The Madoff Investment Fraud

A Social Network Analysis

Wei Sui & Liz Dilworth & Ruoyue Wang
Claremont Graduate University

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1. Introduction to the Madoff Fraud

Bernard Lawrence Madoff was responsible for the largest financial fraud and Ponzi scheme in history, but was once one of the most respected American financial brokers and a legend on Wall Street. In his prime, Madoff was the former non-executive chairman of the Nasdaq Stock Market and operated Bernard L. Madoff Investment Securities (BLMIS) and Madoff Securities International (MSI) [3]. He also assisted the Securities and Exchange Commission (SEC) in creating competitive stock exchange markets in the 1970's and 80's.

Madoff always seemed to make money. He was a respected member of his community and widely regarded as a financial wizard. His relationships with other members of the financial community and within the SEC afforded him a legitimacy that no one ever seemed to question. Madoff intentionally fostered relationships that gave the appearance of trust and fantastic investment returns so people were eager to invest with him. However, he willfully exploited these relationships for his own financial gain. On December 11, 2008 Bernard Madoff was arrested by the Federal Bureau of Investigation and accused of defrauding thousands of investors all over the world out of tens of billions of dollars [1].

Madoff's carefully cultivated social capital and widespread connections contributed to the longevity of his Ponzi scheme. Madoff's Ponzi scheme targeted companies, endowments, royalty, universities, private citizens, and charities, defrauding them of around $65 billion [1]. A Ponzi scheme is an investment scam which operates by generating returns for earlier investors with the funds given by later investors. Due to the nature of this kind of white-collar crime, it had to continually grow in order to have enough funds to sustain itself. Madoff was constantly acquiring new investors because without them, the scam would collapse. The Madoff Ponzi Scheme is significant because the scale of the fraud was unparalleled and because he was technically never caught. Despite receiving reports on Madoff's fraud for nearly a decade, the SEC never conducted a thorough investigation of his financial dealings [1].

Ultimately, what exposed the fraud was the Global Financial Crisis (GFC) of 2008. The GFC caused world-wide pandemonium, with investors withdrawing their money out of the stock market as it continued to plummet. Even Madoff was not immune when the economy crashed because most of his investors withdrew their funds, which he required to perpetuate the Ponzi scheme. Madoff could not generate new investors fast enough to keep up with the withdrawal requests he was receiving and the Ponzi scheme soon ran out of capital. At this point Madoff allegedly admitted to his sons that his company was a massive Ponzi scheme and they notified the authorities [1]. The next day, Madoff was arrested, but by this point he had already had plenty of time to destroy evidence of his crimes, and more significantly, evidence that implicated other individuals and financial institutions in the fraud. Madoff took full responsibility for his crimes, entering a plea of guilty and refusing to assist the prosecution's investigation[1]. Madoff was found guilty of 11 federal felony counts, including mail fraud, perjury, money laundering, securities fraud, wire fraud and sentenced to 150 years in prison, the maximum sentence for his crimes.

1.1 Research Questions

Criminal networks are often small-world networks that operate in some middle space between an open market and formal hierarchy [3]. The need for secrecy to avoid detection can often make ties in criminal networks appear weak. However, criminal networks are still a type of social network and are subject to the usual rules and trends. For instance, people involved in these networks exhibit homophily just like legitimate networks. Criminal networks like Madoff's are often classified as 'dark networks' or networks that engage in illicit activity that cause personal and societal harm [3]. This study will use Social Network Analysis (SNA) in an attempt to uncover attributes of the Madoff Investment Scheme that support the assertion that it is a dark network. Thus, our first research question is:

1. What are the structural attributes of this network that indicate it is a criminal network?

Furthermore, SNA will also be used to discover other entities involved in Madoff's crimes, which is useful because despite his claims that he acted alone, it is clear that Madoff had a vast network of conspirators assisting him. Thus, our second research question is:

2. What central investment firms besides Madoff's were responsible?

2. Background Literature

A study was conducted by Nash et al. to understand how trust in social ties and conducting due diligence affected initial investment amounts and overall loss of capital in financial fraud [8]. Focusing the research by studying the Eron Mortgage Corporation scandal, Nash et al. conducted a survey with 559 victims and created two linear regression models. They found that both social ties and due diligence contributed to people falling prey to financial fraud.

Financial fraud occurs when criminals take advantage of legitimate investment deals. It is therefore important to consider how people go about collecting the information that makes them feel comfortable enough to make an investment deal. This article is focused on two ways in which people collect this information; social networks and conducting due diligence. The goal of this information collection is to reduce information "asymmetry" [8]. However, this asymmetry is present in nearly all investments and financial agreements as one party is generally more knowledgeable than the other. This asymmetry is why trust is such an important aspect of financial transactions and it is precisely what white-collar criminals take advantage of. In other words, within social relationships, trust is what makes people vulnerable to being exploited [8].

Performing due diligence would seem to then ensure that trust is not misplaced within financial relationships. This study is concerned with determining whether conducting due diligence protects investors or leaves them vulnerable to financial exploitation and the authors actually discovered a paradox. When potential investors do not conduct due diligence they are more likely to be defrauded. However, when potential investors conduct due diligence and the frauds are sophisticated enough to fool due diligence probes with falsified documents, investors are then more likely to lose even larger sums of money [8].

This study looked specifically at the fraud conducted by the Eron Mortgage Corporation that stole an estimated $249 million from over 2000 people in British Columbia, Canada [8]. The goal was to understand the effects of both trust in social ties and conducting due diligence on the investors initial investment and their overall loss in the fraud. The study asked two main questions: Did people who invested on the advice of a friend or family member lose more capital than those who used a financial professional? And, were the individuals who checked Enron's credentials more careful with their investment? Bouchard et al. determined that both trust and due diligence increased both initial investments and overall loss meaning that these two seemingly necessary components of financial deals actually make people more vulnerable to financial exploitation.

The next article is concerned with SNA, which many criminologists employ to understand how white-collar criminal networks are connected. Manning conducted a study with the purpose of building upon past SNA of criminal networks by implementing a social capital analysis (SCA) instead [7]. He noted that past studies have conducted SNA on the ego and socio-centric level and he wanted to specifically focus on the BLMIS fraud as it was both recent to the time of this study and had a large social impact. He found that SCA can be used to grow understanding of financial crime as it provides "socio-economic analysis of ego-centric criminal networks" [7]. Manning noted that financial crimes differ depending when they occur in history, but maintained that there are recurring network characteristics that can be used to gain insight into criminal networks. He stated that the study has practical implications because any endeavor to understand financial crime can be enriched with a SCA of the criminal network in question, as it puts focus on the human elements inherent in this type of crime [7].

Manning declared that Madoff's sentencing of 150 years was "indubitably severe" due to the historical precedent of frauds and other Ponzi schemes being conducted on a similar scale [7]. He then proceeded to discuss that there have been prior studies conducted on this subject from a social network perspective . These past studies show that in crimes such as Madoff's, there is a real need to create and preserve social networks so that the criminal can be close to the victim; the relationship between the two parties is the first step in facilitating fraud. Manning maintained that while structural analyses like these past studies are indeed useful, they are limited in that they cannot accurately capture the "human and qualitative qualities" that occur between individuals within social groups, whereas SCA can [7]. Manning's study therefore endeavored to focus on the network interactions within the BLMIS fraud that are "dependent on the persistence of human contact" [7].

Building upon past studies conducted upon BLMIS that utilized SNA to analyze the social network characteristics that went into the Madoff Ponzi scheme, Manning's analysis was aimed at uncovering the human element within the network structure by prioritizing the "qualitative relational interactions" present in the Madoff criminal enterprise [7]. Social capital added a qualitative aspect to SNA and Manning's goal was to thoroughly understand the integral social relationships that are cultivated through repeated interactions that make up the structure of criminal networks. By utilizing SCA in this manner, it was apparent that an understanding of how to foster relationships for the purpose of exploiting them for financial gain is equally important to sophisticated financial engineering abilities in white-collar crimes like that of BLMIS [7].

From a social capital perspective the "ends-means" economic school of thought has great relevance when it comes to fraud [7]. Criminals such as Madoff have no issues perverting their socio-economic relationships for financial gain; white-collar criminals can be characterized as an extreme form of economic rationalists. It should be noted that Madoff purposefully targeted his own community to perpetuate his crimes specifically because of the trust that existed in his personal and professional relationships. He even went so far as to profess being a devout Jew inorder to target the New York Jewish community. Manning discussed other frauds and notes that they all too have a socio-economic element that facilitates their prospective crimes [7].

Manning concluded that all investment frauds have typical social capital characteristics that occur. Most perceived differences that occur are contemporary in nature. In terms of Madoff's crimes, they were only made possible by his keen insight into socio-economic and social interactions, thus he is a typical fraudster: excellent at exploiting social capital. Manning's study shows that there are indeed aspects of fraud that occur repeatedly that can be viewed from a social capital perspective. He was successful in expanding upon SNA approaches conducted to gain understanding of the effects social networks have in criminal enterprise. In regards to the BLMIS fraud, Manning concluded that while the size, scale, and length of the fraud were indeed unusual, Madoff exhibited characteristics of a typical fraudster and committed his crimes in a typical manner [7].

2.1 How to Identify Key Players

This next study was done by Borgatti to improve the efficiency of SNA by designing methods to more accurately identify important points within networks [2]. To begin he identified issues that arise when trying to define key players in networks, both when trying to optimize the network and when trying to fragment them. He identified the key players in network *optimization* as KPP-Pos and the key players in network *fragmentation* as KPP-Neg [2]. Specifically, KPP-Pos are those nodes in a network that are most necessary for passing something through it. Conversely, the nodes that when deleted fragment the network more than any other are referred to as KPP-Neg. The main problem that the study tackled is that classic centrality measures are not actually effective at finding either KPP-Pos or KPP-Neg [2]. Borgatti therefore, had to devise new measures to identify both kinds of key player nodes and presented them in this article.

Borgatti immediately discussed why the seemingly obvious methods of identifying node centrality in order to reveal the nodes most important to a network are ineffective when it comes to identifying which nodes are key players in their networks. Node centrality models do uncover key nodes of social capital, but they are a class of structural measures, which are concerned with identifying components of the network that feed into an individual node [2]. In this study, Borgatti conducted key player research aimed at identifying the individual nodes that are important for the network as a whole [2]. With this in mind Borgatti asserts that new methods for identifying key player nodes that facilitate network cohesion are required as none currently exist.

Borgatti conceived of key players in two distinct ways. The first is concerned with identifying those key players that are critical for maintaining network cohesion and whose removal from the network would cause it to fracture (or become so disparate that it is effectively fractured). He defined the key players whose removal from a network would cause it to lose its cohesion as "Key Player Problem/Negative or KPP-Neg" [2]. The second kind of key player as defined by Borgatti are those individuals who most effectively connect their network together; i.e. the nodes that can connect to all other nodes in their network in the least amount of steps. He refers to the second type of key player as "Key Player Problem/Positive or KPP-Pos" [2]. Borgatti also discussed two distinct ways in which node centrality methods fail at identifying KPP-Pos and KPP-Neg; he referred to them as the goal issue and the ensemble issue. The goal issue occurs because centrality measures were not created specifically for KPP-Pos or KPP-Neg and thus do not provide the best solution for identifying either [2]. The ensemble issue occurs due to both KPP-Pos and KPP-Neg trying to identify which sets of nodes are integral rather than which individual nodes are integral; the nodes most suited for a given task are not necessarily comprised of the nodes that are seen as being the most integral when viewed individually [2].

It should be mentioned that the preexisting graph-theoretic approach methods do actually solve the ensemble issue and are relevant to solving aspects of the goal issue. However, the way in which they solve the ensemble issue does not do so in the way Borgatti required. Graph-theoretic methods "fix the quality of the solution and search for the smallest solution", whereas Borgatti wished, "to fix the size of the solution set and search for the best quality" [2]. To find the key players associated with KPP-Pos and KPP-Neg, Borgatti devised a "combinatorial optimization algorithm and set of success metrics" [2]. Besides measuring for success in regards to KPP-Pos and KPP-Neg, their metrics measure graph cohesion and are applicable to a number of other problems. Nodes whose placement make them most suited for ushering resources through the network receive high scores on KPP-Pos measures. Nodes whose placement would cause the most amount of fragmentation if they were to be removed from the network receive high scores on KPP-Neg measures. Nodes that receive the highest scores on KPP-Pos metrics are those that are found within highly cohesive graphs. Conversely, nodes that receive the highest scores on KPP-Neg metrics are those found in graphs with low cohesion; and in graphs such as these optimization methods do not yield better results than heuristic methods despite costing more[2].

2.2 Resiliency of the Madoff Fraud

In the seminal work conducted by Hardy and Bell (2020), they applied SNA to the Madoff Investment Scheme to better understand sophisticated criminal networks and what contributes to their resilience. Four clusters within the criminal enterprise were found to have vital functions within the network; a core leadership group, a compliance group, a capital group, and a facilitators group [3]. The article built on past studies done to understand the relationships and behaviors of organized crime networks in order to identify the individual and network factors that contributed to the resilience of the Madoff Investment Scheme. Hardy and Bell used SNA as an analytical method to understand the Madoff fraud; a Ponzi scheme of unprecedented network size that defrauded its victims on a never before seen scale.

The article begins with a detailed description of the Madoff Investment Scheme. It notes that similarly to other organized crime networks the Madoff Scheme was composed of a vast web of ties between legitimate and illegitimate networks, although it is unique in both its size and longevity. The Madoff scheme was a multi-billion dollar fraud that spanned several decades and affected more than 4,000 people. Madoff's crimes were made possible through the relationships that he had with close friends, family, clients, and the New York Jewish community [3]. As a registered investment advisor, Madoff abused his position to defraud those within his social circle that trusted him. Due to Madoff targeting those he had personal and professional relationships with in his fraud his crimes were of a social nature, making SNA extremely useful in understanding whom his network was composed of and how it evaded detection for so long.

SNA has been used in past criminological studies to understand the relationships, behaviors, and how groups of people are structured within organized crime. According to the SNA field, criminal associations are referred to as 'dark networks' and are described as "...covert networks operating outside the boundaries of the law" [3]. Dark networks are typically more like groups of individuals with loose ties than a network with hierarchical structure. The relationship between the actors in dark networks often appear weak when viewed with an SNA model, however this can be attributed to criminals' need to avoid detection. In dark networks seemingly loose ties actually depict the types of relationships required for trustworthy communication to take place. While illicit networks garner strength form their legitimate endeavors, illicit networks also face numerous organizational challenges. The clandestine nature of illegal activities requires trade secrecy and security be preserved within the network. For example the ability to observe network members' contributions is significantly limited to avoid detection.

The Madoff network is considered a dark network because it caused significant individual and social harm. It used corruption, illicit collusion, deception, bribery and threats of financial loss in order to perpetuate its fraud. Dark networks are dynamic in nature as they are constantly facing obstacles from both inside and outside the network; known as endogenous and exogenous shocks. Due to the constant challenges they face, dark networks must be resilient in order to be successful. Hardy and Bell maintain that it is important to study this resiliency to understand what vulnerabilities a dark network may have and how the network can be disrupted or destabilized. NA can identify these vulnerabilities by uncovering central nodes, the nodes that are able to take their place in the event of a shock, and bridging nodes which link disparate sections of the networks together [3].

While only Madoff and 14 others were found culpable by the US legal system it is clear that the fraud involved a vast network of individuals [3]. The people involved in the Madoff dark network were a mix of willing and unwilling participants that can be divided into four distinct groups depending on the role they played in the fraud. The *core group* were individuals who ran BLMIS and MSI and controlled legitimate and illegitimate parts of the network. The *compliance group* was made up of individuals and companies responsible for making it appear that the fraud was actually complying with SEC oversight regulations; such as Friehling-Horwitz, Swanson, and Ameriprise Financial. The *capital group* was made up of many feeder funds whose accounts Madoff had full trading authority over. The *facilitators group* consisted of the accountants, banks, and financial services companies who provided the network with its significant flexibility and resiliency [3].

At the structural level the Madoff criminal network facilitated stability through key strategies. This included, "replacing linkages, creating redundancy amongst entities, and by promoting loyalty among core staff and victims alike" [3]. The effect of these strategies are best understood by the 'Shock and Response' Network Resilience Model devised by Bakker et al. (2012). This model states that network resilience is determined by its response to unforeseeable events (exogenous shocks) and unpredictable events (endogenous shocks) that apply pressure to the network [3]. The ability to observe behaviors in an illicit, or dark, network is necessarily restricted in order to protect the clandestine nature of their activities.

The study identified two main factors that made the Madoff Investment Scheme resilient for decades. The first of these factors was intergenerational accounts that contained what Madoff himself called 'sticky money' [3]. The intergenerational accounts referred to the long-term investors whose trust in Madoff's abilities to grow their money made them loyal and unlikely to ever withdraw. The second was the network's ability to borrow against both real and fake investor capital in banks and trading accounts [3]. With these two factors to rely on, the Madoff fraud was able to persist through multiple exogenous and endogenous shocks for decades while remaining undetected. Ultimately, the Madoff Investment Scheme was brought down by the exogenous shock of the 2008 GFC [3]. Due to so many investors withdrawing funds from the stock market Madoff was unable to raise enough money to keep the fraud going and the Ponzi scheme collapsed.

3. Description of the Data Set

3.1 Overview:

There were two sets of data used for this paper. The main dataset was from UCINET software. It demonstrated the finance flows between financial institutions and Bernie Madoff's investment firm (a total of 61 firms). The data was originally collected from news stories, court documents, and government agencies. Below is a list of the firms and the value in the csv file indicated the direction of money movement.

HSBC_Holdings	Banque_Benedict_HentchCie
Genevalor_Benbassat	Genium_Advisors
Phoenix_Holdings	Great_Eastern_Holdings
Thema_Fund	Prospect_Capital
Herald_Lux_Fund	Union_Bancaire_Privee
Capital_Bank_Austria	Sterling_Equities
Cohmad_securities	Nomura_Holdings
Bank_Medici	Stanford_Capital_Mgt
UniCredit_SpA	FIM_Advisers
Pioneer_Alt_Investments	M&B_Capital_Advisors
Rothschild_Cie	Man_Group_PLC
Access_Int_Advisors	Notz_Stucki_Cie
BNP_Paribas	Credicorp_Ltd
EIM_Group	S&P_Investment
Nipponkoa_Insurance	EFG_International_AG
Mirabaud_Cie	Maxam_Absolute_Return_Fund
Zeus_Partners_Ltd	Tremont_Group_Holdings
Banco_Safra	Opperheimer_Funds
CMG	Bradean_Alternatives_Lts
Brighton_Co	Rye_Investment_Funds
Avellino_Bienes	Austin_Capital
Neu_Privat_Bank	Meridian_Capital_Partners
Banco_Santander	Banco_Bilbao_Vizcaya_Argentaria
Optimal_Strategic_US	Kingate_Global_Fund
Sumitomo_Life_Ins	Kingate_Euro_Fund
Fukoku_Mutual_Life	Ascot_Partners
Fix_Asset_Mgt	Gabriel_Capital
Fairfield_Greenwich	Sterling_Stamos_Capital_Mgt
Nordea_Bank_AB	Spring_Mountain_Capital
	Ariel_Capital
	Fortis_Bank_Nederland
	Bernard_Madoff_Investment

Figure 1: list of financial institutions victims

The other dataset used was made for this study. It described some of the financial institutions involved in the Madoff scheme; the data included the location of firms, the firm type, and the amount of potential exposure to the fraud.

3.2 Data Type Description:

Attributes	Data Type	Data Description
firms	String	Name of financial institutions
potential_exp	Double	Amount of each firm's potential exposure to the scheme
px_class	Integer	0: unknow 1: less than and equal to 15 million, classified as minimum exposure. 2: less than and equal to 100 million, classified as moderate exposure. 3: less than and equal to 900 million, classified as heavy exposure. 4: more than 900 million, classified as extreme exposure.
city	String	The city of each financial institution's headquarters

country	String	The country of each financial institution's headquarters
investor_type	String	Identify the type of financial institution
country_code	Integer	1: DOMESTIC 2: UNKNOWN 3: INTERNATIONAL
continent_code	Integer	1: EUROPE 2: NORTH AMERICA 3: SOUTH AMERICA 4: ASIA 5: UNKNOWN 6: AFRICA 7: ANTARCTICA 8: AUSTRALIA

Table 3.1 Data Types Description

3.3 Data Value Description

	firms	city	country	investor_type	country_code	continent_code	px_class
count	60	55	57	60	60	60	60
Unique value	60	27	18	43	3	8	5
Top	N/A	New York	USA	Bank	1 (USA)	1 (Europe)	3 - heavy exposure
Frequency	1	10	18	17	18	27	17

Table 3.2 Data Value Description for Categorical Variables

	potential_exp
number of records	50
mean amount	1,012,034,000
standard deviation	1,722,986,000
minimum	600,000
25%	32,750,000
50%	280,000,000
75%	1,000,000,000
maximum	7,500,000,000

Table 3.3 Data Value Description for Continuous Variable

Missing Value Description

Attribute names	Number of missing values
city	5
country	3
potential_expinvestor_type	10
investor_type	4

Table 3.4 Missing Value Description for all Attributes

4. Visualization(s) of the Network

The amount of potential exposure was classified into 4 groups: minimum exposure (≦ $15 million), moderate exposure (≦ $100 million), heavy exposure (≦ $900 million), and extreme exposure (> $900 million). Figure 4.1 compared the network distribution among domestic firms, international firms, and firms with unknown locations. The node size demonstrated the impact of potential exposure; the bigger a node's size, the larger its investment was. Figure 4.1 also showed that most firms from the United States were located in New York City, but the Madoff scheme had a larger financial impact on the international firms. Figure 4.2 identified 45% of the victims' firms were located in Europe, 32% in North America, 10% in Asia, and 3% were located in South America. Figure 4.3 showed that 28% of the financial institutions were banks (as indicated by the black nodes), 23% were hedge funds, and 13% were investment management firms. Banks do not usually share investment strategies with competitor banks. Therefore, this network graph showed that, as banks compete with other banks, they try to reserve investment services exclusively for their own clients. Except for one instance where the banks were affiliated, banks did not recruit other banks in the Madoff network.

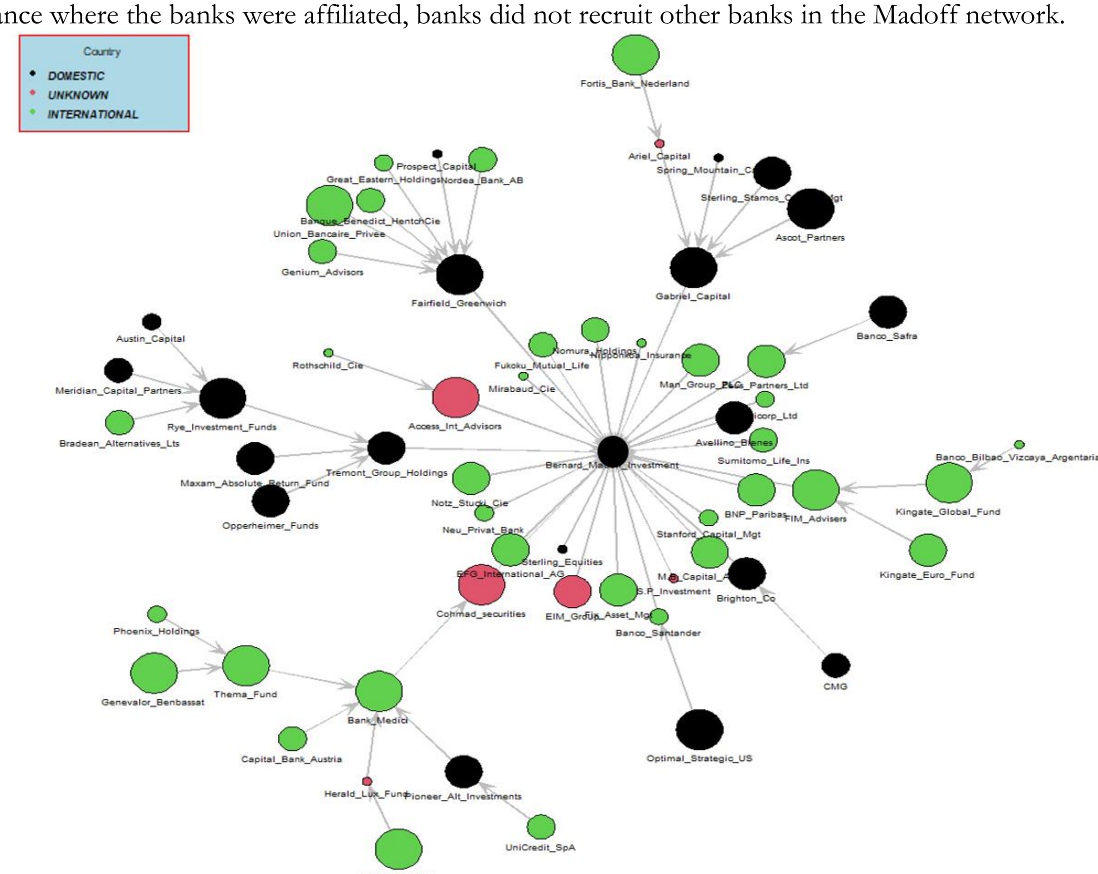

Figure 4.1 Network Visualization (Domestic Firms vs. International Firms)

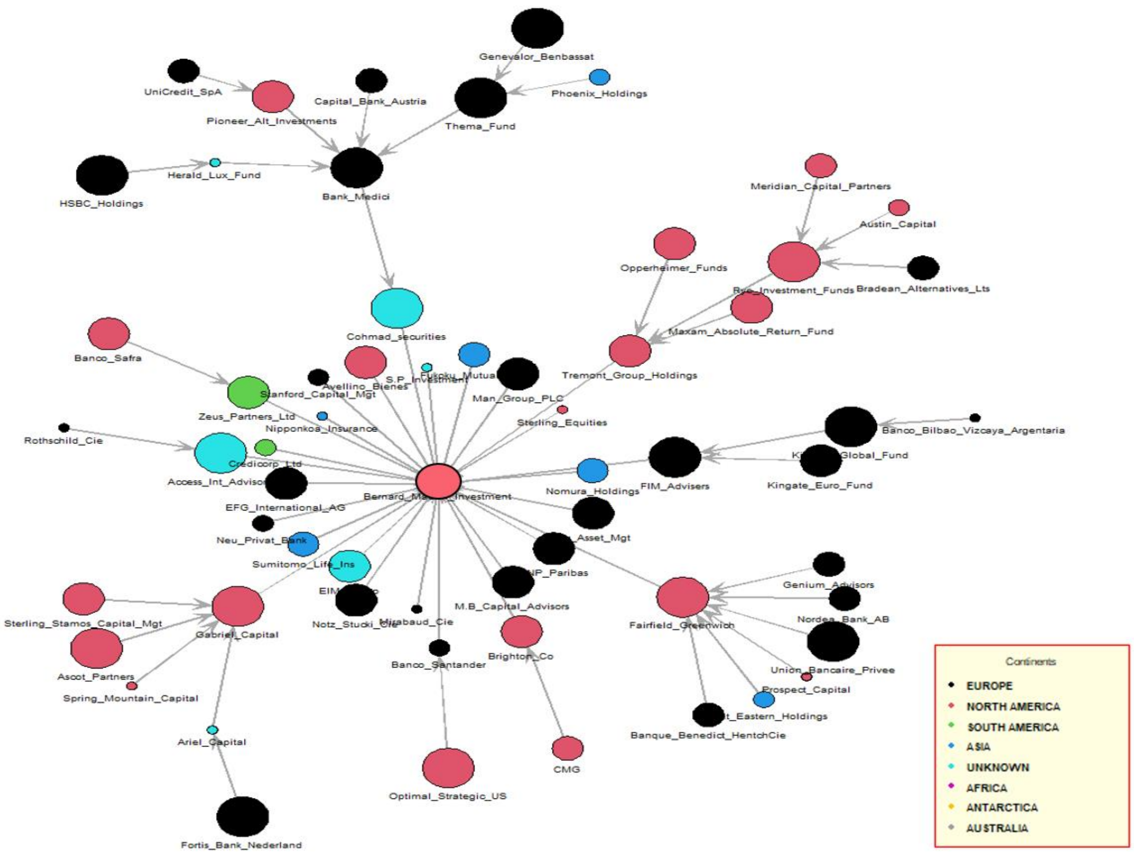

Figure 4.2 Network Analysis From 7 Continents and Unknown Location

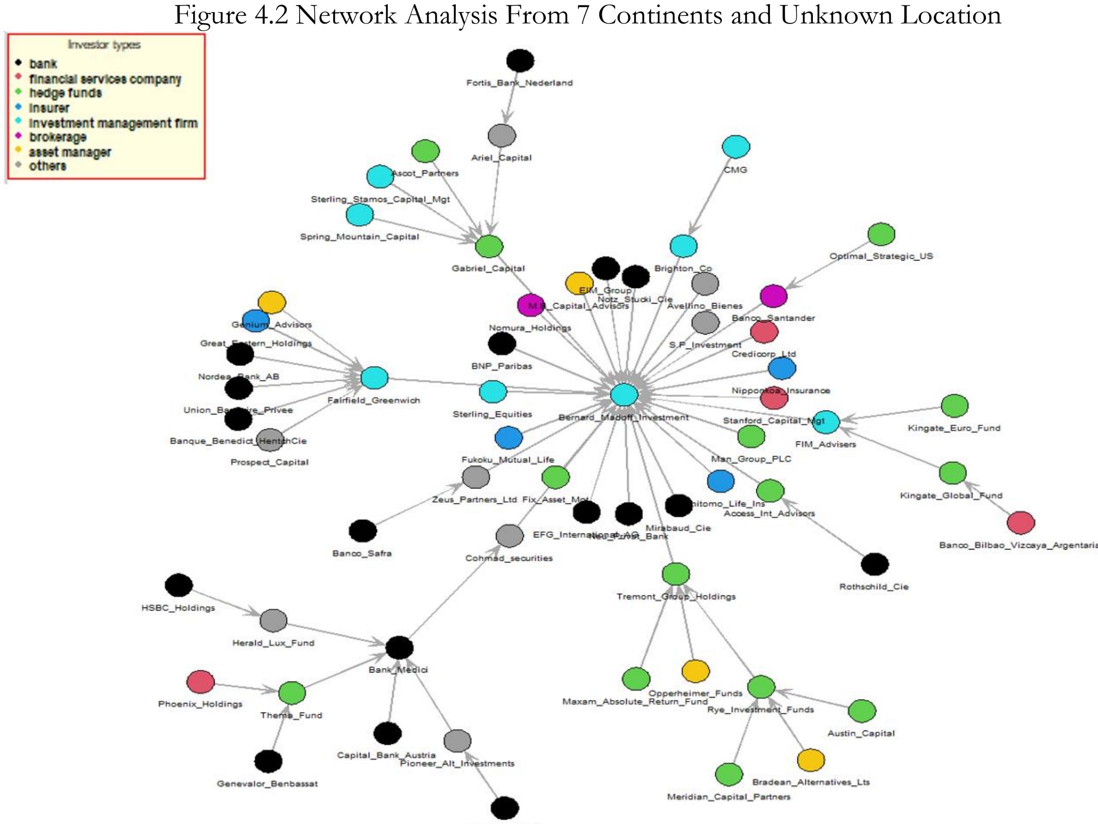

Figure 4.3 Network Analysis based on Investor Types

5. SNA of the Network

5.1 Social Network Analysis

Term	Value	Interpretation of value
Size	61	There are 61 of members (nodes) in this network
Density	0.01639344	The proportion of observed ties in number of possible ties is 0.01639344
Components	61	There are 61 subgroups in this network, since the network size is 61, which means there is no subgroups
Diameter	3	This network is compact, it takes 3 steps to connect 2 nodes.
Clustering coefficient	0	The proportion in this network formed closed triangle is 0

Table 5.1 five number basic analysis

Firms	Degree	Betweenness
Bank_Medici	4	8.0
Cohmad_securities	1	4.5
Thema_Fund	2	3.0
Fairfield_Greenwich	6	3.0
Tremont_Group_Holdings	3	3.0
Rye_Investment_Funds	3	3.0
Gabriel_Capital	4	2.5

Table 5.2 Centrality Analysis Sort by Betweenness

The dataset showed that the financial flow among firms was only in one direction; all of the money went to Madoff's firm. As there were no other subgroups for money transactions, there was no transitivity, or closed triangles, in the network. The major feeders of the Madoff Ponzi Scheme can be identified by degree of centrality analysis. Fairfield Greenwich brought 6 firms into the network, both Bank Medici and Gabriel Capital brought in 4 firms, and Tremont Group Holdings and Rye Investment Funds brought 3 firms into the network. Bank Medici played a more significant role in the network than the other firms though, since the 4 firms it brought into the fold, in turn, brought 4 more firms into the network. Similarly, Cohmad Securities only directly recruited 1 other network member, but indirectly recruited a total of 8 financial firms.

5.2 ERGM Model

Based on the 5 number summary analysis, the transitivity was 0. This states that there was no reciprocity or homophily in the network. Figure 5.3 is the comparison of the null model with the preferential attachment model for country codes: 1 = domestic firms, 2 = unknown location and, 3 = international firms. The data size is only 61, which is relatively small, thus the model indicated high standard errors. However, according to the results of the preferential attachment model, the estimates are negative and the p-values for "gwidegre" are smaller than 0.05, which is statistically significant. Therefore, the results indicated that a preferential attachment effect occurred in this network.

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Summary of model fit
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Formula:   madoffnet ~ edges

Iterations:  7 out of 20

Monte Carlo MLE Results:
      Estimate Std. Error MCMC % z value Pr(>|z|)
edges  -4.0943     0.1302      0  -31.45   <1e-04 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

     Null Deviance: 5073.8  on 3660  degrees of freedom
 Residual Deviance:  612.3  on 3659  degrees of freedom

AIC: 614.3    BIC: 620.5    (Smaller is better.)
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==========================
Summary of model fit
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Formula:   madoffnet ~ edges + gwidegree(0.1, T) + nodefactor("country_code")

Iterations:  3 out of 20

Monte Carlo MLE Results:
                           Estimate Std. Error MCMC % z value Pr(>|z|)
edges                       -2.3073     0.1632      0 -14.140  < 1e-04 ***
gwideg.fixed.0.1            -4.1877     0.5349      0  -7.829  < 1e-04 ***
nodefactor.country_code.2  -0.3326     0.2623      0  -1.268  0.20468
nodefactor.country_code.3  -0.4286     0.1441      0  -2.975  0.00293 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

     Null Deviance: 5073.8  on 3660  degrees of freedom
 Residual Deviance:  511.9  on 3656  degrees of freedom

AIC: 519.9    BIC: 544.7    (Smaller is better.)
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Figure 5.3 Null Mode (Base Model) (Top) vs. Preferential Attachment Model (Bottom)

6. Alternate Methodological Analyses

As previously noted, a 2006 paper by Borgatti devised new methods to improve SNA efficiency by identifying important sets of nodes in a network, called "key players" [2]. Using his methods as an alternate methodological analysis, this study would be able to see which parts of the Madoff network are the most crucial for network cohesion; a measure of the connectedness and togetherness among actors of a given network. Borgatti found that there were 2 distinct kinds of key players, KKP_Pos and KPP_Neg [2]. Nodes that optimize network cohesion (aka KKP_Pos) relate to in-degree centrality measures and are used to identify sets of nodes that are best suited to pass things such as money, information, etc. through the network. Nodes that optimize network fragmentation (aka KKP_Neg) relate to betweenness centrality measures and could be used to identify sets of actors that the Madoff crime network could not afford to lose.

Additionally, Borgatti identified 2 issues with using classic centrality models to identify these types of nodes, which he termed the "goal" and "ensemble" issues [2]. The *goal* issue occurs because centrality measures were not created specifically for KPP-Pos or KPP-Neg. The *ensemble* issue occurs because both KPP-Pos and KPP-Neg are concerned with identifying sets of integral nodes, rather than individual integral nodes. To address these issues, Borgatti devised an algorithm and a set of success metrics for identifying both KKP_Pos and KKP_Neg. Applying Borgatti's key player network analysis to Madoff's Investment Fraud could aid in identifying the members of the network who had crucial roles in Madoff's crimes, by observing who was responsible for high amounts of indirect recruitment for the Madoff investment network.

7. Discussion of Results

This study's first research question was: *What are the structural attributes of this network that indicate it is a criminal network?* The R Statnet package was used to create a network visualization of the financial flow among investor firms associated with the Bernie Madoff investment fraud. The result was a star-shaped network that showed that all of the money went to a single location, Madoff's company. No reciprocity, transitivity, or homophily were found within this network. Therefore, the shape of this network grew in importance as it was the main feature that identified the Madoff network as a criminal network. The flow of the money also proved that this network was indeed a Ponzi scheme; the money gained from later investors went to earlier investors. Regarding the first research question, the defining characteristic of this network was its star-shape, however, Hardy and Bell state that small-world networks are often indicative of criminal networks so additional analyses should be run [3].

An ERGM model was performed to test for preferential attachment in the network and nodefactor was used to identify the nodes more likely to form ties than others. According to the results, the estimate is below 0 and the p-value is smaller than 0.05. This means there is a preferential attachment effect in the network. The implication of this result is that as with typical preferential attachment networks, the rich, or in this case Madoff, continued to get richer. The results also proved that international firms are more likely to form ties than others. As the p-value of country code 3 = international firms, is smaller than 0.05, which is statistically significant. The implication of this result is that many of Madoff's ties were based in Europe, which meant that much of the money that was lost in the fraud was based out of Europe.

This study's second research question was: *What central investment firms besides Madoff's were responsible?* As previously mentioned, the centrality analysis identified the 3 major feeders for the Madoff Investment Scheme; Fairfield Greenwich Group (6 recruitments) and Bank Medici and Gabriel Capital (4 recruitments each). Additionally, the betweenness centrality analysis revealed that Cohmad Securities was the top feeder, albeit indirectly, with 8 recruitments. Inadvertently, through growing the network on Madoff's behalf these firms also increased the amount of investors who were financially exposed. The implication of these results are that the 4 aforementioned firms were the most responsible members of Madoff's network in terms of perpetuating the enormous fraud.

7.1 Limitations & Further Research

This study contains some limitations. The UCINET dataset used for this study consisted of a limited selection of investment firms within the network and was not exhaustive in terms of who was involved and affected by this fraud. A larger, more comprehensive dataset would reflect the real-world network of Madoff's victims. Madoff's scheme lasted for more than 20 years and Ponzi schemes usually end or become exposed when they cannot recruit new members to the network; they typically do not last very long. To better understand the Madoff network as a Ponzi scheme, future datasets should include a time series of when firms first initiated their investments. It would also be beneficial to observe whether firms ever collected annual returns before the Ponzi scheme's end, and if so, what amount. A further research goal could be to uncover how Madoff's Ponzi scheme was able to operate for so long without detection. This could be accomplished by comparing the Madoff network to network structures of other Ponzi schemes.

8. References:

[1]: Arvedlund, E. 2009. *Too good to be true: the rise and fall of Bernie Madoff.* New York: Portfolio.

[2]: Borgatti, S.P. 2006. Identifying sets of key players in a social network. *Computational and Mathematical Organization Theory* 12(1): 21–34.

[3]: Hardy, J., & Bell, P. (2020). Resilience in sophisticated financial crime networks: a social network analysis of the madoff investment scheme. *Crime Prevention and Community Safety*, *22*(3), 223–247. https://doi.org/10.1057/s41300-020-00094-7

[4] "Madoff Fraud - UCINET Software." https://sites.google.com/site/ucinetsoftware/datasets/covert-networks/madofffraud (accessed Dec. 13, 2020).

[5]: "Madoff Fraud Data," *Google Docs*. https://docs.google.com/spreadsheets/d/13TbyQWFGmOhCd8nLoWEf_RDonmjjG3DpFVdHE7fbAYU/edit?usp=drive_web&ouid=111911631782166604161&usp=embed_facebook (accessed Dec. 13, 2020).

[6]: "Madoff's Victim List - The Wall Street Journal." http://s.wsj.net/public/resources/documents/st_madoff_victims_20081215.html (accessed Dec. 13, 2020).

[7]: Manning, P. (2018). Madoff's ponzi investment fraud: a social capital analysis. *Journal of Financial Crime*, *25*(2), 320–336.

[8]: Nash, R., M. Bouchard, and A. Malm. 2018. Twisting trust: Social networks, due diligence, and loss of capital in a Ponzi scheme. *Crime, Law and Social Change* 69(1): 67–89.