using those probabilities, a series of adjacency matrices are sampled. Finally, the exposures are determined using either the standard maximum entropy or minimum density method. This methodology is called hence after XGBOOST-MAXE. Overall, the performance of MAXE coupled with the alternative construction of prior probabilities follows similar patterns with the Minimum Density approach.

Finally, take also into account that the accuracy metric is important in the central banks financial stability stress testing activities and network simulation, as it describes actual relationships in the system. Furthermore for measuring the second round effects of a

Table 6
Similarity measures assessment between actual and estimated interbank matrix. Best performing models marked in gray.[2]

Hamming	**MAXE**	**ANAN**	**HALA**	**BARA**	**DREH**	**CIMI**	**LOGIT-MD**	**XGBOOST-MD**	**LOGIT-MAXE**	**XGBOOST-MAXE**
In sample	0.881	0.946	0.919	0.881	0.88	0.938	0.946	**0.947**	0.889	0.891
Out of sample	0.889	**0.952**	0.924	0.889	0.889	0.942	0.95	0.949	0.891	0.895
All sample	0.883	0.947	0.921	0.883	0.883	0.939	0.947	**0.948**	0.889	0.888
Accuracy	**MAXE**	**ANAN**	**HALA**	**BARA**	**DREH**	**CIMI**	**LOGIT-MD**	**XGBOOST-MD**	**LOGIT-MAXE**	**XGBOOST-MAXE**
In sample	0.922	0.958	0.946	0.922	0.922	0.959	0.958	**0.964**	0.929	0.932
Out of sample	0.927	0.963	0.951	0.927	0.927	0.96	0.961	**0.965**	0.928	0.933
All sample	0.923	0.96	0.948	0.923	0.923	0.959	0.959	**0.964**	0.926	0.937
Jensen	**MAXE**	**ANAN**	**HALA**	**BARA**	**DREH**	**CIMI**	**LOGIT-MD**	**XGBOOST-MD**	**LOGIT-MAXE**	**XGBOOST-MAXE**
In sample	0.243	0.323	0.294	**0.242**	0.255	0.332	0.332	0.344	0.256	0.267
Out of sample	**0.254**	0.312	0.302	0.254	0.273	0.36	0.328	0.369	0.272	0.304
All sample	0.246	0.32	0.296	**0.246**	0.26	0.34	0.331	0.351	0.264	0.280
Cosine	**MAXE**	**ANAN**	**HALA**	**BARA**	**DREH**	**CIMI**	**LOGIT-MD**	**XGBOOST-MD**	**LOGIT-MAXE**	**XGBOOST-MAXE**
In sample	0.859	0.774	0.793	**0.859**	0.84	0.762	0.738	0.714	0.822	0.800
Out of sample	0.852	0.773	0.786	**0.852**	0.82	0.747	0.751	0.703	0.835	0.782
All sample	0.857	0.773	0.791	**0.857**	0.834	0.758	0.742	0.711	0.825	0.796
MAE	**MAXE**	**ANAN**	**HALA**	**BARA**	**DREH**	**CIMI**	**LOGIT-MD**	**XGBOOST-MD**	**LOGIT-MAXE**	**XGBOOST-MAXE**
In sample	0.747	0.799	0.781	0.746	0.757	0.792	0.795	**0.736**	0.747	0.693
Out of sample	0.765	0.764	0.78	0.766	0.795	0.828	0.776	**0.746**	0.785	0.748
All sample	0.752	0.789	0.781	0.752	0.768	0.803	0.79	**0.739**	0.757	0.707

Table 7
Similarity measures assessment between actual and estimated interbank matrix averaging the Maximum Entropy (MAXE) and Minimum Density (ANAN) algorithms, with and without the inclusion of an XGBOOST prior, during crisis and non-crisis period.

Accuracy	MAXE	ANAN	MAXE XGBoost prior	ANAN XGBoost prior
Crisis Period	0.947	0.965	0.965	0.978
MAE	**MAXE**	**ANAN**	**MAXE XGBoost prior**	**ANAN XGBoost prior**
Crisis Period	99.30%	95.20%	84.10%	88.15%

Table 8
Similarity measures assessment between actual and estimated interbank matrix. Difference between the ANAN algorithm and the ANAN including an XGBOOST prior increases as Network increases.

Accuracy	16 Banks	15 banks	14 banks
Accuracy Crisis Period	1.5%	1.32%	1.15%
MAE Crisis Period	10%	8%	6.4%

banks defaulting in the system and quantification of risk the MAE is very relevant metric.

We did not included Musmeci methodology in the results because both in our case, but also as indicated based on Anand et al. (2018), is not superior to CIMI, which belongs also to the family of probabilistic methods. The reason we refer to it in the paper is for literature completeness purposes. On the details of the implementation of Musmeci algorithm, we followed Anand et al. (2018).

In order to complement our XGBOOST-Anan (XGBOOST-MD) we also combine the MAXE entropy model with the XGBOOST model by filtering the MAXE matrix through a binary matrix deriving from interbank linkages probability estimates (based on XGBOOST) using bootstrapping. This methodology is called hence after XGBOOST-MAXE (Table 6). Overall, the performance of Maxe coupled with the alternative construction of prior probabilities follows similar patterns with the Minimum Density approach.

The in sample and out of sample periods refer to stress and non-stress periods i.e. 5 year of data 2014–2019 broken down to non-crisis 3.5 years (70%) and crisis 1.5 years (30%). The crisis period is from March 2015 (Grexit fears peaked) to September 2016 (Greek banks recapitalized). Investigating further the proposed approach, we focus on a particular stress period for the Greek financial system and compare the XGBOOST – MAXE, XGBOOST–ANAN (XGBOOST–MD) vs the respective agnostic MAXE and ANAN reconstructing methods. We focus on the accuracy and MAE as we deem them more relevant for the quantification of risk under a stress testing setup. Table 7 below summarizes the two metrics between the two groups of algorithms.

Our empirical results show a sizable improvement in the two measures against the benchmark, signaling that the proposed method of estimating more accurate prior probabilities, may lead to more accurate reconstruction of networks. The following charts depict the XGBOOST – ANAN vs ANAN during the crisis period Figs. 4 and 5.

Assessing the improvement in the reconstruction of network based on our analysis we conclude that the accuracy increase is more sizable in periods where a shock hits the network making it more useful for quantification of risk. In addition, the improvement will be more sizable as the number of participants increases since agnostic measures will lose their forecasting ability. To provide more evidence on this front we run two simulations one where we exclude 1 bank and in the second one we exclude 2 banks from the network. So in the first case we have a network of 15 banks participants and in the latter case 14 participants. Table 8 provides the marginal benefit in the MAE and the accuracy for the three network setups. The improvement is estimated as the difference between ANAN and XGBoost – MD (XGBoost Priors in ANAN)

Based on this analysis increasing the number of banks participants may lead to significant improvement using a more informed prior estimation method like XGBoost since agnostic method error increases with the size of the network.

6. Conclusions

We propose an innovative approach to model the probability of interlinkages in an interbank network with the use of Extreme Gradient Boosting algorithm, i.e. forecast the probability of a pair of banks entering into an interbank market borrower - lender relationship taking into account their financial characteristics and their past observed behavior. Our purpose is to depart from agnostic assumptions usually employed in interbank matrix allocation algorithms and take into account the financial features of the banks when assigning prior link probabilities. The exposure allocation follows the Minimum Density algorithm developed by Anand et al. (2015).

Our main finding is that machine learning algorithms outperforms the benchmark Logistic Regression model in interbank link forecasting and this outperformance is also reflected when similarity measures on overall Greek interbank network are performed. In addition, the proposed machine learning technique achieves improved overall performance when compared to a wide range of interbank allocation matrix techniques already existing in the financial literature.

In particular, in this framework we propose a new method that employs machine learning in order to increase the accuracy of agnostic algorithms in reconstructing a financial network. The XGBOOST method is combined with both Maximum Entropy (MAXE) and Minimum Density (ANAN). The main contribution of this paper is that we enrich the information generally available for financial networks with variables that are available for the publication of banks financial statements (ensemble method). A set of agnostic models, i.e. models that the exposure allocation algorithm does not include prior information, are used as a benchmark to measure the additional benefit for applying machine learning in estimating prior network probabilities. By comparing the results between the agnostic algorithms and the ensemble method we see an increase in the accuracy and a decrease in the MAE of the financial networks on average

Our findings provide valuable insight in the context of system wide stress test development where a misrepresentation of the agent interaction links could lead to understatement or overstatement of the final result. An additional innovation of our approach lies in the incorporation of financial indicators and balance sheet data as determinants in the network structure production. This can allow supervisors and analysts to run specific scenarios and examine their impact in the interbank market structure paving in this way the road to a new category of network stress testing exercises.

For future investigation one could easily depart from our approach by applying a different allocation algorithm based on the structure of the interbank market that interests him. Additionally the use of alternative machine learning techniques could be further investigated, such as Neural Networks and or Support Vector machines since the granularity and regular reporting of interbank exposures can lead to large size datasets prone to non-linear behavior patterns. Furthermore interbank market allocation can be imported as a separate module in a holistic system wide stress systems where in sequential steps under a given scenario the interbank matrix can be adjusted based on banks defaulting and exiting the market.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix. Classification Evaluation Measures

Translating sensitivity and specificity as the accuracy of positive (i.e. solvent) and negative (i.e. insolvent) cases, respectively, we use a set of combined performance measures that aim to provide a more credible evaluation. In particular, sensitivity and specificity are defined as follows:

$$Sensitivity = \frac{TP}{TP+FN},\ Specificity = \frac{TN}{TN+FP}$$

where:

TP = True Positive, TN = True Negative, FN = False Negative and FP = False Positive.

We can define the following metrics (Bekkar et al., 2013) which can be found in Table 5 and compare the Accuracy of the XGBOOST vs the Logit model in modeling the information prior (interbank linkage probability) that is used in ensemble methods.

Index	Index Name	Formula
G-mean	geometric mean	√(sensitivity*specificity)
LM	negative likelihood ratio	(1-sensitivity)/specificity
LP	positive likelihood ratio	sensitivity/(1-specificity)
DP	Discriminant power	$\sqrt{3}/\pi$ [log(sensitivity/(1-sensitivity)) +log(specificity/(1-specificity))]
BA	balanced accuracy	1/2 (sensitivity+specificity)
WBA	weighted balanced accuracy	0.75*sensitivity+0.25*specificity
Γ	Youden's index	sensitivity-(1-specificity)

CRediT authorship contribution statement

Anastasios Petropoulos: Conceptualization, Methodology. **Vasilis Siakoulis:** Software, Data curation, Writing – original draft. **Panagiotis Lazaris:** Software, Data curation, Writing – original draft. **Sotirios Chatzis:** Writing – review & editing.

References

Amundsen, E., & Arnt, H. (2012). Contagion risk in the danish interbank market. In *Proceedings of the danmarks nationalbank working paper 25*.

Anand, K., Craig, B., & von Peter, G. (2015). Filling in the blanks: Interbank linkages and systemic risk. In *Proceedings of the BIS working paper 15* (pp. 625–636).

Anand, Kartik, van Lelyveld, Iman, Banai, Ádám, Friedrich, Soeren, Garratt, Rodney, Hałaj, Grzegorz, et al. (2018). The missing links: A global study on uncovering financial network structures from partial data. *Journal of Financial Stability, 35*(C), 107–119 Elsevier.

Baral, P., & Fique, J. (2012). Estimation of bilateral connections in a network: Copula vs.maximum entropy. Mimeo.

Bargigli, L., di Iasio, G., Infante, L., Lillo, F., & Pierobon, F. (2016). Interbank markets and multiplex networks: Centrality measures and statistical null models. In A. Garas (Ed.), *Interconnected networks. Understanding complex systems*. Cham: Springer.

Bekkar, M., Kheliouane, H., & Taklit, A. (2013). Evaluation measures for models assessment over imbalanced data sets. *Journal of Information Engineering and Applications, 3*(10).

Cao, Jie, Wen, Fenghua, & Eugene Stanley, H. (2021). Measuring the systemic risk in indirect financial networks. *The European Journal of Finance*.

Cimini, G., Squartini, T., Garlaschelli, D., & Gabriella, A. (2015). Systemic risk analysison reconstructed economic and financial networks. *Scientific Reports*, 15758.

Cinelli, M., Ferraro, G., Iovanella, A., et al. (2021). Assessing the impact of incomplete information on the resilience of financial networks. *Annals of Operations Research, 299*, 721–745.

Drehmann, M., & Tarashev, N. (2013). Measuring the systemic importance ofinterconnected banks. *Journal of Financial Intermediation, 22*(4), 586–607.

Duarte, Fernando M., & Jones, Collin (2017). Empirical network contagion for U.S. financial institutions. In *Proceedings of the staff reports 826*. Federal Reserve Bank of New York.

Halaj, G., & Kok, C. (2013). Assessing interbank contagion using simulated networks. *Computational Management Science, 10*, 157–186.

Luitgard, A. (2020). Distress and default contagion in financial networks. *Mathematical Finance, 30*(3), 705–737 July.

Maringer, D., Craig, B., & Paterlini, S. (2021). Constructing banking networks under decreasing costs of link formation. *Computational Management Science*. https://doi.org/10.1007/s10287-021-00393-w.

Mistrulli, P. E. (2011). Assessing financial contagion in the interbank market: Maximum entropy versus observed interbank lending patterns. *Journal of Banking and Finance, 35*(5), 1114–1127.

Musmeci, N., Battiston, S., Caldarelli, G., Puliga, M., & Gabrielli, A. (2013). Bootstrapping topological properties and systemic risk of complex networksusing the fitness model. *Journal of Statistical Physics, 151*, 720–734.

Upper, C., & Worms, A. (2004). Estimating bilateral exposures in the German interbankmarket: Is there a danger of contagion? *European Economic Review, 48*(4), 827–849.

Van Lelyveld, I., & Liedorp, F. (2006). Interbank contagion in the Dutch banking sector: A sensitivity analysis. *International Journal of Central Banking, 31*, 99–133.