Can Correlation-Based Networks Capture Systemic Risks in a Financial System?

The Case of Lehman's Collapse

By

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Submitted to

Central European University

Department of Economics

In partial fulfilment of the requirements for the degree of

Master of Arts in Economics

Supervisor: Professor Andrea Canidio

Budapest, Hungary

2012

Abstract

In this thesis, I evaluate whether systemic risks in a financial system can be captured by a network built using only publicly available data. I construct the correlation-based network of publicly traded US banks based on stock prices prior to Lehman's collapse, and I assess whether this network could have predicted which bank stocks would suffer the biggest drops in prices after Lehman's collapse. I find that a correlation-based network built using the Minimal Spanning Tree method can tell us some valuable information about systemic risk. I show that some of the stocks with the highest drops lie close to Lehman in the tree. Moreover, when I consider the length of the path between every bank's node and Lehman, I find that a 10 percent increase in the path length to Lehman is associated with a 0.081 standard deviations decrease in the price drop on average. Importantly, the network is a better predictor of the price drops than simply the correlation with Lehman. Robustness tests show that using two alternative methods to construct the tree (the threshold- and the partial correlation-based one) were unable to predict price drops. Therefore I conclude that it does matter how the network is constructed if we want to capture systemic risks. In this example not all the correlation-based networks can capture these risks, only the Minimal Spanning Tree.

Acknowledgements

I would hereby like to express my gratitude to the people who helped me in writing this thesis. First, I would like to thank *Andrea Canidio*, my supervisor, who provided with patient but demanding guidance throughout the research, and *Júlia Király*, my second advisor, who gave me valuable comments on the paper. Discussions with *Ádám Szeidl, Albert-László Barabási* and *Péter Kondor* were extremely useful after I have settled down on the final topic of my thesis. But beforehand, I had the opportunity to have discussions on the broader topic, the interbank markets and relations with *Júlia Király*, *Edina Berlinger, Márton Michaletzky* and *Dániel Havran*, these were indispensable for starting off. Also, I am heavily indebted to *Gábor Orbán* and *Péter Kadocsa* at AEGON Hungary Fund Management Co. for their help in assembling the data I worked with. Last but not least, I owe special thanks to my *friends and family* for supporting me while writing the thesis.

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1. Introduction

On January 23, 2000 Stephen Hawking said in San Jose Mercury News: "I think the next century will be the century of complexity" (Barabasi, 2012). In fact, the world has always been complex, however, now we have data and computational techniques which enable us to analyze the nature and the consequences of such complexity.

One very important aspect of this complexity is that contagion might be present: in the case of people (i.e. diseases can spread) as well as in the case of financial institutions. This latter implies that the vulnerability of a financial system is not only the sum of the vulnerabilities of the institutions, but it is higher than that. Therefore Financial Stability departments have started to realize that it is not enough to analyze the risks of financial institutions on their own, but they need to take into account that these institutions are nodes in a complex network, hence the external effects of their risks need also be considered (see for example Haldane, 2009 and ECB, 2010).

The empirical literature of financial networks mainly uses non-public data on interbank transactions. However, assessing systemic risks and identifying banks that bear most of these risks might also be desirable for institutions that are not able to access transactional data other than their own. For example commercial banks are interested in the risks of their counterparties. Since a network-based approach would provide them additional information on their counterparties, it would be beneficial for them to access any information about the financial network they are part of. Therefore the question is whether a network able to capture systemic risks can be constructed based only on publicly available data. In my thesis I intend to answer this question.

I want to employ the approach of the so-called "correlation-based networks", namely I construct the network using the correlations of stock returns of the most capitalized US banks that are publicly traded. The main question is whether a network constructed in this way tells us anything about the systemic risks of the banks. That is, can we say anything about the external effects of one banks' failure?

In order to assess this question I will use the case of the failure of Lehman Brothers. I am interested in whether a network constructed from stock price data prior to Lehman's collapse could have been used to predict which banks would suffer the biggest losses in their stock prices on the day Lehman collapsed (15/9/2008).

I will use different techniques to construct the correlation-based network. First, I will use the Minimal Spanning Tree (MST) method, which is the most common in the literature. As I will show, the MST can predict some of the banks who suffered the biggest losses. Also, there is a positive relationship between the path length to Lehman and the losses: I find that a 10 percent increase in the path length to Lehman is associated with a 0.081 standard deviations decrease in the price drop – on average. I also show that the network is a much better predictor than the correlation with Lehman: the correlation coefficient with Lehman has insignificant effect on the stock price drop after Lehman's collapse.

The result of this analysis is important because this tells us that banks that lie close to a failing bank in the MST will tend to suffer higher drops in their prices than the others. Therefore if a bank is surrounded by many banks (i.e. it is in a central position, where many banks lie close to it), then this particular bank's failure would be much more problematic than another – not central positioned – bank's.

In order to check for robustness, I will apply two alternative methods to construct the network. One of them is the threshold-based method, which connects two stocks, if their correlation is above a certain threshold. Then I will suggest an extension of this method: that will be the partial correlation-based one. In this case I will consider two stocks being connected if their partial correlation is significantly different from zero.

Both the threshold- and the partial correlation-based methods proved not to be useful. Since in the year prior to its collapse, Lehman had relatively low correlations with the other banks, these two methods led to too highly connected networks, so there were practically no variations in the path length to Lehman (i.e. no variation in the explanatory variable). Hence I find that it does matter how the network is constructed if we want to capture systemic risks. In this example not all the correlation-based networks can capture these risks, only the Minimal Spanning Tree.

The structure of the thesis is the following. In the next chapter I am going to describe the literature of financial networks dealing with systemic risks, and the literature of correlation-based networks. I intend to show how correlation-based networks are usually built, and for what purpose they are used. Then Chapter 3 will describe the dataset which I will use in the empirical part of my thesis, and also the methods used to build up the network to assess how banks were related to Lehman Brothers before its failure. In Chapter 4 I will show the results I obtained, then Chapter 5 concludes. An Appendix at the end of the thesis lists the analyzed banks along with some results and properties of the banks.

2. Related Literature

To the best of my knowledge this thesis is the first work trying to capture systemic risks using publicly available data. Therefore the literature that is related to my thesis consists of papers that deal with systemic risks from a theoretical point of view or using non-public data, and papers using publicly available data for constructing networks, but these networks are not built to assess systemic risks.

One strand of the financial network literature dealing with systemic risks consists of theoretical papers. Most of them look for contagious effects (e.g. Allen and Gale, 2000, Gai and Kapadia, 2010 and Cipriani and Guarino, 2008) or the effect of the uncertainty that the system being complex might cause (Caballero and Simsek, 2009). The other strand consists of empirical analyses of the networks (see for example Dungey and Martin, 2001, Becher, Millard and Soramaki, 2008, Arnold et al., 2006 and Berlinger, Michaletzky and Szenes, 2011)[2]. These empirical papers are mainly written by authors who have the access to data on interbank transactions.

In the lack of actual data on links between banks one can only use publicly available data, for example stock prices. The advantage of using stock prices – beyond its public availability – is that they might contain a lot of fundamental information on the corresponding bank. While one kind of non-public transactional data can capture only one way of interdependence of banks (among many), prices can reflect all of them.

One common feature of the papers using stock prices to construct a network is that all of them use the correlations of stock returns to evaluate whether two companies are connected or not. However, the basic problem is that for every pair of stocks, a correlation coefficient exists, therefore using all the coefficients, one would get a fully connected graph, from which

[2] There is an extensive collection of papers in the Financial Network Analytics Library, available at http://fna.fi/library/.

practically no interesting information can be extracted. Therefore a filtering procedure is needed, which selects those coefficients (which represent edges), that are relevant in a particular sense.

After Mantegna (1999), most of the papers in the literature of stock correlation-based networks uses the following filtering procedure. Mantegna suggests to apply a function on the correlations in order to obtain a measure that fulfills the axioms that define an Euclidean metric. The point is to have a number for every pair of stocks that can be regarded as their distance. Afterwards he uses these distances to determine the Minimal Spanning Tree (MST) connecting all the stocks of the portfolio[3]. Using US stock market data, Mantegna's major result is that branches in his tree correspond to existing economic taxonomies, that is, to business sectors. Hence Mantegna shows that this method leads to a result that is economically meaningful.

Mantegna's filtering procedure seems to lead to sensible results, hence a number of papers on correlation-based networks uses this method to filter data. Using US stock prices, Vandewalle et al (2001) investigate the topology exhibited by the MST[4]. Bonanno et al (2003) compare the Minimal Spanning Tree obtained from real data with a tree that can be obtained from model-generated data (e.g. data generated by a one-factor model). The authors show that while in real trees there exists some hierarchy among nodes (i.e. some nodes have many connections, while most of the nodes have few connections), model-generated trees cannot show this hierarchical structure. Onnela et al (2003a) define a dynamic tree as the sequence of trees that one can get when moving the time window used to compute correlation and hence to construct a Minimal Spanning Tree. In this framework they show how the tree changes over time.

[3]In the Methodology section I will describe the method in more details.

[4]For example, the authors show that the degrees indeed follow a power-law distribution, as it is usually found in real networks (see Barabasi and Albert, 1999 for the reasons)

Using the dynamic tree approach, Onnela et al (2003b) investigate the effect of Black Monday (19/10/1987). However, as they analyze the network as a whole, their only result is that the tree "shrinks", that is, the distances between stocks decrease. This is not surprising, as it is a well-known stylized fact that correlations tend to increase during crises, and the distance of two stocks is – by definition – a monotonically decreasing function of their correlation.

So far, I have described papers in which the correlation-based network is a Minimal Spanning Tree of the stocks in the particular portfolio. However, in Onnela et al (2003c) the authors examine another filtering method resulting in asset graphs instead of asset trees[5]. The method is to accept those edges that are under a certain distance threshold, and drop the others. This can lead to a graph in which (i) cycles can be present, (ii) not necessarily will all nodes be connected, and even (iii) several graphs can emerge at the same time (i.e like different clusters).

Similarly to Onnela et al (2003c), Tse, Liu and Lau (2010) suggest a threshold-based method instead of the MST approach. The authors discuss that the MST suffers a substantial loss of information (and thus loss of usefulness) as edges of high correlations are often removed while edges of low correlations are retained just because of their topological conditions fitting the topological reduction criteria. Therefore they use the threshold-based method, but instead of using threshold on distances as in Onnela et al (2003c), they connect those stocks having a correlation higher than a certain threshold[6].

[5]Actually, the set of asset trees is just a subset of the one of asset graphs, but in the cited paper they use these two terms to differentiate between networks obtained using the MST method or a threshold-based one (respectively).

[6]As the distance in Onnela et al (2003c) is a strictly monotone decreasing function of the correlation, using threshold on the distance or a corresponding threshold on the correlation results in the same filtering. However, when referring to threshold-based networks, from now on, I will think of the latter one.

Serrano, Boguna and Vespignani (2009) provide a critique for both the Minimal Spanning Tree and the threshold-based method. The authors note that one of the big limitations of the MST is that spanning trees are by construction acyclic, that is, these networks are overly structural simplifications that destroy local cycles, clustering coefficient and the clustering hierarchies often present in real world networks. These drawbacks are not present in the threshold-based method, however, the introduction of an artificial threshold drastically removes all information below the cut-off.

Hence Serrano, Boguna and Vespignani (2009) propose an alternative to the two criticized methods. Using their terminology, they extract the so-called backbone of a fully connected graph. They use weighted edges and for each node, they keep the statistically significant[7] ones. However, the backbone method is not applicable in the case of this thesis because – as I will show in the Results section[8]– the correlation coefficients are too close to each other, thus no significant edges would emerge for any of the nodes.

Compared to the above described papers, this thesis will have several novelties. First, to the best of my knowledge, there is no paper in the literature of correlation-based networks that uses only one sector. In the thesis I will build the correlation-based network of banks. Second, there is no paper that intends to make use of these networks to identify systemic risks. Third, I will suggest an extension of the threshold-based method (the partial correlation-based one) to filter connections between stocks. The extension will be twofold: (1) I will compute partial correlations, and (2) I will use the p-values of the estimates to evaluate whether two stocks are connected or not. Both the threshold- and the partial correlation-based methods will be used to discuss the robustness of networks capturing systemic risks.

[7]Statistical significancy in this case corresponds to whether an edge's weight is significantly higher than what a uniform distribution would imply.

[8]See Figure 5.

3. Data and Methodology

3.1 Data

The main question of my thesis is whether correlation-based networks can be used to evaluate banks' systemic risks. To answer this question I will check whether such a network could have been used to assess the effect of the collapse of Lehman Brothers on the other banks' stock prices. For this exercise, I am going to need bank stock prices prior to the collapse to build the network, and the closing stock prices before and after the day of Lehman's collapse to calculate the drop in their value. The time series of stock prices for the network need not be too long: I am going to use only one year data before Lehman's collapse because then the uncovered relationships will be relevant (up to date). On the other hand, they should be enough observations to have reliable estimates for the correlations.

I have downloaded daily closing stock prices for the 200 most capitalized US banks[9] from Bloomberg for the period between 1980 and nowadays, and Lehman Brothers' daily closing stock prices from 1994 to its collapse from Yahoo Finance[10]. However, based on the reasons discussed above, I chose the period 13/09/2007 - 12/9/2008[11] to build the network, and I calculated drops in stock prices based on the closing prices of 12/9/2008 and 15/9/2008[12].

Moreover, from the original 200 US bank stocks, I had to drop 51 because in this period they were not traded continuously. Therefore eventually in the empirical investigation I have 160

[9]Due to technical reasons I could only sort by market capitalization as of 18/4/2012, therefore I have downloaded data in large quantities for bank stocks that are currently traded.

[10]http://finance.yahoo.com/

[11]I have downloaded longer time series than that because having more data can cause no harm, but it let me check for robustness (i.e. what happens if longer or shorter interval is used for the analysis).

[12]There were no trade on 13/9/2008 (Saturday) and 14/9/2008 (Sunday).

stocks (159 currently traded banks and Lehman Brothers) for the period 13/09/2007-15/9/2008[13].

3.2 Methodology

In order to build a stock correlation-based network, I will need correlations between all pairs of stocks. I will use contemporaneous correlations between logarithmic stock returns. The logarithmic return of stock *i* at time *t* is defined as:

$$r_i(t) = \ln\left(P_i(t)\right) - \ln(P_i(t-1)) \tag{3.1}$$

where $P_i(t)$ denotes the closure price of stock *i* at time *t*. Then the correlation coefficient between each pair of stocks *i* and *j* will be computed using the usual formula:

$$\rho_{ij} = \frac{\sum_t (r_i(t) - \overline{r_i})(r_j(t) - \overline{r_j})}{\sqrt{\sum_t (r_i(t) - \overline{r_i})^2 \sum_t (r_j(t) - \overline{r_j})^2}}$$

where $\overline{r_k}$ denotes the average return of stock *k* over the given time period. This will result in the correlation matrix of the 160 stocks.

In the literature overview, I have mentioned some ways in which the relevant connections can be filtered from the correlation matrix. Now I will discuss the Minimal Spanning Tree and the threshold-based methods, and I will suggest an extension of the latter one, which I will call the partial correlation-based method.

3.2.1 The Minimal Spanning Tree method

The Minimal Spanning Tree method is the most commonly used one in the correlation-based network literature, and it will be the most useful for my investigations as well. The Minimal Spanning Tree, as its name suggests, has the following properties: (1) it is a tree, that is there are no cycles in it; (2) it is spanning, that is every node is involved; and (3) it is minimal, that

[13] A list of these banks can be found in the Appendix along with some of their properties.

is the sum of all the distances between adjacent nodes (the sum of the length of the edges) is minimized. Because of the last property, one needs to define a metric, which measures the distance between two stocks. It is done in the following way (this is discussed in details in Onnela, 2002).

First, we normalize the returns: we subtract their means and divide them by their standard deviations.

$$x_i(t) = \frac{r_i(t) - \overline{r_i}}{\sqrt{\frac{1}{T}\sum_t (r_i(t) - \overline{r_i})^2}}$$

Here, $x_i(t)$ denotes the normalized return of stock *i* at time *t*.

Now, if we denote the vector of normalized returns of stock *i* by $\boldsymbol{x_i}$, then the Euclidean distance we are after is the following:

$$d_{ij} = \|\boldsymbol{x_i} - \boldsymbol{x_j}\| = \sqrt{\sum_t \left(x_i(t) - x_j(t)\right)^2} =$$

$$= \sqrt{\sum_t (x_i(t))^2 + \sum_t (x_j(t))^2 - 2\sum_t x_i(t)\, x_j(t)} \qquad (3.2)$$

Because of the normalization:

$$\sum_t (x_i(t))^2 = 1$$

$$\sum_t (x_j(t))^2 = 1$$

$$\sum_t x_i(t)\, x_j(t) = \rho_{ij}$$

Therefore the distance between stocks *i* and *j* can be computed using the following function of the correlation coefficient:

$$d_{ij} = \sqrt{2(1 - \rho_{ij})} \qquad (3.3)$$

This metric fulfills the three axioms of an Euclidean metric:

(i) $d_{ij} = 0$ iff $i = j$

(ii) $d_{ij} = d_{ji}$

(iii) $d_{ij} \leq d_{ik} + d_{kj}$

As this distance metric has been defined as the Euclidean distance between the two return vectors, these properties must hold, hence I do not provide formal proofs for them. But I note that the first two properties' validity can be seen easily, while the third one can be proved using equations (3.2) and (3.3).

When one has these distances between every pair of stocks, an algorithm is needed to solve the following minimization problem: minimize the sum of distances, such that all the stocks are involved, and no cycles are created. This problem can be solved by either Kruskal's algorithm or Prim's one (for details see Kruskal, 1956 and Prim, 1957, respectively).

3.2.2 Alternative methods

3.2.2.1 The threshold-based method

Minimal Spanning Tree is not the only method to filter correlations. Another way is what Tse, Liu and Lau (2010) use. They take all the correlation coefficients, and apply a threshold-based filtering: if the correlation between two stocks is above a certain threshold, we say that these two stocks are connected, otherwise they are unconnected. The edges are not weighted in this case, that is, we do not define a distance metric between two adjacent stocks[14], all the edges have the same length.

In this case, as Tse, Liu and Lau (2010) note, we lose less information compared to the MST case. Here, we let cycles exist. However, it is not sure that every stocks will be included in

[14]When I will need the distance between two stocks, I will use the number of edges along the path from one node to the other.

one graph. It can happen that several graphs will emerge, and it can also happen that some stocks will not be connected with anyone.

3.2.2.2 The partial correlation-based method

To the best of my knowledge, partial correlations have not been used in the literature to build up a network. However, as I discuss in this section, this method could capture the one-to-one connections between two stocks better than the ordinal correlation-based approaches, therefore this method could be a meaningful extension of the threshold-based method.

I construct the network in the following way. I compute partial correlations between two stocks (i.e. I control for all the others), and if the coefficient is significantly different from zero[15], then I regard those stocks as being connected.

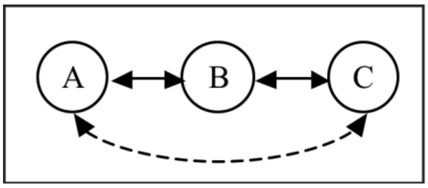


Figure 1: Illustration for the rationale behind using partial correlations instead of ordinal ones

The rationale behind this method is that it accepts less spurious connections. In order to see this, consider three stocks: stock A, B and C. As it is presented in Figure 1, suppose that stocks A and B, and B and C have a lot in common, so they need to be connected directly, while A and C need to be connected only indirectly (through node B). However, if the correlation between A and B, and the correlation between B and C are sufficiently high, then the correlation between A and C will be high as well. Now the correlation between A and B, and B and C are ones that truly represent direct connections, while the correlation between A and C is spurious. If we use ordinal correlations to draw the graph, then the edge between A and C will also be drawn because of the high correlation coefficient. But if we use partial

[15]I use p-values to make decision on significancy, and I do not care about whether the partial correlation is significantly negative or positive because both of them represent some kind of a connection.

correlations, then the effect of B will be sorted out from the coefficient between A and C, and therefore it will be less spurious, and no direct connection will be drawn. This will be closer to the real network.

The difference between the threshold-based and the partial correlation-based approaches is obvious: the threshold-based method would accept the edge between A and C, while the partial correlation-based one would not. However, as the MST does not let cycles emerge, it might handle the spurious connections better than the threshold-based one. The difference between the partial correlation-based network and the MST is that the MST leads to a much stronger filtering. The case that I presented in the figure need not be always the case when a loop emerges, that is, it may well be the case that A-B, and B-C as well as A-C must be connected because they are all truly in connection with each other. In that case the A-C connection remains significant after controlling for B, therefore the partial correlation-based method will keep this edge. However, the MST would not let this connection remain present.

Nevertheless, thinking about the partial correlation-based network makes one more argument for using MST instead of the threshold-based method: even though the MST drops some of the highest correlations and forces cycles to disappear, it can often be the case that most of them really are spurious.

In the empirical part of the thesis (i.e. in the next chapter), I am going to use the MST method to investigate the systemic risk-capturing ability of a correlation-based network. Then I will try these two alternative methods in order to see whether they lead to similar results or not. I will show that the MST really has some predicting power. However, when I construct networks using other methods (i.e. I check for robustness), I will conclude that only the MST has this property, and not generally all the correlation-based networks.

4. Results

4.1 Losses after Lehman's collapse

In the thesis, I define the "loss after Lehman's collapse" for a particular stock by calculating the logarithmic return[16] between the closing prices before and after Lehman Brothers filed for bankruptcy protection (i.e. closing prices on 12/9/2008 and 15/9/2008). Then I will divide this by the standard deviation[17] of the stock's return, that is, I will express the losses in terms of standard deviations[18]. Figure 2 shows the losses that were at least as high as one standard deviation.

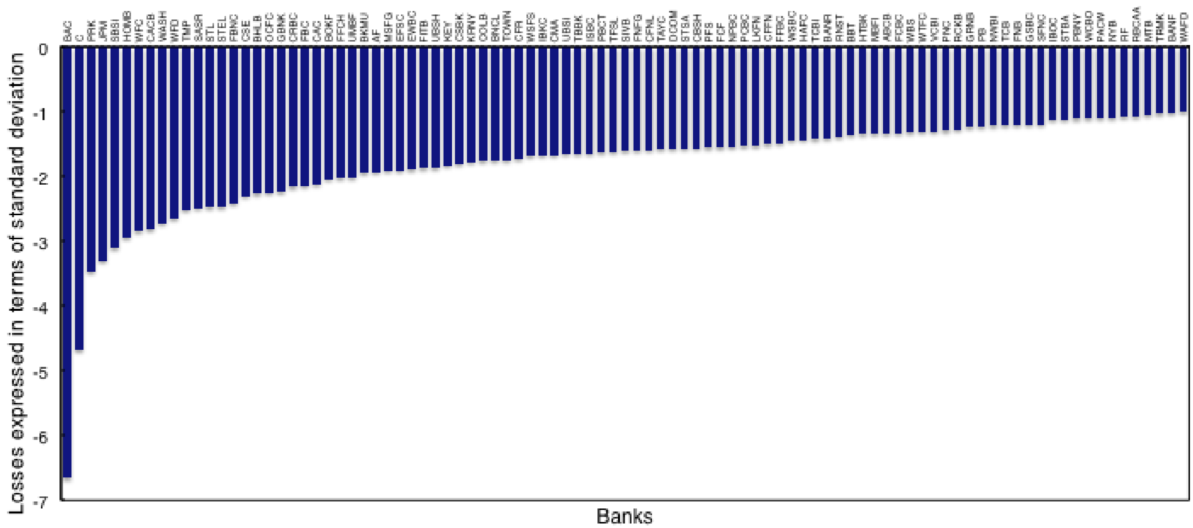


Figure 2: Losses in stock prices higher than one standard deviation on the day of Lehman's failure

As this figure is not completely legible, I list the banks that suffered the highest losses[19] in Table 1. Later on, I will pay more attention to these banks.

[16]As in equation 3.1.

[17]The standard deviation will be computed by the usual formula: $\sigma_i = \sqrt{\frac{1}{T}\sum_t (r_i(t) - \overline{r_i})^2}$. For this calculation, I will use returns from the 1-year period before Lehman's failure.

[18]I express the losses in terms of standard deviations in order to account for the different volatility of stocks.

[19]I chose those banks, who suffered a loss that were so high, that its probability – using the usual normality assumption for stock returns – was below 0.005.

Table 1: The highest losses on the day of Lehman's collapse[20]

ID	Name	Loss (in terms of st.dev.)
BAC	Bank of America	-6.664
C	Citigroup	-4.684
PRK	Park National Corp.	-3.473
JPM	JPMorgan Chase & Co.	-3.302
SBSI	Southside Bancshares	-3.108
HOMB	Home Bancshares	-2.946
WFC	Wells Fargo & Co.	-2.849
CACB	Cascade Bancorp.	-2.819

4.2 Predicting the effect of Lehman's collapse

4.2.1 The case of the Minimal Spanning Tree

Following the description in the Methodology section, the construction of a Minimal Spanning Tree consists of the following steps: (1) calculate the correlation coefficients for every pair of stocks, then (2) apply the formula in the equation (3.3) to get the distances between stocks, and finally, (3) use Kruskal's or Prim's algorithm to solve the minimization problem, that I discussed in the Methodology section. I did all these steps using Matlab (in step 3, Matlab used Kruskal's algorithm)[21]. Then I got the tree that can be seen in Figure 3.

In this figure, we can see that Lehman does not have a central position, it is rather a "leaf" on a "branch", that is, it has only one connection, and all the nodes close to Lehman has pretty few connections as well. In terms of systemic risks, this can be interpreted in the following way. If we think that the tree really captures systemic risks, then Figure 3 suggests that the failure of Lehman would not endanger many of the other financial institutions, and hence it would not lead to the collapse of the whole financial system. Instead, the collapse of Lehman

[20]The Appendix lists all the banks being investigated along with the losses in their stock prices – expressed both in terms of logarithmic returns and of standard deviations.

[21]As I have mentioned in the Data section, I used 160 bank stocks' daily closing prices from the period between 13/09/2007 - 12/9/2008 to construct the network.

would lead to high drops in only few stock prices: these drops would be the highest in the case of banks lying close to Lehman, and they would be smaller, the farther a stock is lying.

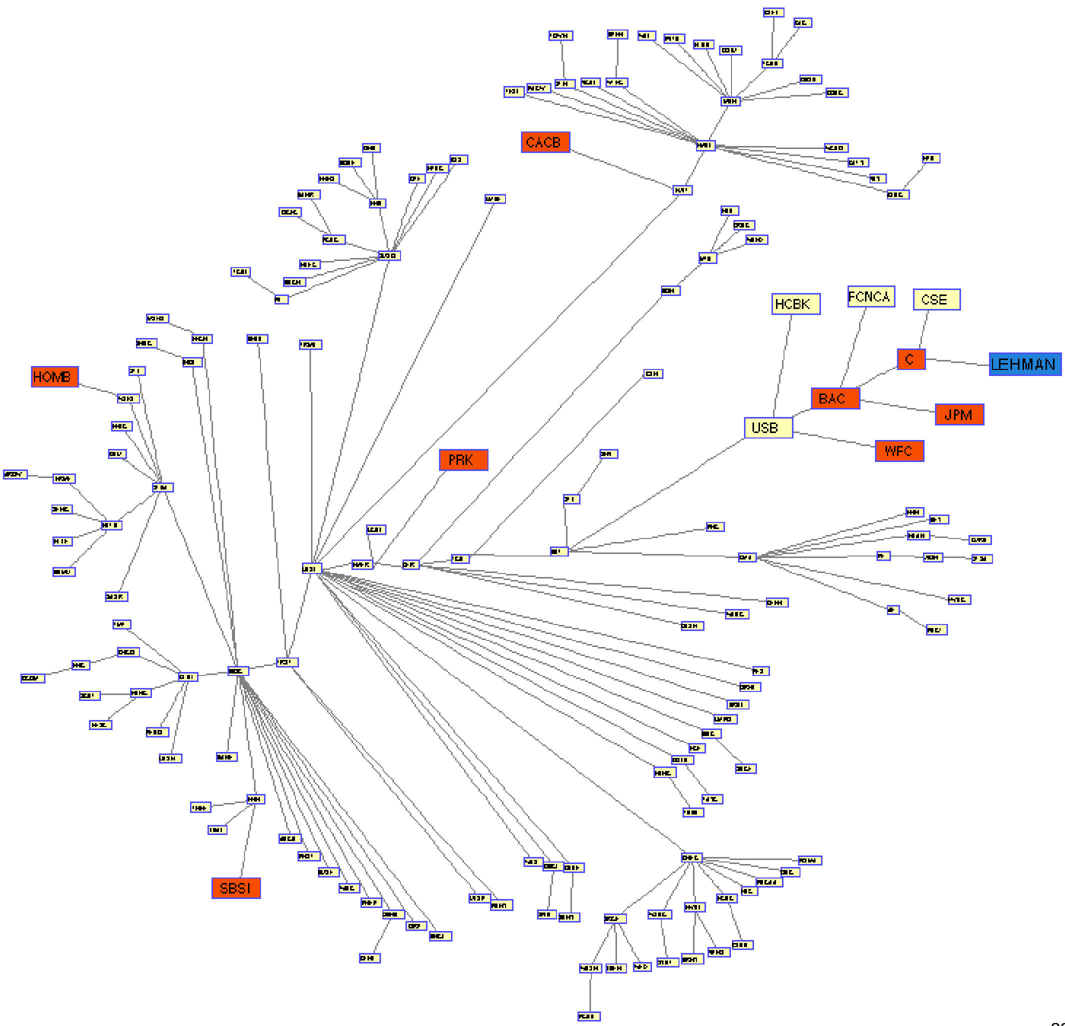


Figure 3: The MST of banks based on one year stock return data prior to Lehman's failure[22]

As the position of nodes that correspond to banks with the highest losses is visible in Figure 3 (they are the big orange rectangles), the statement above can be evaluated easily. It can be seen, that half of the banks in Table 1 lie close to Lehman, they are the first, the second, the fourth and the seventh highest loss-suffered banks. Therefore it is only partly true what is suggested by the tree: some of the highest drops are indeed suffered by banks lying close to

[22]I made visible the position of Lehman Brothers (the big blue rectangle), those banks, that lie close to Lehman (big yellow rectangles), and banks that suffered the biggest losses (see Table 1; in the figure, they are the big orange rectangles).

Lehman, however, there are big drops in stocks lying far from it as well (and even, some of the banks lying close to Lehman did not suffer high drops).

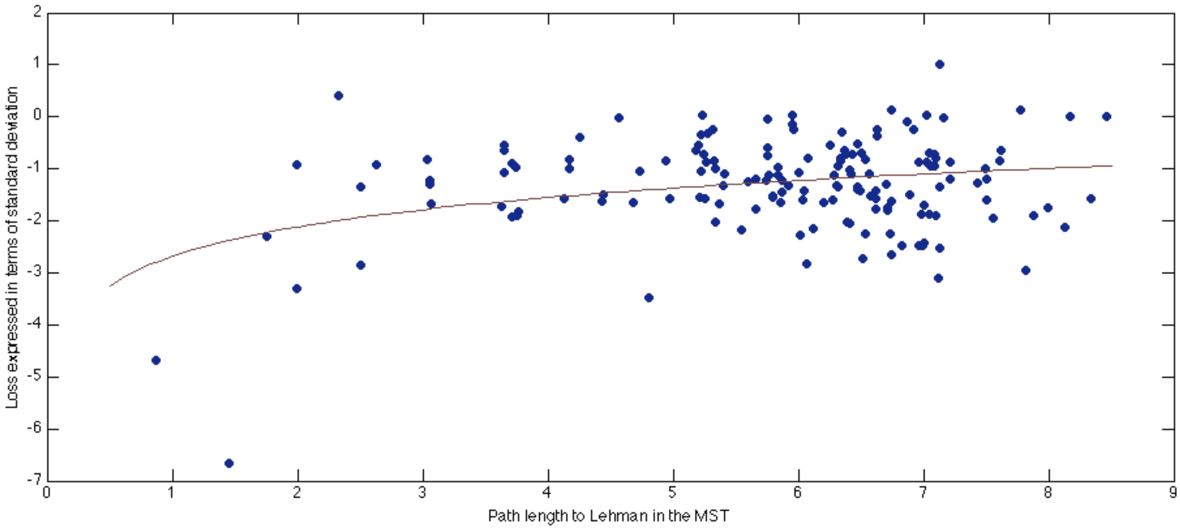


Figure 4: Correspondence between path length to Lehman and suffered loss in stock price

Now, I turn to a more formal way of investigating the relationship between the tree and the stock price drops. In Figure 3, one can see the position of the stocks with the highest losses, however, if one intends to make a quantitative relationship between the MST and the losses, than the picture of the tree is not enough. Therefore I created a variable called "PathLength", which measures the length of the path from Lehman to another node (stock) in the tree (i.e. it is the sum of the length of the edges[23] between a stock and Lehman). In Figure 4 I depicted the correspondence between the path length to Lehman and the loss on the day of its failure: the rationale behind doing so is to not only see some particular story (i.e the position of the banks in Table 1), but having some insight into some systematical relationship, if any (e.g "banks with higher losses tend to lie closer to Lehman").

[23]The length of an edge is the distance of the nodes it connects (where the distance is calculated by the formula in equation 3.3).

Figure 4 suggests that the relationship between the path length and the loss is slightly positive, and it might be nonlinear. To assess this relationship quantitatively, I ran some regressions (see Table 2).

First, assuming a linear relationship between the losses and the path length, I regressed the losses on the path length. The coefficient on the path length is statistically significant, and it shows that if a bank lies 1 unit farther from Lehman, then its drop in the stock price was (on average) 0.128 standard deviations less, ceteris paribus (see column 1 in Table 2). This effect is rather small. In order to see this, I note that the average distance between two adjacent nodes in the tree (as of equation 3.3) is 0.71. This is the average length of the edges. Since the path length is the sum of the length of the edges between a particular bank and Lehman, a one unit increase in the path length is approximately the same as having one additional node between that bank and Lehman (i.e. the connection is "one step" more "indirect"). Thus a one unit increase in the path length is high, while the 0.128 standard deviation decrease in the loss is low, therefore this is a small effect.

Table 2: Regression output: Loss in stock price regressed on correlation and/or path length to Lehman in the MST

VARIABLES	(1) Loss	(2) Loss	(3) Loss	(4) Loss
PathLength	0.128*** (0.0482)		0.163** (0.0636)	
Log(PathLength)				0.812*** (0.201)
Corr		-0.961 (0.887)	0.958 (1.149)	
Constant	-2.033*** (0.289)	-0.901** (0.365)	-2.620*** (0.761)	-2.678*** (0.351)
Observations	159	159	159	159
R-squared	0.043	0.007	0.047	0.094

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2 also shows that using the MST for predicting Lehman's effect is better than simply using correlations with Lehman. I wanted to check whether constructing the MST provide any additional information than just considering the correlations because if using correlations is at least as good as the MST, then there is no point in working with the latter. The second column contains the result when I regressed the losses on the correlation coefficient. Here, I have that the coefficient on the correlations is not significant. Also, the R-squared is substantially lower then in the MST case.

The third column provides more evidence for that using MST is better than using correlations. When I control for the correlation coefficient, the path length variable remains significant: that is, even if correlation with Lehman is kept constant, then the path length between a bank stock and Lehman has a significant effect on the price drop. To put it another way, this means that the structure of the tree and the position of a particular stock is what really matters, instead of the correlation between Lehman and that particular stock.

Finally, as Figure 4 suggests that the relationship between the loss and the path length may not be linear (the impact of path length on losses seems to be stronger for small path lengths and weaker for greater path lengths), I regressed losses also on the logarithm of the path lengths (see column 4 in Table 2, the corresponding curve is shown in Figure 4). Now I have that a 10 percent increase in the path length from Lehman is associated with a 0.081 standard deviations decrease in the price drop – on average, ceteris paribus. This is again a small effect. However, it is statistically significant, and now, the R-squared is much higher than in the linear case.

To summarize these results, it can be stated, that the MST has some predicting power.It is certainly stronger than just simply relying on the correlations between a particular stock in focus (in this case Lehman) and all the others.

The result of this analysis is important because this tells us that banks that lie close to a failing bank in the MST will tend to suffer higher drops in their prices than the others. Therefore if a bank is surrounded by many banks (i.e. it is in a central position, where many banks lie close to it), then this particular bank's failure would be much more problematic than another – not central positioned – bank's.

Considering the robustness of these findings, here, I note that I had almost the same results as presented above when I used different time-windows[24] or when I measured the losses after Lehman's collapse in a different way[25]. Therefore in this sense, the results proved to be robust. In the next subchapter, I am going to check whether the results are robust in the sense that whether other methods to construct the network would perform just as well as the MST.

4.2.2 The case of alternative methods

4.2.2.1 The threshold-based network

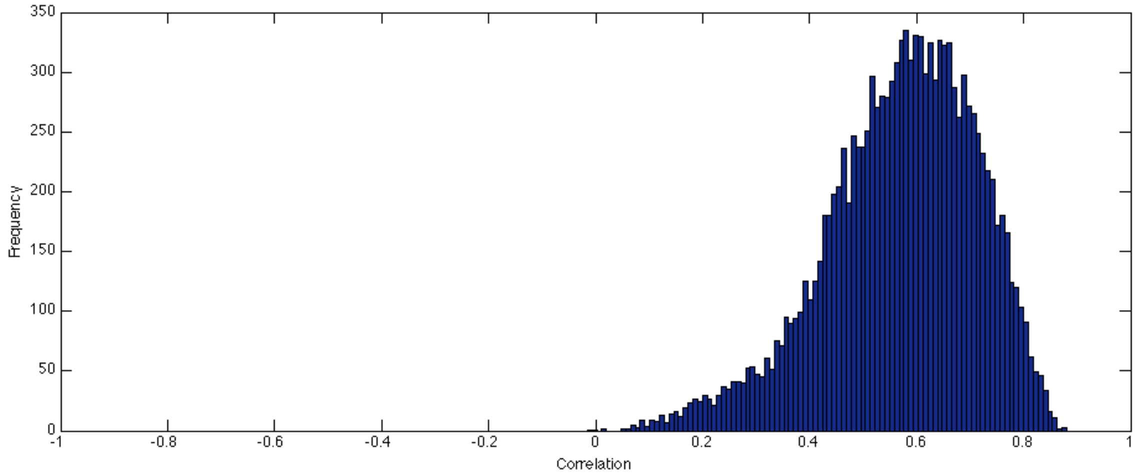
In the exercise of predicting Lehman's effect, Figure 5 illustrates the basic problem of the threshold-based method. In the top panel, we can see that the correlation coefficients between bank stocks in the given period were pretty high. The mean correlation is 0.57, their median is 0.58. This means that if I choose the threshold to be around 0.6, then I will only filter approximately the half of all the 12,720 connections[26]. However, at the same time, I have to choose the threshold so as to Lehman be connected. Based on the bottom panel of Figure 5 this means that the threshold must be at most 0.6198. Therefore if Lehman is connected, then

[24] That is, when I used 2 years, 1.5 years, 6 months and 3 months data prior to Lehman's collapse to construct the network.

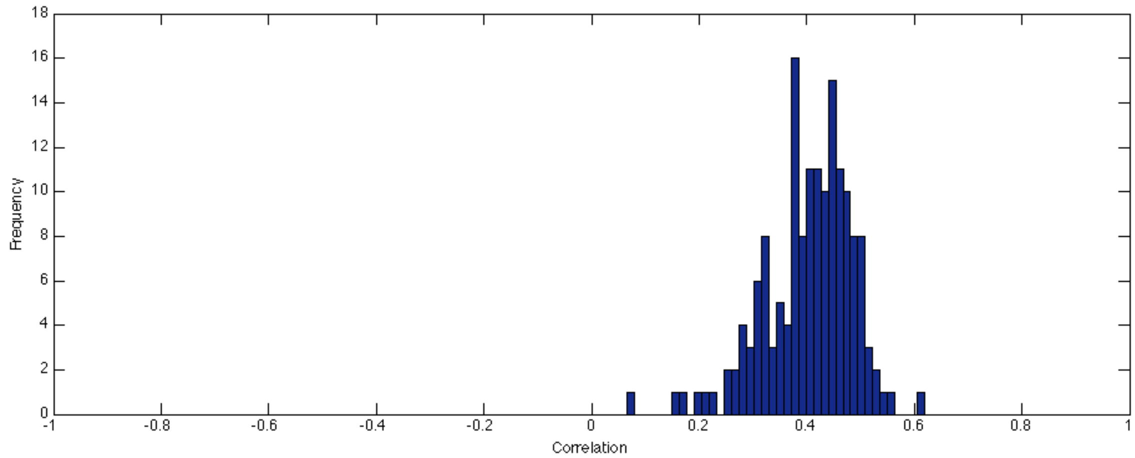
[25] When I measured the price drop as the logarithmic return between the closing prices before and after Lehman's collapse, but without dividing by the standard deviation. And also, when I measured the drop as the change in weekly returns before and after Lehman's failure.

[26] There are 160 banks, and since there is no meaning of the direction of a connection, the number of connections in a fully connected network can be computed as N*(N-1)/2, that is 160*159/2 = 12,720.

I have a graph where the number of connections is too high.



Panel A: Distribution of the correlation coefficients between every pair of stocks (i.e the distribution of the entries in the lower triangle of the correlation matrix)



Panel B: Distribution of the correlation coefficients between Lehman and all the other stocks

Figure 5: Distribution of correlation coefficients

Having a high number of connections is a problem because of two reasons. First, the network cannot be plotted in a legible way, thus no information can be extracted from the structure of the tree. Second, practically there is no variation in the path length[27] from Lehman: almost all of the nodes are two or three steps far from Lehman (almost half of them are 2 steps far from Lehman, the other half is 1, 3 or 4 steps far from it, or they are unconnected)[28]. And there is no relationship between losses and path lengths to Lehman.

[27]In this case the path length between two stocks is defined as the number of edges along the path from one stock's node to the other's.

[28]The Appendix contains all the banks along with their path lengths to Lehman in the MST as well as in the threshold- and in the partial correlation-based networks. I indicated when a bank was not in the particular graph by the label "unconn" (i.e. unconnected).

To assess this relationship more formally, I ran some regressions: I regressed the loss on the path length to Lehman in the threshold-based network (see Table 3, columns 5 and 6). When I used the highest possible threshold so as to Lehman still be connected (i.e. the threshold equals 0.6198), the path length is statistically insignificant. The case of a smaller threshold is – not surprisingly – even worse. For both cases, the R-squared values are much lower than what I got using the MST method.

Table 3: Regression output: Loss in stock price regressed on path length in networks that are built using alternative methods

VARIABLES	(5) Loss	(6) Loss	(7) Loss	(8) Loss
PathLength (threshold=0.6198)	0.170			
	(0.148)			
PathLength (threshold=0.6)		0.116		
		(0.157)		
PathLength (p-value=0.01)			0.0261	
			(0.0429)	
PathLength (p-value=0.05)				0.0118
				(0.108)
Constant	-1.685***	-1.544***	-1.395***	-1.321***
	(0.377)	(0.387)	(0.293)	(0.308)
Observations	137	141	112	159
R-squared	0.010	0.004	0.003	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The reason why the MST method is more fruitful is a property that Tse, Liu and Lau (2010) described as one of its drawbacks: that is, the edges of low correlations are retained just because of their topological conditions fitting the topological reduction criteria. Here, this is exactly what we want because the correlations of Lehman are too low. What the MST does is that it puts every bank in the network, and in order to do so, it accepts the most relevant edges for every nodes. This means that even if a bank has many highly correlated counterparts, the MST will accept only the most relevant connections (the highest correlations), and it will sacrifice the others to be able to accept at least one edge (the most relevant one) for banks that do not have high correlations with the others. The results show that even though this property may be a disadvantage of the MST in some circumstances (see Tse, Liu and Lau, 2010), it makes the MST more useful for the current purpose (i.e. making correspondence between the path length to Lehman in the network and the drop in price after Lehman's collapse).

4.2.2.2 The partial correlation-based network

Since the threshold-based network proved not to be useful to predict Lehman's effect, here I consider an extension of that method. The extension is twofold: first, I use partial correlations instead of ordinal ones, second, I consider two stocks to be connected if their partial correlation is significantly different from zero.

To evaluate significancy, I use thresholds on the p-value. I use both the 1% and the 5% significance level as a threshold because the 1% level lead to half of the highest loss-suffering banks being not connected, while the 5% level lead to a similar problem as in the threshold-based network case, that is, too many connections emerge.

The network using the 1% level is depicted in Figure 6 (the network of the 5% level was not legible). Here, again, Lehman is a blue rectangle, and the banks suffering the highest losses are in the orange rectangles. It can be seen, that four banks from the group of the highest loss-suffering banks (Table 1) are unconnected. Out of the other four, only Citigroup is close to Lehman.

When I define path length as the number of edges along the path from Lehman to a particular bank, this case is similar to the threshold-based one: while the variation in the path lengths is higher now, there is no correspondence between closeness and losses.

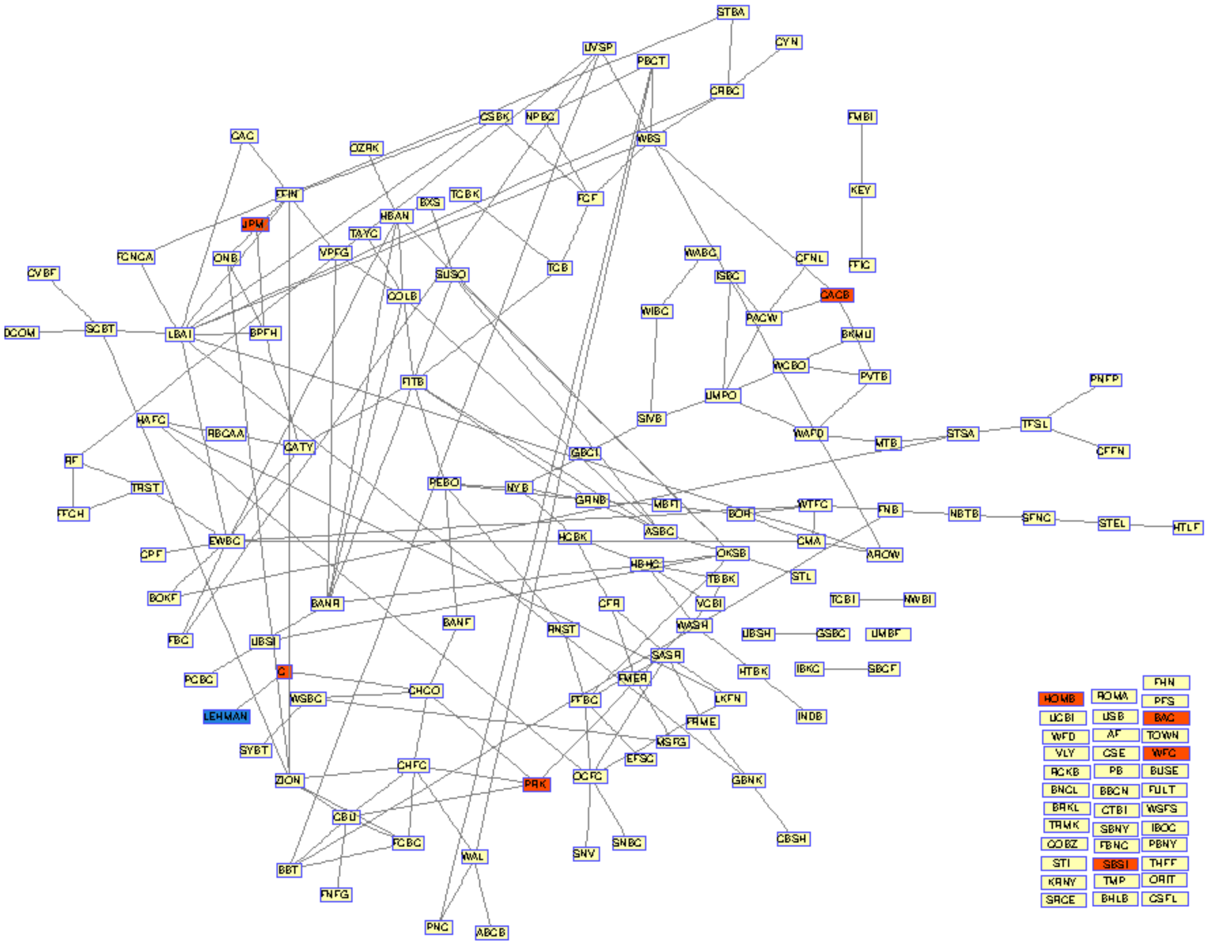


Figure 6: The graph of the partial correlation-based network (p-value=0.01)

Again, I would like to assess this question more formally, so I regressed losses on path lengths in the partial correlation-based networks. Column 7 in Table 3 shows the result when I used the p-value of 0.01 as a threshold, and column 8 corresponds to the case of the p-value of 0.05. In both cases, the coefficients on the path length variables are very statistically insignificant.

Here, the problem is similar to the one of the threshold-based one. Some of the banks (including some banks with the highest losses) have only insignificant partial correlations (with p-values higher than 0.01). Therefore either they are not connected, and hence the network cannot predict their price drop (which is problematic especially because some of the banks with highest losses are among them); or when the p-value-threshold is higher, then the network will be too connected (which is a problem that I have already discussed in the threshold-based case).

To conclude the result of these robustness tests, we can state that it *does* matter how the network is constructed if we want to capture systemic risks. In this example not all the correlation-based networks can capture systemic risks, only the Minimal Spanning Tree.

5. Conclusion

The main question of this thesis was whether systemic risks in a financial system can be captured by a network that is built using only publicly available data. To answer this question I constructed the correlation-based network of publicly traded US banks based on stock prices prior to Lehman's collapse, then I assessed whether this network could have been used to predict which bank stocks would suffer the biggest drops in prices after Lehman's collapse.

I found that if the correlation-based network is built using the Minimal Spanning Tree method, then it can tell us some valuable information about systemic risks. I showed that in the case of Lehman's collapse, some of the stocks with the highest drops lie close to Lehman in the tree. Moreover, when I considered the length of the path between every bank's node and Lehman, I found that a 10 percent increase in this path length to Lehman was associated with a 0.081 standard deviations decrease in the price drop – on average. Importantly, the network proved to be a better predictor of the price drops than just simply using the correlation with Lehman.

Robustness tests showed that using two alternative methods (the threshold- and the partial correlation-based one) were unable to predict price drops. Therefore I concluded that it does matter how the network is constructed if we want to capture systemic risks. In the case of Lehman's failure, not all the correlation-based networks capture these risks, only the MST.

Considering further research in this topic, it would be interesting to use other publicly available information on stocks as well. For example returns on bonds issued by banks could be used instead of stock prices. One of the advantages of using bonds is that their return might capture the company's default risk better than stock prices. However, as a bank may issue bonds with different maturities, different types, and with different risks at the same time, one should think over thoroughly how to handle the different conditions of bonds in order to get comparable variables.

References

Allen, F. and D. Gale (2000). Financial contagion. *Journal of Political Economy*, 108(1), 1-33.

Arnold, J., M. L. Bech, W. E. Beyeler, R. J. Glass and K. Soramaki (2006). The topology of interbank payment flows. Staff Report No. 243, Federal Reserve Bank of New York

Barabasi, A.-L. (2012). Network Science, Class1: Introduction [PowerPoint slides]. Retrieved from http://www.socnet.se/netsci/

Barabasi, A.-L. and R. Albert (1999). Emergence of scaling in random networks. *Science*, 286, 509–512.

Becher, C., S. Millard and K. Soramaki (2008). The network topology of CHAPS Sterling. Working Paper No. 355, Bank of England

Berlinger E., M. Michaletzky and M. Szenes (2011). A fedezetlen bankkozi forintpiac halozati dinamikajanak vizsgalata a likviditasi valsag elott és utan. *Kozgazdasagi Szemle*, 3, 229-252.

Bonanno, G., G. Caldarelli, F. Lillo and R. N. Mantegna (2003). Topology of correlation-based minimal spanning trees in real and model markets. *Physical Review E*, 68, 046103

Caballero, R. J. and A. Simsek (2009). Fire sales in a model of complexity. NBER Working Paper No. 15479, National Bureau of Economic Research

Cipriani, M. and A. Guarino (2008). Herd behavior and contagion in financial markets. *B.E. Journal of Theoretical Economics*, 8, Article 24.

Dungey, M. and V. L. Martin (2001). Contagion across financial markets: An empirical assessment. New York Stock Exchange Conference Paper, February 16-17.

ECB (2010). Financial Stability Review, June 2010. European Central Bank

Gai, P. and S. Kapadia (2010). Contagion in financial networks. Working Paper No. 383, Bank of England

Haldane, A. (2009). Rethinking the Financial Network. Speech delivered at the Financial Student Association, Amsterdam, April 2009.

Kruskal, J. B. (1956). On the shortest spanning subtree of a graph and the traveling salesman problem. *Proceedings of the American Mathematical Society*, 7, 48-50.

Mantegna, R. N. (1999). Hierarchical structure in financial markets. *European Physical Journal B*, 11, 193-197.

Onnela, J. P. (2002). Taxonomy of Financial Assets. M.Sc. Thesis, Helsinki University of Technology, Finland

Onnela, J. P., A. Chakraborti, K. Kaski, J. Kertesz and A. Kanto (2003a). Dynamics of market correlations: Taxonomy and portfolio analysis. *Physical Review E*, 68, 056110

Onnela, J. P., A. Chakraborti, K. Kaski and J. Kertesz (2003b). Dynamic asset trees and Black Monday. *Physica A*, 324, 247

Onnela, J. P., A. Chakraborti, K. Kaski, J. Kertesz and A. Kanto (2003c). Asset trees and asset graphs in financial markets. *Physica Scripta*, T106, 48-54.

Prim, R.C. (1957). Shortest connection networks and some generalizations. *Bell System Technical Journal*, 36, 1389-1401.

Serrano, M. A., M. Boguna, and A. Vespignani (2009). Extracting the multiscale backbone of complex weighted networks. *Proceedings of the National Academy of Sciences*, 106, 6483–6488.

Tse, C. K., J. Liu., F. C. M. Lau (2010). A network perspective of the stock market. *Journal of Empirical Finance*, 17(4), 659-667.

Vandewalle, N., F. Brisbois, and X. Tordoir (2001). Self-organized critical topology of stock markets. *Quantitative Finance*, 1, 372-375.

Appendix

Table 4: List of banks with some of their properties
(sorted based on losses in terms of standard deviations)

ID	Name	Loss in stock price on 15/9/2008		Simple approach		Path length to Lehman						Average market cap in the period being analyzed (billion $)
		In terms of st.dev.	Log. Return	Corr with Lehman	Partial corr with Lehman	In the MST	In the MST when partial corr used	In the p.corr based network (p=0.01)	in the p.corr based network (p=0.05)	In the thresh.-based network (Corr= 0.6198)	In the thresh.-based network (Corr= 0.6)	
LEHMAN	Lehman Brothers Holdings											
BAC	Bank of America	-6.66	-23.97%	0.56	0.04	1.45	4.91	Unconn.	4	2	2	154.47
C	Citigroup	-4.68	-16.42%	0.62	0.28	0.87	1.20	1	1	1	1	115.63
PRK	Park National Corp.	-3.47	-12.70%	0.46	-0.10	4.81	28.07	3	3	2	2	0.93
JPM	JPMorgan Chase & Co.	-3.30	-10.68%	0.52	0.02	1.99	2.43	7	2	2	2	146.25
SBSI	Southside Bancshares	-3.11	-9.35%	0.34	0.01	7.12	28.09	Unconn.	2	3	3	0.30
HOMB	Home Bancshares	-2.95	-7.33%	0.30	0.04	7.82	19.75	Unconn.	3	3	3	0.42
WFC	Wells Fargo & Co.	-2.85	-10.09%	0.50	-0.17	2.50	3.66	Unconn.	3	2	2	99.73
CACB	Cascade Bancorp.	-2.82	-10.35%	0.35	-0.07	6.07	19.71	7	2	3	3	0.28
WASH	Washington Trust Bancorp	-2.72	-7.98%	0.42	0.05	6.52	25.65	6	2	3	3	0.32
WFD	Westfield Financial	-2.65	-4.09%	0.31	0.02	6.74	18.54	Unconn.	3	Unconn.	Unconn.	0.31
TMP	Tompkins Financial Corp.	-2.52	-7.07%	0.29	0.09	7.13	19.77	Unconn.	3	3	3	0.42
SASR	Sandy Spring Bancorp.	-2.49	-7.15%	0.41	-0.01	6.99	17.35	7	3	3	3	0.38
STL	Sterling Bancorp.	-2.48	-7.98%	0.49	0.10	6.96	9.52	8	2	2	2	0.25
STEL	Stellar One Corp.	-2.47	-5.93%	0.20	-0.08	6.83	19.70	9	5	Unconn.	Unconn.	0.33
FBNC	First Bancorp/Troy NC	-2.42	-7.95%	0.38	-0.07	7.01	23.35	Unconn.	3	3	3	0.26
CSE	Capital Source	-2.30	-9.89%	0.44	0.19	1.75	17.46	Unconn.	3	Unconn.	2	3.12
BHLB	Berkshire Hills Bancorp.	-2.27	-6.54%	0.37	0.06	6.02	19.75	Unconn.	3	3	3	0.28
OCFC	Ocean First Financial Corp.	-2.25	-5.40%	0.30	-0.03	6.73	14.99	7	3	Unconn.	Unconn.	0.21
GBNK	Guaranty Bancorp.	-2.24	-10.38%	0.35	-0.06	6.54	19.76	7	3	3	3	0.29
CRBC	Citizens Republic Bancorp.	-2.17	-10.84%	0.38	-0.18	5.55	26.82	7	2	3	3	0.67
FBC	Flagstar Bancorp.	-2.14	-12.02%	0.38	0.01	6.12	13.88	7	3	Unconn.	3	0.34
CAC	Camden National Corp.	-2.12	-5.37%	0.16	-0.02	8.13	17.42	6	3	Unconn.	Unconn.	0.22
BOKF	BOK Financial Corp.	-2.04	-4.82%	0.32	-0.09	6.41	19.85	8	3	3	3	3.50
FFCH	First Financial Holdings	-2.02	-7.44%	0.42	-0.07	6.39	15.09	8	3	3	3	0.27
UMBF	UMB Financial Corp.	-2.02	-4.92%	0.45	-0.02	5.34	25.72	Unconn.	3	2	2	1.88
BKMU	Bank Mutual Corp.	-1.94	-4.01%	0.36	-0.08	7.56	13.24	10	3	3	2	0.52
AF	Astoria Financial Corp.	-1.93	-5.74%	0.54	0.12	3.71	15.08	Unconn.	2	2	2	2.19
MSFG	Main Source Financial Group	-1.91	-6.05%	0.37	0.05	7.10	20.82	4	3	3	3	0.31
EFSC	Enterprise Financial Services	-1.91	-6.81%	0.29	0.01	7.88	7.17	7	2	4	3	0.28
EWBC	East West Bancorp.	-1.90	-8.36%	0.49	0.10	3.76	12.68	7	2	2	2	0.99
FITB	Fifth Third Bancorp.	-1.88	-8.16%	0.43	0.13	6.98	10.36	5	3	2	2	9.32
UBSH	Union First Market Bankshares	-1.87	-7.13%	0.32	-0.17	7.05	31.75	Unconn.	3	3	3	0.27
KEY	KeyCorp	-1.83	-7.61%	0.48	0.03	3.77	17.45	Unconn.	3	2	2	7.28
CSBK	Clifton Savings Bancorp.	-1.81	-3.51%	0.35	-0.08	6.71	18.51	6	3	3	3	0.28

KRNY	Kearny Financial Corp.	-1.78	-4.22%	0.39	-0.02	6.62	29.23	Unconn.	4	3	3	0.81
COLB	Columbia Banking System	-1.76	-8.50%	0.35	0.13	5.66	19.76	6	3	Unconn.	Unconn.	0.40
BNCL	Beneficial Mutual Bancorp.	-1.76	-2.86%	0.33	0.00	6.71	23.39	Unconn.	3	Unconn.	Unconn.	0.89
TOWN	Towne Bank	-1.75	-4.70%	0.07	-0.17	7.99	15.12	Unconn.	4	Unconn.	Unconn.	0.41
CFR	Cullen/Frost Bankers	-1.73	-4.14%	0.50	0.03	3.63	18.51	6	3	2	2	3.15
WSFS	WSFS Financial Corp.	-1.69	-4.90%	0.37	-0.14	7.01	29.29	Unconn.	2	2	2	0.31
IBKC	Iberiabank Corp.	-1.67	-4.92%	0.44	-0.06	5.37	19.75	Unconn.	3	2	2	0.61
CMA	Comerica	-1.67	-6.42%	0.52	-0.07	3.07	13.84	8	3	2	2	5.15
UBSI	United Bankshares	-1.65	-5.91%	0.48	-0.21	4.68	2.42	7	1	2	2	1.22
TBBK	The Bancorp.	-1.65	-7.69%	0.32	0.03	6.20	25.66	5	2	Unconn.	Unconn.	0.14
ISBC	Investors Bancorp.	-1.64	-3.31%	0.39	-0.07	5.86	18.64	9	2	2	2	1.56
PBCT	People's United Financial	-1.63	-3.71%	0.46	-0.02	4.43	24.44	5	3	2	2	5.69
TFSL	TFS Financial Corp.	-1.62	-2.47%	0.27	0.08	6.74	18.62	10	3	Unconn.	Unconn.	3.87
SIVB	SVB Financial Group	-1.60	-3.62%	0.46	0.13	6.04	19.71	7	3	2	2	1.62
FNFG	First Niagara Financial Group	-1.60	-4.27%	0.44	-0.13	6.28	22.13	5	3	2	2	1.43
CFNL	Cardinal Financial Corp.	-1.59	-4.90%	0.23	0.05	7.51	22.11	9	2	Unconn.	Unconn.	0.20
TAYC	Taylor Capital Group	-1.58	-7.38%	0.28	0.02	6.62	20.93	7	3	Unconn.	Unconn.	0.15
DCOM	Dime Community Bancshares	-1.57	-4.68%	0.36	-0.24	8.34	18.59	6	1	3	3	0.53
STSA	Sterling Financial Corp/WA	-1.57	-9.88%	0.42	-0.03	4.97	17.41	9	4	2	2	0.66
CBSH	Commerce Bancshares	-1.56	-3.21%	0.47	-0.01	4.13	14.40	8	3	2	2	3.11
PFS	Provident Financial Services	-1.56	-4.66%	0.41	0.16	5.25	32.97	Unconn.	2	3	2	0.88
FCF	First Commonwealth Financial C.	-1.56	-5.29%	0.43	0.08	5.21	26.79	7	3	2	2	0.83
NPBC	National Penn Bancshares	-1.54	-5.55%	0.41	-0.16	5.80	27.99	6	4	3	2	1.10
PCBC	Pacific Capital Bancorp.	-1.53	-7.09%	0.48	0.04	5.80	24.59	8	2	2	2	0.87
LKFN	Lakeland Financial Corp	-1.53	-4.68%	0.32	0.00	6.58	16.17	8	4	3	3	0.26
CFFN	Capitol Federal Financial	-1.51	-2.60%	0.34	-0.15	4.44	19.83	11	3	3	3	2.78
FFBC	First Financial Bancorp.	-1.49	-5.11%	0.36	-0.08	6.89	5.98	6	2	3	3	0.46
WSBC	WesBanco	-1.44	-5.65%	0.43	0.03	5.87	11.97	3	2	3	3	0.59
HAFC	Hanmi Financial Corp.	-1.43	-4.93%	0.32	-0.16	6.05	13.80	8	3	3	3	0.31
TCBI	Texas Capital Bancshares	-1.43	-4.12%	0.28	-0.16	6.49	18.63	Unconn.	3	3	3	0.50
BANR	Banner Corp.	-1.41	-5.80%	0.43	0.17	6.62	3.62	6	2	3	3	0.29
RNST	Renasant Corp.	-1.39	-4.52%	0.44	0.08	6.47	7.19	5	3	3	3	0.42
BBT	BB&T Corp.	-1.36	-4.81%	0.51	-0.06	2.51	22.12	5	2	2	2	16.87
HTBK	Heritage Commerce Corp.	-1.35	-4.95%	0.38	0.09	7.13	12.02	7	3	3	3	0.19
MBFI	MB Financial	-1.34	-4.16%	0.46	0.02	6.32	17.44	6	3	2	2	1.02
ABCB	Ameris Bancorp.	-1.34	-5.27%	0.39	-0.14	6.47	23.24	5	3	3	3	0.19
FCBC	First Community Bancshares	-1.33	-4.86%	0.38	-0.13	5.92	19.74	4	2	3	3	0.37
WBS	Webster Financial Corp.	-1.32	-4.46%	0.45	0.09	5.40	25.64	6	3	2	2	1.36
WTFC	Wintrust Financial Corp.	-1.31	-4.44%	0.44	0.08	6.31	14.99	7	3	2	2	0.72
VCBI	Virginia Commerce Bancorp.	-1.31	-4.74%	0.34	0.18	6.70	26.86	4	3	Unconn.	Unconn.	0.22
PNC	PNC Financial Services Group	-1.30	-3.56%	0.51	0.04	3.06	23.25	5	3	2	2	22.62
RCKB	Rockville Financial	-1.27	-3.54%	0.30	0.00	7.43	26.90	Unconn.	3	Unconn.	Unconn.	0.26
GRNB	Green Bankshares	-1.24	-5.53%	0.31	0.03	5.60	10.65	5	2	Unconn.	Unconn.	0.24
PB	Prosperity Bancshares	-1.23	-3.74%	0.50	0.15	5.74	29.22	Unconn.	3	2	2	1.34
NWBI	Northwest Bancshares	-1.22	-2.78%	0.43	-0.03	5.87	19.81	Unconn.	3	3	3	1.25
TCB	TCF Financial Corp	-1.21	-4.67%	0.50	0.14	3.06	11.56	6	3	2	2	2.09

FNB	FNB Corp.	-1.20	-3.78%	0.41	-0.04	5.66	16.15	6	3	2	2	1.07
GSBC	Great Southern Bancorp.	-1.20	-3.99%	0.32	-0.07	7.21	30.54	Unconn.	3	Unconn.	3	0.20
SFNC	Simmons First National Corp	-1.20	-3.81%	0.41	0.11	7.50	18.53	8	4	3	3	0.42
IBOC	International Bancshares Corp.	-1.12	-3.28%	0.49	0.14	5.77	29.29	Unconn.	3	2	2	1.58
STBA	S&T Bancorp.	-1.12	-3.03%	0.43	0.20	6.29	28.03	8	3	2	2	0.82
PBNY	Provident New York Bancorp.	-1.11	-3.16%	0.47	0.22	5.84	7.20	Unconn.	1	3	3	0.50
WCBO	West Coast Bancorp/OR	-1.10	-4.63%	0.37	-0.09	6.57	18.53	9	3	3	2	0.22
PACW	PacWest Bancorp.	-1.10	-4.26%	0.39	-0.22	6.42	20.92	8	1	2	2	0.78
NYB	New York Community Bancorp.	-1.10	-2.70%	0.50	0.15	5.41	22.12	5	2	2	2	5.87
RF	Regions Financial Corp.	-1.08	-5.00%	0.52	0.07	3.65	15.04	7	3	2	2	11.09
RBCAA	Republic Bancorp.	-1.08	-3.88%	0.35	0.04	6.00	12.68	7	3	3	3	0.46
MTB	M&T Bank Corp.	-1.05	-3.04%	0.48	0.07	4.73	16.21	10	3	2	2	8.86
TRMK	Trustmark Corp.	-1.04	-3.49%	0.42	-0.13	5.22	20.99	Unconn.	3	2	2	1.23
BANF	Bancfirst Corp.	-1.02	-2.51%	0.46	0.08	6.41	9.58	3	3	2	2	0.68
WAFD	Washington Federal	-1.00	-2.86%	0.47	-0.01	5.34	17.32	9	3	2	2	1.77
FRME	First Merchants Corp.	-0.99	-3.35%	0.41	0.03	7.49	18.55	8	3	3	3	0.41
BOH	Bank of Hawaii Corp.	-0.99	-2.43%	0.49	0.16	4.17	15.06	7	3	2	2	2.53
SRCE	1st Source Corp.	-0.98	-4.10%	0.43	-0.01	5.84	17.51	Unconn.	3	3	2	0.48
FHN	First Horizon National Corp.	-0.97	-5.13%	0.48	-0.17	3.74	30.49	Unconn.	3	2	2	1.85
ASBC	Associated Banc-Corp.	-0.96	-2.94%	0.44	-0.15	6.32	9.43	6	2	2	2	2.97
SNBC	Sun Bancorp. Inc/NJ	-0.95	-2.93%	0.45	0.12	7.06	17.46	8	3	3	3	0.29
PVTB	Private Bancorp.	-0.94	-2.86%	0.37	-0.02	7.09	18.51	8	3	3	3	1.06
USB	U.S. Bancorp.	-0.93	-2.42%	0.53	0.03	1.99	3.67	Unconn.	3	2	2	55.71
HCBK	Hudson City Bancorp.	-0.91	-2.16%	0.43	-0.12	2.63	23.26	6	2	2	2	8.68
HBAN	Huntington Bancshares	-0.89	-4.76%	0.46	0.11	3.71	5.98	7	2	3	2	3.24
BRKL	Brookline Bancorp.	-0.87	-2.33%	0.37	-0.01	5.27	25.67	Unconn.	3	3	2	0.64
TCBK	Trico Bancshares	-0.87	-3.32%	0.44	0.15	7.03	18.64	7	2	2	2	0.27
BPFH	Boston Private Financial Holdings	-0.87	-4.07%	0.38	0.12	7.21	12.64	6	2	Unconn.	Unconn.	0.54
CHCO	City Holding Co	-0.87	-2.38%	0.39	0.05	6.96	10.78	2	2	3	3	0.63
INDB	Independent Bank Corp.	-0.85	-2.48%	0.45	0.05	6.34	16.21	8	2	2	2	0.44
HTLF	Heartland Financial USA	-0.85	-2.85%	0.38	0.09	7.61	20.91	10	4	3	3	0.34
UCBI	United Community Banks	-0.84	-3.81%	0.46	0.08	4.94	23.38	Unconn.	3	3	3	0.64
GBCI	Glacier Bancorp.	-0.84	-2.76%	0.40	-0.16	5.33	20.92	6	3	2	2	1.06
SYBT	SY Bancorp.	-0.82	-2.69%	0.39	0.06	6.54	13.15	4	3	3	3	0.33
FMER	First Merit Corp.	-0.81	-2.65%	0.50	-0.04	4.17	19.71	5	3	2	2	1.58
STI	SunTrust Banks	-0.81	-3.03%	0.54	-0.07	3.04	21.00	Unconn.	3	2	2	17.45
CTBI	Community Trust Bancorp.	-0.81	-2.35%	0.44	-0.05	6.34	22.12	Unconn.	3	2	2	0.44
COBZ	CoBiz Financial	-0.80	-3.37%	0.47	0.10	7.10	24.61	Unconn.	3	3	2	0.27
ROMA	Roma Financial Corp.	-0.80	-1.90%	0.40	-0.01	6.08	26.90	Unconn.	3	3	3	0.45
BXS	Bancorp South	-0.74	-2.27%	0.41	-0.09	5.76	7.11	7	3	2	2	1.91
CHFC	Chemical Financial Corp.	-0.72	-2.38%	0.48	0.13	5.24	20.90	3	3	2	2	0.59
CATY	Cathay General Bancorp.	-0.71	-2.84%	0.40	-0.05	6.43	11.49	6	3	2	2	1.01
OKSB	Southwest Bancorp.	-0.71	-2.54%	0.31	-0.18	7.09	4.79	7	2	3	3	0.24
SBCF	Seacoast Banking Corp. of Florida	-0.71	-3.06%	0.25	0.09	6.38	20.94	Unconn.	4	Unconn.	Unconn.	0.19
BUSE	First Busey Corp.	-0.71	-2.29%	0.40	-0.11	6.51	7.20	Unconn.	2	3	3	0.65
THFF	First Financial Corp. (Indiana)	-0.70	-2.33%	0.39	0.10	7.05	22.07	Unconn.	4	3	3	0.45

CYN	City National Corp.	-0.66	-1.99%	0.46	0.07	3.65	27.98	8	3	2	2	2.48
FFIN	First Financial Bankshares	-0.65	-1.46%	0.39	0.01	6.37	17.35	5	3	3	3	0.91
FFIC	Flushing Financial Corp.	-0.64	-1.89%	0.42	-0.07	7.62	17.47	Unconn.	2	2	2	0.38
SUSQ	Susquehanna Bancshares	-0.63	-2.32%	0.47	0.02	5.18	8.30	6	2	2	2	1.55
FMBI	First Midwest Bancorp.	-0.59	-2.00%	0.49	-0.03	5.76	25.70	Unconn.	2	2	2	1.23
CVBF	CVB Financial Corp.	-0.56	-2.09%	0.43	0.01	5.20	19.86	6	3	2	2	0.92
SNV	Synovus Financial Corp.	-0.55	-1.99%	0.48	0.09	3.65	16.19	8	3	2	2	4.47
ONB	Old National Bancorp.	-0.55	-1.69%	0.40	-0.05	6.26	19.76	5	3	2	2	1.11
PNFP	Pinnacle Financial Partners	-0.53	-1.78%	0.45	0.12	6.47	11.86	11	3	3	3	0.58
WABC	Westamerica Bancorp.	-0.39	-1.11%	0.43	0.08	4.25	15.03	9	2	2	2	1.50
ZION	Zions Bancorp.	-0.38	-1.70%	0.48	0.02	4.26	18.55	4	3	2	2	4.43
ORIT	Oritani Financial Corp.	-0.38	-0.90%	0.26	-0.06	6.63	22.15	Unconn.	2	3	3	0.60
FULT	Fulton Financial Corp.	-0.34	-1.14%	0.46	-0.05	5.22	17.41	Unconn.	4	2	2	1.93
HBHC	Hancock Holding Co	-0.32	-0.95%	0.47	0.17	5.28	24.47	5	2	2	2	1.34
VLY	Valley National Bancorp.	-0.31	-0.82%	0.45	0.09	6.35	29.24	Unconn.	4	2	2	2.38
WIBC	Wilshire Bancorp	-0.25	-0.85%	0.33	-0.07	6.63	20.88	8	3	3	3	0.27
CBU	Community Bank System	-0.25	-0.65%	0.44	0.09	6.92	20.92	4	2	2	2	0.67
UMPQ	Umpqua Holdings Corp	-0.24	-1.06%	0.45	-0.03	5.32	18.51	8	2	2	2	0.87
BBCN	BBCN Bancorp.	-0.23	-0.75%	0.31	-0.12	5.96	15.10	Unconn.	4	3	3	0.31
SBNY	Signature Bank	-0.15	-0.50%	0.27	-0.17	5.95	24.51	Unconn.	3	3	3	0.94
NBTB	NBT Bancorp.	-0.10	-0.30%	0.38	-0.12	6.87	17.36	7	4	3	2	0.77
CPF	Central Pacific Financial Corp.	-0.05	-0.22%	0.44	-0.12	5.76	13.86	8	3	2	2	0.47
OZRK	Bank of the Ozarks	-0.02	-0.07%	0.27	-0.09	4.57	7.16	8	3	3	3	0.39
WAL	Western Alliance Bancorp.	-0.01	-0.07%	0.38	-0.05	7.16	22.06	4	3	3	2	0.45
AROW	Arrow Financial Corp.	0.02	0.04%	0.22	0.02	8.46	15.04	7	3	Unconn.	Unconn.	0.24
CSFL	Centerstate Banks	0.02	0.06%	0.17	0.00	8.17	16.27	Unconn.	4	Unconn.	Unconn.	0.17
PEBO	Peoples Bancorp.	0.03	0.09%	0.40	0.10	7.03	8.38	4	2	3	3	0.23
TRST	TrustCo Bank Corp. NY	0.03	0.10%	0.48	-0.01	5.23	13.89	8	2	2	2	0.72
UVSP	Univest Corp. of Pennsylvania	0.04	0.17%	0.38	0.06	5.95	15.08	6	3	3	3	0.34
VPFG	ViewPoint Financial Group	0.13	0.24%	0.32	-0.16	6.74	18.55	6	3	4	3	0.40
SCBT	SCBT Financial Corp.	0.14	0.49%	0.41	0.12	7.78	17.41	5	2	3	3	0.34
FCNCA	First Citizens BancShares	0.42	0.99%	0.40	0.17	2.33	17.39	7	3	Unconn.	3	1.62
LBAI	Lakeland Bancorp.	1.01	3.53%	0.37	-0.11	7.13	16.22	6	2	3	3	0.28