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Examining the network components of a Medicare fraud scheme: the Mirzoyan-Terdjanian organization

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Abstract White-collar crime researchers have noted the stagnating nature of white-collar crime research and data, calling for use of a wider-range of methodological procedures to uncover the empirical reality of white-collar crime and offending in the U.S. Using a collection of archival data, the present study examines the structural components of the Mirzoyan-Terdjanian organization, a transnational organized crime network that defrauded the United States Medicare system out of more than $100 million. Policy implications that can be derived from the use of social networking techniques will be discussed.

Introduction

In 2010, the United States spent over $2.6 trillion on healthcare, representing roughly 18% of its total gross domestic product [4]. Under some estimates, up to 10% of this $2.6 trillion investment was lost to fraud [38]. While staggering, this trend is neither new nor surprising. Since its 1960 inception, Medicare and other health programs in the United States have been characterized by attempts to defraud and abuse the system [37]. Recently, the Medicare system has been subjected to less individualized fraudulent activity and instead, current trends indicate a growing number of widespread schemes to defraud by organized or semi-organized criminal groups [35, 49]. In 2010, one of these multifarious, highly organized fraud schemes was uncovered in the United States. The culprits: an Armenian-American criminal group known as the Mirzoyan-Terdjanian Organization. In carrying out their fraud scheme, the Mirzoyan-Terdjanian Organization stole the identities of legitimate doctors and filed applications fraudulently billing Medicare for procedures that were never performed. Through the creation of at least 118 "phantom" clinics in 25 different states, the group facilitated the

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success of counterfeit Medicare applications by obtaining the stolen identities of approximately 3000 of its patients between 2006 and 2010 [82]. While the Federal Bureau of Investigation was eventually successful in dismantling the Medicare scheme, massive financial damage was done prior to any interventions. In total, it is estimated that the Mirzoyan-Terdjanian Organization was able to defraud Medicare out of more than $100 million dollars [19].

Past research has examined a multitude of characteristics, components and consequences of health care fraud in the United States. Prior research has examined fraud committed by doctors [36, 37], mortgage lenders [52, 57], loan examiners [10], psychologists [27, 28], and even home health care workers [54, 56]. Less empirical attention, however, has been paid to fraud that results from a transnational criminal network, such as the Mirzoyan-Terdjanian Organization. Given the recurrent trend of healthcare fraud in the U.S., two questions guide the present research. First, how was the Mirzoyan-Terdjanian ring organized? Second, how did the compositional structure of the Organization facilitate the success and the eventual failure of their Medicare fraud scheme? In order to understand the success of this fraud scheme, one must first understand the compositional organization of those involved. As a result, social network analysis will be used to explain how the scheme was implemented. These analyses are intended to inform the field about a growing problem that has been subjected to limited empirical examination [51]. The study of organized crime has historically been shaped by the role that race/ethnicity plays in the formational of organized criminal networks. The analyses presented here explore a unique, and by some accounts, growing form of organized crime that is shaped by the actor's Armenian-ethnic heritage [32]. In fact, no research has explored Armenian-based criminal networks involved in healthcare fraud in the United States. Descriptive social network analysis, as done in this study, can ultimately be used to identify unique cultural variants that explain the differences in the structural composition of organized criminal networks with different ethnic backgrounds. Further, the identification of the circumstances and structures that kept the Mirzoyan-Terdjanian Organization thriving can be used by law enforcement to more expeditiously detect and dismantled similar groups. More broadly, the research conducted here can inform our understanding of criminal behavior in organized networks. The social and criminal capital that is associated with criminal networks is often considered one of the primary ways of facilitating crime [45]. As a result, systematically analyzing individual criminal groups is a viable way to gain a greater understanding of criminal behavior generally [83]. Given an understanding of organizational structure in criminal groups, policy makers and law enforcement agencies can begin to develop policy directives that target the specific causal mechanisms required to dismantle these fraud endeavors.

Defining white-collar & organized crime

The fields of both organized crime and white-collar crime have routinely sought to redefine their main concepts and propositions, based on widespread disagreement over what should really constitute a white-collar crime or what embodies an organized criminal network. Prior to any substantive application of these concepts, one must not only clearly define both terms, but must clearly specify how these concepts are related to each other.

White-collar crime

If one takes an *offender*-based definitional approach, healthcare fraud is considered a white-collar crime if it is carried out by a health care professional, but not if it is carried out by a member of a criminal network. In this, an offender-based approach defines white-collar crime and criminality according to who engages in the behavior [64, 74]. Conversely, if one uses an *offense*-related approach, the distinction of offender becomes unimportant [14]. An offense-related approach, according to Daly [14], focuses on how the actual crime was committed, rather than the characteristics of the individual offender(s) (see also [33, 34, 62, 85]).[1] White-collar crime research has devoted massive amounts of attention to definitional issues on what constitutes a white-collar crime and offender. However, according to Fredrichs [24], much of the definitional debate can be eliminated if greater care is given to operationalization of the specific white-collar crime under investigation. Instead, what we define as white-collar crime should be driven by the goals of one's research. To this end, the following research applies an offense-based definition, founded on the characteristics of the organization's criminal acts, rather than on the individuals committing the acts.

The concept of white-collar crime, as introduced 75 years ago, still does not subscribe to a universal definition of the concept. It is no surprise that the link between white-collar crime and the acts of organized criminal networks is often subject to added scrutiny. Related research suggests, however, that in some instances *white-collar offenders* do engage in *organized crime* [10]. If in some instances white-collar offenders can engage in organized crime, the inverse could also be true. Simply, that organized criminal networks, "for all intents and purposes" engage in white-collar crimes ([10]: 520). As Shapiro [62] pointed out, "it is time to integrate the 'white-collar' offenders into mainstream scholarship by looking beyond the perpetrator's wardrobe and social characteristics and exploring the modus operandi of their misdeeds…" (p. 363). Once the applicability of an organized crime model to white-collar offending is understood; the dynamics, patterns and motivations of criminal networks can be revealed, many of which may have been overshadowed by early interpretations of white-collar offending [10, 11].

However, there are some important distinctions between traditional corporate or white-collar offending and organized criminal networks that need to be specified.[2] In contrast to corporate or organizational crime, in which the primary goal is the pursuit of corporate interests, in organized crime networks the purpose of the organization itself is illegal activity for personal and group profit [10, 41]. Accordingly, the structure of organized crime networks is largely related to this goal. Organized crime is

[1] Many scholars have been critical of the offense-based approach (e.g., [26]; Steffensmeier [69]), suggesting that an offense-focused definition is too broad and encompasses too many low-level, white-collar offenses and offenders. Further, opponents suggest that the definition is too narrow in that it omits the traditional, rich and powerful white-collar offenders [74].

[2] Some scholars define corporate crime as distinct from white-collar crime (e.g., [25]), while others define white-collar crime as the umbrella term under which multiple forms of crime such as organized, corporate, governmental, and other related crime typologies are housed (e.g. [23]).

premeditated and organized not only in that criminal behavior is rationally calculated in advance, but more so that the purpose of the criminal organization itself is to facilitate criminal activities for group and personal gain [11, 29]. Calavita and Pontell [10] argue that if offender-based definitions of white-collar and organized crime are replaced with definitions that focus on the nature of the acts themselves, it can be determined that the types of fraud committed by organized criminal networks are in fact white-collar offenses.

Organized crime

Whether a crime is committed by an individual or by a criminal network depends in large part on the specific nature of the crime. According to Finckenauer [21], certain crimes cannot be committed by sole actors, due to their overwhelmingly complex and multifaceted structure. Instead, one should focus on the specific nature of the crime to determine the appropriate classification of the criminal network. Early research on organized crime emphasized the existence of an ethnicity-based conspiracy underlying the structure of organized criminal networks in the United States. This research determined that these networks were primarily organized around family lineage [29]. Most recently, however, 'enterprise models' of organized crime have become the dominant framework for explaining the structure of criminal networks. The enterprise model asserts that organized criminal networks are driven by local and economic business conditions, just like any licit organizations or businesses [31, 41, 42].

Criminal organizations Finckenauer [21] claims that networks exhibiting four common characteristics, warrant their inclusion as a criminal organization or network. These characteristics include: criminal sophistication, structure, self-identification, and an authority derived from the group's reputation (see also [31]). Criminal networks may exhibit more or fewer of the characteristics, however if the network substantially lacks any of the hypothesized characteristics, it should not be considered a true organized criminal network [31]. In accordance with Finckenauer's [21] conditions required to fit the definition of an organized crime network, the United Nations Center for International Crime Prevention [76], defines organized criminal networks as "a structured group of three or more persons existing for a period of time and acting in concert with the aim of committing one or more serious crimes or offences in order to obtain, directly or indirectly, a financial or other material benefit" (p. 48).

Transnational crime networks The definitional conditions described above provide a solid foundation from which researchers can operationalize definitions of organized criminal networks; however, the nature of organized crime has changed significantly over the last two decades. While defining 'organized crime' in the U.S. has been a historically divided debate, the inclusion of transnational organized crime definitions has only added fuel to the fire [47]. The need to loosen definitions of what constitutes organized crime can be attributed to several main factors: the globalization of economies, advances in transport and communications technology, and the enormous increase of immigration [21]. Globalization of the world's economies increased the rate in which goods and services move across national boundaries, more so than ever before. This ultimately means that businesses have much more contact with other countries, such as those of Eastern Europe and the Former Soviet Union. Second, there has been a massive increase in communication and transportation technologies [21, 84]. Advances in our ability to communicate have made national borders seemingly irrelevant in controlling the flow of communication in and out of the country. Additionally, advances in transportation have facilitated the increase in not only the movement of goods but also the movement of people. As a result, we have seen a massive increase in the number of legal (and illegal) immigrants entering the United States [47, 84].

Collectively, these conditions have made organized crime extremely hard to control as well as define. Current trends indicate a growing increase in the number of organized criminal networks that exist beyond national borders. We are now faced with transnational criminal organizations more so than ever in the past [47]. To clearly specify, a criminal network is considered "transnational" if:

> "(a) Crime is committed in more than one state [i.e., country]; (b) It is committed in one state but a substantial part of its preparation, planning, direction or control takes place in another state; (c) It is committed in one state but involves an organized criminal group that engages in criminal activities in more than one state; or (d) It is committed in one state but has substantial effects in another state" ([76]: 48-49).

While individual members of a criminal network may comprise a family, gang, or cartel, this distinction is not important to the definition; again, focus should center on the specific nature of the offense [33, 34, 62, 85]. In the criminal underworld this requires the ability and reputation to use violence or the threat of violence to facilitate criminal activities, over a significant amount of time, across several national borders [21, 31, 47].

Armenian organized crime

Prior to examining the specific components of the Mirzoyan-Terdjanian Organization, the context in which this organized criminal network developed must first be articulated. Armenia is a country that has been characterized by conflict since the early nineteenth century, when it was divided between Russia and the Ottoman Empire [12, 65, 73]. During the First World War, conflict in Armenia continued to escalate, which ultimately resulted in the systematic extermination (i.e., genocide) of Armenian nationals by the Ottoman Empire [13, 65, 87]. By 1918, Armenia was able to become independent, but, due to Russian expansion, was forced to denounce its independence and became part of the Soviet Union in 1920 [29, 65]. It was not until 1991 that Armenia became independent again [13]. It was out of this continued conflict that organized criminal groups were able to flourish.

In the context of Armenian criminal networks, the designation of organized crime is not consistent with American perceptions of Mafia-style networks. According to Serio (1998: 19, as cited in [1]: 207), organized crime in Armenia is simply "a basic system of relationships and access among various sectors of society with the [Communist] Party in the dominate role and the traditional underworld playing a relatively minor part”. After the fall of communism in Eastern Europe, law enforcement agencies were incapable of dealing with the increase in criminal activity; as a result, criminal groups like the Mirzoyan-Terdjanian Organization stepped in. The collapse drove elite communist bureaucrats to the criminal underworld in an attempt to take advantage of political and economic opportunities [2, 84]. This inability of the legal system to attend to the massive economic and social changes occurring allowed criminal organizations to serve as a pseudo- legal system where contracts, property rights, and business disputes could be enforced. In addition, these groups are often formed around a particular enterprise [13]. According to the Tri-State Joint Soviet Émigré Organized Crime Project (1997), criminal networks like the Mirzoyan-Terdjanian Organization, create loose network structures that are based solely on an as-needed basis to assist in the commission of an illicit scheme. In this, the opportunity to commit a crime comes first, (e.g., the decentralized and document-ridden Medicare system) and the necessary organizational structure to facilitate the criminal attempt comes second.

As alluded to, the majority of actors involved were Armenian nationals or immigrants, who maintained strong ties to Armenia, whether it was through regular travel, transfer of criminal proceeds to individuals living in Armenia, or various other connections to known criminals residing in Armenia [19]. Ties to Armenia were facilitated though a “Vor”, which is a Russian-based term translated as “thief-in-law”. This leadership role is common in many criminal networks originating from Eastern Europe [19, 29, 82]. A “Vor” refers to a member of a select group of high ranking criminals from Russia and the former Soviet Union who receives support from other criminals, using that support to offer protection and resolve disputes among members [20, 29, 82]. Specifically, the Mirzoyan-Terdjanian network operated under the guidance of “Vor” Armen Kazarian. Acting on the directives of “Vor” Armen Kazarian and other unknown conspirators in Armenia, the Mirzoyan-Terdjanian network observed an opportunity to commit fraud on a widespread and lucrative scale, and organized their network to facilitate the scheme. The opportunity observed by this group highlights the vulnerabilities in our largest federally funded health care program, Medicare.

Defrauding medicare

The Medicare system was developed in the mid-1960s, after President Lyndon B. Johnson signed legislation, which mandated that certain groups (i.e., disabled, poor, elderly) be provided access to health care in the United States [37, 54, 82]. The Medicare program operates at the federal level and was specifically developed to provide access to health care for individuals who are disabled or elderly[3] [53, 54, 56]. Fraud, according to Geis et al. [27], is the intentional use of deception or misrepresentation for financial or economic gain. Within the context of Medicare, fraud is the intentional misuse of the Medicare program in order to obtain funds that otherwise would not have been acquired [56].

[3] At the state level, a similar program, Medicaid, provides health care coverage for poor and impoverished individuals. However, the offenses of the Mirzoyan-Terdjanian Organization specifically targeted the federally funded Medicare program.

Early research on fraud occurring in the health care industry found that fraud is likely to occur in large part as a result of the structure of the program and the reluctance of the program developers/proponents to suspect that even health care providers themselves would take advantage of the system [27, 58]. A common theme in this early research contends that broad changes in the health care delivery system led to the high rates of fraud seen today [54]. Krause [38] found that two attributes of the U.S. health care system make it susceptible to fraud: documentation and decentralization.

Documentation The first attribute of the U.S. health care system that makes it especially susceptible to fraud is the program's heavy reliance on documentation [38, 39]. Documentation in the health care industry is used to establish the amount and appropriateness of services provided by health care professionals. Documentation of services not only provides a record of payment, but forms the basis for post-payment review should fraud be suspected. However, the efficacy of post-payment reviews based on submitted documentation is limited especially given the requirement that Medicare makes payments to providers within 30 days of submission [43]. As Sparrow [67, 68] has argued, an individual who is truly intent on committing health care fraud will avoid the types of documentation known to illicit post-payment reviews. The health care system's heavy reliance on documentation, while providing some sort of control, often works to bury crime in a massive paper trail that can only be unveiled once payment has been made [38, 39].

Decentralization The second attribute of the Medicare program that increases susceptibility to fraud is the decentralized structure of the system itself. Major federal health care programs operate under a broad federal framework, facilitated by public or private regional agents or authorities [38, 43]. The decentralized nature of the U.S. health care system not only increases the number of potential fraud targets, it again permits fraud offenders to mask their illegal behavior under layers of administrative complexity [38, 39].

The medicare scheme

If the money available in the health care system provides the motive for fraud, then the structure of the health care system provides the opportunity [43]. Research on opportunity suggests that structural complexity, as evidenced by the Medicare program, will increase opportunities that are conducive to fraud [57]. Wang and Holtfreter [85] find that "enhanced complexity creates problems of communication, coordination, and control, thus offering more opportunities for violations and providing greater protection from discovery" (p. 157).

The Mirzoyan-Terdjanian Organization facilitated their scheme to defraud Medicare through the use of at least 118 "phantom clinics" beginning in 2006 [82]. A "phantom clinic" is a health care provider that exists only on paper or simply, a location where there are no doctors on site, and no medical examinations being performed [75, 82]. The Mirzoyan-Terdjanian Organization followed a four step process in the development of a "phantom clinic". First, they would steal the identity (i.e., date of birth, social security number, and medical license number) of a legitimate doctor. Second, using the newly stolen identity, the Organization would file paperwork to create a health care business, subsequently filing an application to Medicare under the newly incorporated health care facility.[4] Third, bank accounts for the newly created clinics would be opened, again using the stolen doctor's identity. Bank accounts were created in order to receive payments from Medicare, and were often times opened by Armenian immigrants who would then leave the United States after opening multiple bank accounts [82]. The final and most important step in the process involved the Organization fraudulently obtaining the identities (i.e., names, social security numbers, addresses, and dates of birth) of thousands of legitimate Medicare recipients. With the four steps completed, the Organization was able to defraud the Medicare system. The network submitted bills to Medicare for services allegedly rendered by a legitimate physician, but whose identity had been stolen, to numerous patients, whose identities had also been stolen [77, 82].

Current focus

White-collar crime researchers have noted the stagnating nature of white-collar crime research and data, calling for use of a wider-range of methodological procedures to uncover the empirical reality of white-collar crime and offending in the U.S. [64]. One route would be the application of social network analysis, which links individual and organizational-level actors in a network based on interdependent relationships, or ties [63, 64, 86]. Given the recurrent trend of healthcare fraud in the United States and the repeatedly cited need for white-collar crime to include measurement of criminal networks like the Mirzoyan-Terdjanian Organization, two interrelated questions guide the present research. First, how was the Mirzoyan-Terdjanian ring organized? Second, how did the compositional structure of the Mirzoyan-Terdjanian Organization facilitate the success and the eventual failure of their Medicare fraud scheme?

Methods

Data

The incomplete, undefined, and dynamic nature of criminal networks such as the Mirzoyan-Terdjanian Organization, require the use of archival data to develop relationship connections between criminal actors in the network [3, 40]. Publically available data including court documents (i.e., unsealed federal indictments), FBI investigative reports, and various news reports from major print media outlets (e.g., *LA Times, Washington Post, NY Times*) were used to map the known portion of the Mirzoyan-Terdjanian Organization network that was implicated in the massive scheme to defraud the U.S. Medicare system.

Because social network analysis is concerned with relationships between actors in a network, the actors involved in the Mirzoyan-Terdjanian fraud network will be mapped

[4] Often times, the supposed Medicare provider's newly created business address listed on the Medicare applications would be nothing more than the address of an empty store front, or simply the address for a mailbox at the UPS store (see [77, 82]).

using several nodal-level attributes [86]. In this study, nodal-level attributes were uncovered through the obtained archival data: geographic location, criminal charges, sex, age, familial relationships, country of origin, counts of overt criminal acts, and case disposition.[5] 'Participants' in the developed network are defined as any individual who was cited in a federal indictment that implicated their participation within the scheme to defraud Medicare.[6] In total, there were 70 actors indicted in five states: New York (n = 46), Georgia (n = 6), California (n = 10), Ohio (n = 6) and New Mexico (n = 7).[7]

Analytic strategy

The main focus of this exploration is to describe the compositional structure of the Mirzoyan-Terdjanian network and how this structure allowed the group to operate undetected for multiple years. In doing so, it becomes pertinent to discuss several structural characteristics of criminal networks that should be considered in the following analyses. One way to measure structural composition is through the identification of important or central individuals in the network. Predominate actors are those who are heavily involved, or central in relationships with other individuals within the network [7, 18, 86].[8] Measures of actor centrality, as advocated by Freeman [22] are critical to the understanding of a specific group's structure.[9] From a policy standpoint, identifying and removing individuals who meet certain structural conditions will have the greatest effect on disrupting the flow of information (or resources) through the network, when the ultimate goal is dismantling the criminal operation [17, 46].

Further considerations need to be made, given the anomalous nature of criminal networks. In addition to basic measures of degree centrality, targeting criminal networks like the Mirzoyan-Terdjanian Organization requires emphasis on measures of betweenness amongst actors [16, 17, 66]. The betweenness measure of nodes within a network provides an indication of how important any node is in facilitating the transference of information and material to the rest of the network. Measures of closeness centrality, however, are not as pertinent within criminal networks given their unclear and often fuzzy boundaries, however closeness centrality measurement often provides added clarification in interpreting ties between nodes[10] [5, 6]. In addition to the various

[5] Geographic location, sex, age, familial relationships, criminal charges, and case disposition were coded for in this study, however, the analyses that follows focuses specifically on connections between actors in the network based on their shared involvement in a criminal activity. The remaining nodal attributes were used to generate demographic descriptive data not used in analyses.

[6] See Appendix for demographic nodal attributes of implicated actors.

[7] The final sample size is based on 70 individual actors. Five actors (i.e., Robert Terdjanian (New York 1 & New York 2), Pogos Satamyan (New York 1 & California), Artur Manasarian (New York 1 & Georgia), Aron Chervin (New York 1 & New York 2), and Khoren Gasparian (New Mexico & Georgia)) were listed on more than one indictment.

[8] Based on the unit of analysis, involvement is based on the actors' participation in the sixteen criminal acts.

[9] Centrality measures in this study include degree-centrality, closeness centrality, and betweenness centrality. Additional measures of brokerage were also included in an attempt to inform policy.

[10] To stay resilient and dynamic, criminal networks need to be dynamic. Due to these unique characteristics, analysis requires an examination beyond the existence of a simple tie between two nodes, and instead should measure the change of that connection over time [40, 66]. Unfortunately, given the nature of the data used in this analyses, the problematic characteristics as described by Sparrow [66], could not be avoided and thus remain as a limitation to the analytic strategy employed.

measures of centrality described above, brokerage measures will also be analyzed to determine the actors who are in advantageous positions to broker the flow of resources to various sects of the network [16, 17]. Measures of networking components in this study were analyzed using R statistical software [61].

Results

Detection of "the scheme"

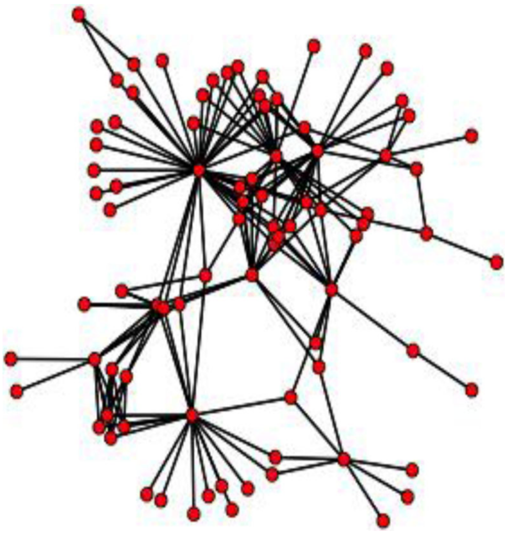
In an overwhelming majority of cases, the Medicare system detected the fraudulent nature of the claims submitted by the Organization; however, detection was only after hundreds of thousands of dollars in claims had been paid (Federal Bureau of Investigation 2010). Detection of the Organization's fraudulent activity was possible because the network often billed in a suspicious manner. According to court indictments, the Organization often billed for services that were not of the kind performed by the doctor whose stolen identity was used to file the claim.[11] Additionally, the Organization billed for rare and extremely expensive medical procedures,[12] increasing the likelihood of a post-review audit [53]. The success of the Mirzoyan-Terdjanian Organization was a direct result of a decentralized system in that the success of the organization did not depend on any one "phantom clinic". Aware that detection of the "phantom clinics" was unavoidable, the Organization insured that all the accounts opened on behalf of the clinic were in the name of a stolen identity, or of an associate who has already left the country [82]. Additionally, the network withdrew and/or transferred Medicare payments rapidly once they were deposited in the fraudulent accounts (see also [77]).

Network characteristics

Once the network had been disrupted, FBI investigative reports made it possible to partially map the activities of the individuals involved in the Mirzoyan-Terdjanian Organization. Overall, the Mirzoyan-Terdjanian network appears to be organized around several main actors (i.e., nodes), based on participation in the sixteen criminal charges (see Fig. 1). In total, there were 70 individuals implicated in the criminal activities of this network, with an average age of roughly 43.21 years of age. The seventy participants were subsequently named on six separate federal indictments from five different states. Specifically, the

[11] In one example, the Organization used the identity of a dermatologist to create a phantom clinic on the west coast of the United States. Instead of billing for a procedure common to dermatology, the group submitted a claim saying the dermatologist had performed heart tests (see [82]).

[12] Rare and expensive procedures were billed with regularity to Medicare. In one extreme example, the group submitted a series of claims for sleep studies (i.e., laboratory experiments designed to detect sleep disorders) claiming that the studies were conducted by a surgeon, family practitioner, or an otolaryngologist, amongst others (see [77]).

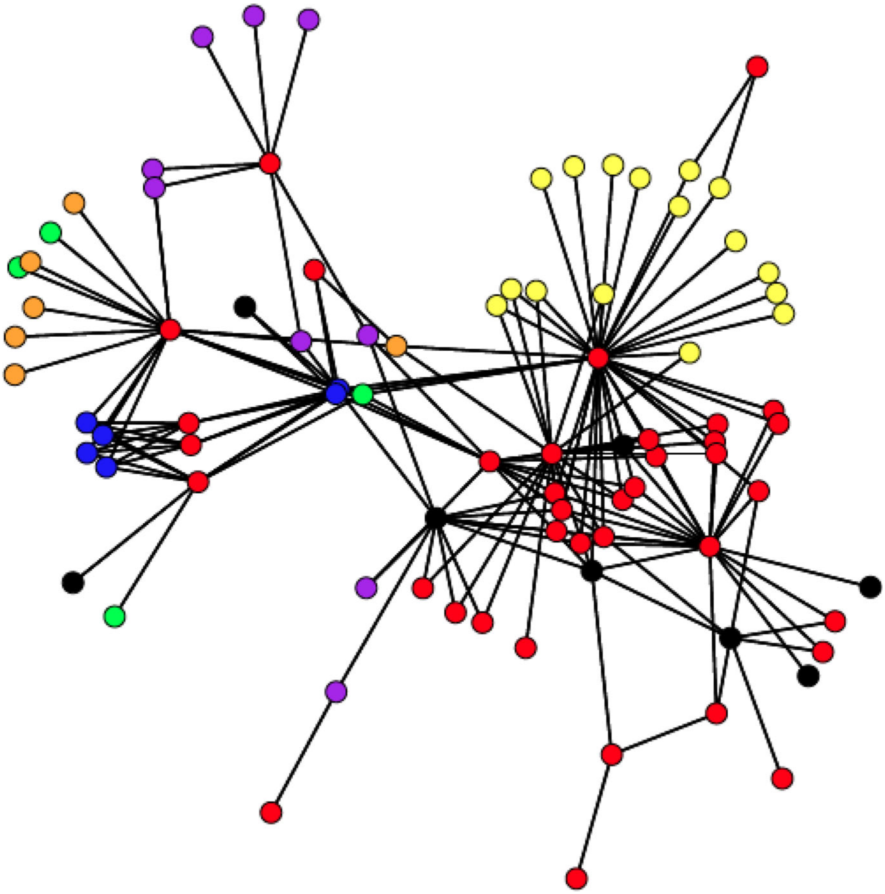


= actor

Fig. 1 Visualization of the entire criminal network

group was involved in sixteen punishable criminal offenses including; racketeering, health care fraud, bank fraud, money laundering, mail fraud, wire fraud, identity theft, credit card fraud, immigration fraud, sale of medical information, conspiracy to commit mail fraud, conspiracy to commit wire fraud, conspiracy to commit money laundering, conspiracy to commit bank fraud, and forged securities [77–82] (Figs. 2-3).

Notably, there were a relatively small number of women implicated in the network. The small role of female actors is a common trend in the majority of not only organized white-collar crimes, but in organized criminal networks overall (Steffensmeier and Allan [70]). While a gendered examination of organized criminal involvement is outside of the focus of the current study, one potential explanation may be that "among men involved in illicit pursuits, women are seen as less likely to have criminal capital or valued traits and competencies, such as trustworthiness, criminal capabilities, nerve to carry out a scheme, worthwhile social connections, and the mettle or ambition to profit highly" (Steffensmeier & Terry [71], as cited in Steffensmeier et al. [72]: 454). According to the FBI, other actors, like those of non-Armenian decent, also played minor roles in scheme [82]. For example, Marta Roman, who was named in the New York indictment, was accused of selling a list of patient names to the Mirzoyan-Terdjanian Organization that she obtained from the hospital where she worked. It does not appear that actors, like Marta Roman, facilitated the crime beyond providing the initial information to the Organization. In this, it may be possible that the Mirzoyan-Terdjanian Organization strategically placed certain actors on the periphery, due to their goals of secrecy and resiliency. Ultimately this requires an analysis of specific nodal attributes related to the actor's position within the network [16, 17].



N= 70
[*] Nodes correspond to individual actors.
[**] ● = New York 1 (U.S. v Armen Kazarian et al.); ● = New York 2 (U.S. v Aron Chervin et al.); ● = Georgia (U.S. v Artur Manasarian et al.); ● = New Mexico (U.S. v Rita Petrosyan et al.); ● = Ohio (U.S. v Karen Chilyan et al.); ● = California (U.S. v Pogos Satamyan et al.); ● = Actor named on more than one indictment.

Fig. 2 Visualization of network, by indictment

Bipartite analysis In a bipartite graph, there are two sets of nodes, with all lines between nodes belonging to the different subsets [86].[13] The Mirzoyan-Terdjanian Organization represents a two-mode network in that actors (i.e., N_1) are represented based on their involvement in a variety of criminal charges (i.e., N_2). Based on the graphical depiction presented in Fig. 4 (as well as the variable distributions presented in Table 1), it becomes apparent that the Mirzoyan-Terdjanian Organization was primarily involved in health care fraud.[14] In total, 37 actors or approximately 52% of the sample

[13] Importantly, nodes in one set are adjacent to other nodes in the same set; instead, nodes in set one are adjacent to nodes in the second set. In the case presented above, set 1 = individual actor, set 2 = criminal charge [86].
[14] Health care fraud in this context is defined as the intentional misuse of a federal health care program (i.e., Medicare) in order to obtain funds that otherwise would not have been acquired [56].

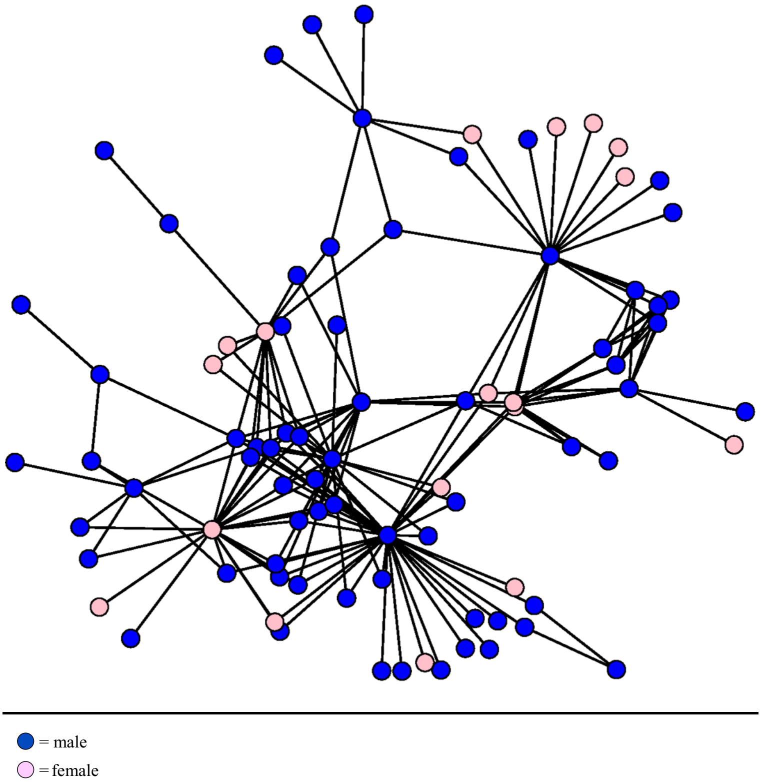


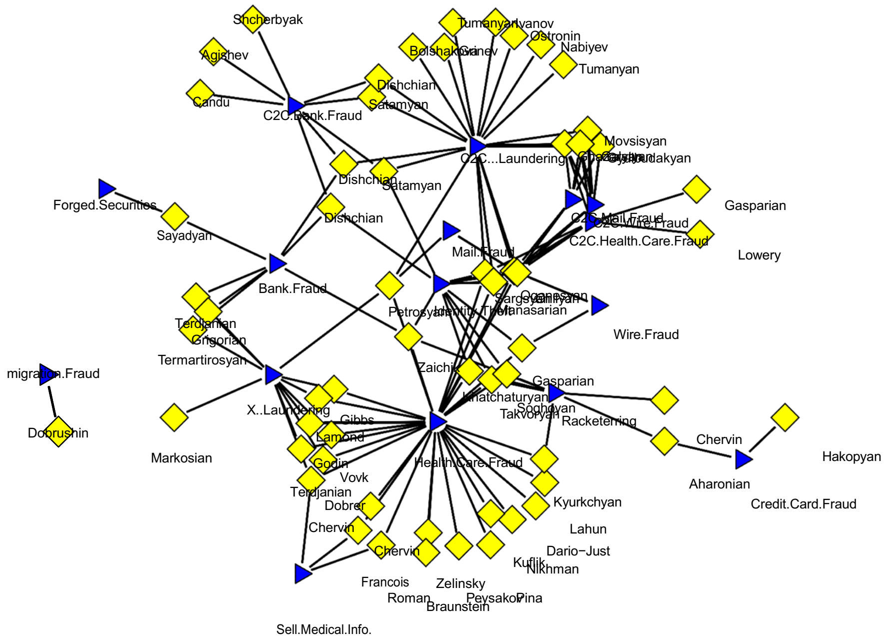
Fig. 3 Visualization of the entire network, by gender

was directly involved in the scheme to defraud the Medicare program. It is no surprise that the majority of the additional criminal acts that the Mirzoyan-Terdjanian Organization committed, were a direct result of their overarching plan to defraud Medicare. Charges of bank fraud, money laundering, and identity theft etc. were necessary to facilitate the success of their primary criminal activity (i.e., Medicare fraud) (Table 2).

Centrality

Researchers have conceptualized centrality (or actor importance) in a variety of ways (see [5, 17, 18, 86]). In this analysis a central actor is defined as someone who has numerous ties to other actors within the network (i.e., degree centrality). Additionally, a central actor is an individual who is close, in terms of path distance, to others in the network (i.e., closeness centrality) or relatedly, as an actor who lies on the shortest path between numerous pairs of actors (i.e., betweenness centrality).

Nodal-level degree centrality The simplest conceptualization of actor or nodal centrality is that prominent individuals must be active in the network, or simply they must have a large number of ties to other involved actors, or in this case be involved in a



= actor

= indictment

Fig. 4 Bipartite visualization of criminal charge involvement

large amount of criminal activity [22, 86].[15] An actor within the network that has high centrality, when measured by the number of ties of a specified actor, is often directly connected or is adjacent to a larger number of additional actors in the network [86]. Actors with high levels of degree centrality become important individuals within the network, as they operate as "a major channel of relational information" or a "crucial cog" in the network ([86]: 179). Alternatively, an actor with low degree centrality would indicate low involvement in relational processes and as a result, their removal would have minimal effect on the remaining ties in the network [17].

Measures of nodal degree centrality in this analysis are operationalized as a count of the number of ties a specific actor possesses within a network, based on involvement on sixteen criminal charges [17, 22, 86]. The average number of ties in the Mirzoyan-Terdjanian Organization was approximately 2.4, meaning that on average, each actor in the network was connected to other actors by roughly 2 criminal acts. Four actors within the network seem to be driving this average. Several actors possess the greatest degree centrality. Specifically, Davit Mirzoyan, Robert Terdjanian, Karen Chilyan and Eduard Oganesyan possess the highest level of degree centrality (i.e., 6.0, 7.0, 8.0 & 8.0, respectively). Based on the measurement of degree centrality, these individuals were the most involved in the criminal activities in the network; however, simple involvement in criminal activity does not necessarily indicate centrality or importance.

[15] The equation used to measure nodal-level degree centrality is as follows ([86], p. 179): [$C'_d(n_i) = d(n_i)/g - 1$]

Table 1 Descriptive statistics for main nodal attributes

Nodal Attributes	n	Mean	SD	Min.	Max.
Age[a]	70.00	43.21	12.69	20.00	74.00
Male	70.00	0.75	-	-	-
Indictments[b]	6.00	1.11	0.31	1.00	2.00
Overt Acts[c]	218.00	36.33	23.17	1.00	22.00
Sentence Length[d]	16.00	69.69	44.35	12.00	144.00
Charge					
Racketeering	22.00	-	-	-	-
Health Care Fraud	37.00	-	-	-	-
C2C[e] Heath Care Fraud	9.00	-	-	-	-
Bank Fraud	13.00	-	-	-	-
C2C[e] Bank Fraud	7.00	-	-	-	-
Money Laundering	18.00	-	-	-	-
C2C[e] Money Laundering	18.00	-	-	-	-
Identity Theft	14.00	-	-	-	-
Credit Card Fraud	7.00	-	-	-	-
Immigration Fraud	3.00	-	-	-	-
Sale of Medical Info.	2.00	-	-	-	-
Mail Fraud	3.00	-	-	-	-
C2C[e] Mail Fraud	6.00	-	-	-	-
Wire Fraud	2.00	-	-	-	-
C2C[e] Wire Fraud	6.00	-	-	-	-
Forged Securities	1.00	-	-	-	-

$N = 70$ individual actors

[a] Age at the time of arrest

[b] Number of indictments per actor

[c] Count of the number of overt acts included in indictments by actor

[d] Sentence length measured in months. To date, 16 actors have been sentenced to prison

[e] Designation for Conspiracy to commit charge

Nodal-level Betweenness centrality To further delineate which actors were most important in the network, analyses of betweenness centrality was conducted. Betweenness centrality, in this context, refers to the extent to which individual actors (i.e., nodes) lie on the shortest path between other actors in the network [17, 22]. Betweenness centrality, according to Wasserman and Faust [18], contends that interactions between two actors, who are not adjacent in a network, might depend on other actors in the group.[16] The actors who lie on the shortest path between these two nonadjacent actors would ultimately have the power to control the interactions of the two nonadjacent actors.

[16] The equation used to measure nodal-level betweenness centrality is as follows ([86]: 190): $C_B(n_i) = \sum_{j<k} g_{jk}(n_i)/g_{jk}$

Table 2 Actor centrality measures

Indictment	Actor Name		Degree	Betweenness	Closeness
New York(1)	Armen	Kazarian	2.00	10.38	0342
	Davit	Mirzoyan	6.00	160.47	0.400
	Robert	Terdjanian	7.00	313.41	0.410
	Aleksandr	Avetisyan	3.00	41.15	0.350
	Herayer	Baghoumian	4.00	41.18	0.380
	Pogos	Satamyan	4.00	41.17	0.379
	Artur	Yepiskoposyan	5.00	88.91	0.393
	Vagan	Stepanian	3.00	18.66	0.261
	Varujan	Amroyan	2.00	3.49	0.257
	Jacob	Pogosian	3.00	22.47	0.357
	Karen	Simonian	3.00	22.47	0.357
	Vartan	Boyzadzhyan	3.00	46.17	0.382
	Artur	Manasarian	1.00	0.00	0.254
	Gourgen	Mirimanian	3.00	46.17	0.382
	Manuk	Muradakhanyan	3.00	22.48	0.357
	Liana	Soghoyan	3.00	24.07	0.363
	Tikran	Takvoryan	3.00	24.07	0.363
	Gayane	Khatchaturyan	3.00	24.07	0.363
	Gagik	Kyurkchyan	2.00	10.38	0.342
	Anna	Zaichik	4.00	64.80	0.386
	Aron	Chervin	1.00	0.00	0.254
	Karen	Aharonian	2.00	3.49	0.257
	Armen	Grigorian	2.00	7.01	0.297
	Karen	Markosian	1.00	0.00	0.272
	Anna	Termartirosyan	2.00	7.01	0.297
	Michael	Dobrushin	1.00	0.00	0.228
	Samvel	Hakopyan	1.00	0.00	0.233
	Rafik	Terdjanian	2.00	7.01	0.297
New York (2)	Vyacheslav	Dobrer	2.00	6.55	0.340
	Harold	Pina	1.00	0.00	0.326
	Ross	Kuflik	1.00	0.00	0.326
	Michael	Lamond	2.00	6.54	0.340
	Vadim	Chervin	1.00	0.00	0.326
	Galina	Vovk	2.00	6.55	0.340
	Valiantsina	Lahun	1.00	0.00	0.326
	Lynn	Braunstein	1.00	0.00	0.326
	Yuri	Zelinsky	1.00	0.00	0.326
	Luba	Godin	2.00	6.55	0.340
	Judson	Dario-Just	1.00	0.00	0.326
	Begay	Francois	2.00	41.50	0.329
	Natan	Peysakov	1.00	0.00	0.326
	Marta	Roman	2.00	41.50	0.329

Table 2 (continued)

Indictment	Actor Name		Degree	Betweenness	Closeness
	Milana	Nikhman	1.00	0.00	0.326
	William	Gibbs	2.00	6.55	0.340
Ohio	Karen	Chilyan	8.00	387.79	0.420
	Eduard	Oganesyan	8.00	387.79	0.420
	Lilit	Galstyan	4.00	13.86	0.218
	Arus	Gyulbudakyan	4.00	13.86	0.281
	Julieta	Ghazaryan	4.00	13.86	0.281
	Marine	Movsisyan	4.00	13.86	0.281
Georgia	Gegham	Sargsyan	4.00	222.17	0.404
	Khoren	Gasparian	1.00	0.00	0.240
	Sahak	Tumanyan	1.00	0.00	0.272
	Hamsik	Tumanyan	1.00	0.00	0.272
	Toni	Lowery	1.00	0.00	0.240
New Mexico	Rita	Petrosyan	4.00	229.48	0.404
	Igor	Ostronin	1.00	0.00	0.272
	Sergei	Ivanov	1.00	0.00	0.272
	Artur	Nabiyev	1.00	0.00	0.272
	Yvgeny	Grinev	1.00	0.00	0.272
	Tatiana	Bolshakova	1.00	0.00	0.272
California	Vachagan	Dishchian	3.00	186.30	0.332
	Vahe	Vahe Dishchian	2.00	39.34	0.281
	Andranik	Satamyan	2.00	39.34	0.281
	Haroutyoun	Dishchian	3.00	15,820	0.314
	Nicolae	Candu	1.00	0.00	0.212
	Vitalina	Shcherbyak	1.00	0.00	0.212
	Nikolay	Agishev	1.00	0.00	0.212
	Grisha	Sayadyan	2.00	84.00	0.272
	Allen	Sayadyan	2.00	4.95	0.301
		Mean	2.400	42.30	0.315
		Graph Centralization	0.398	0.484	0.336

Measures of betweenness centrality are important for dark networks in that these measures have the ability to reveal those actors who are in a position to broker the flow of information, resources, etc. to other parts of the network. Based on these measures, we see that again, several actors are driving the mean betweenness score of the network ($\bar{x}$ = 42.30). Consistent with the measures of degree centrality, Eduard Oganesyan, Robert Terdjanian and Karen Chilyan possess the highest betweenness centrality measures (i.e., 387.79, 313.41, and 387.79, respectively). In addition, Rita Petrosyan, one of only eighteen women in the network, had the fourth highest betweenness centrality measure (i.e., 229.48). Based on the amount of each actors' betweenness centrality measures, the actors named above were in strategically advantageous positions, in that they provided a conduit for which the operations to occur.

Nodal-level closeness centrality An additional measure of actor importance, closeness centrality, was also included in the analyses. When operationalized, closeness centrality provides a measure of how close each actor is on the established paths to other actors [18, 22, 86].[17] Closeness centrality can be conceptualized simply as a measure of how efficiently information or resources can travel to other actors in the network [22, 86]. Actors located on short paths to other nodes would be indicative of network density, in that information can be spread quickly to a large number of actors. This would be consistent with the higher level of clustering exhibited by small-scale networks [44]. The average closeness centrality score in the network was 0.315. But again, it appears that several actors are driving this average. Karen Chilyan, Eduard Oganesyan, Davit Mirzoyan, and Robert Terdjanian have the highest closeness scores in the network (0.420, 0.421, 0.400, and 0.410, respectively). This means that these actors are in strategic positions because they are farther from other actors in the network and are in a position that is protected because they are not a close to other actors in the network. This is common amongst dark networks who operate in a way that ensure their leaders are distanced from the activities of the group as a means to reduce the likelihood of detection for the most important actors in the network [40].

Brokerage

Brokerage is widely used in the social networks literature to characterize actor position in a network [8, 17, 86]. While basic centrality measures (i.e., degree, closeness, and betweenness) highlight those actors who are most important within a given network, added measures of structural position can be used to further determine the actors, upon whose removal, would cause the most disruption in the network. According to Everton [17], actors who provide the only connection between two other actors are in a brokering position. As a result, any flow of information, knowledge, or products from one actor to another must pass through the brokering actor [6, 17, 86]. Actors who occupy these positions possess primary access to information and resources and if necessary, can redirect and control the flow of information or resources to their advantage [9]. To this end, Gould and Fernandez [30] identified five types of brokerage structures that could be identified within a network, based on their group position: coordinator, gatekeeper, representative, itinerate, and liaison (pp. 91–93).[18]

Within the Mirzoyan-Terdjanian network two brokerage structures can be identified (see Table 3): itinerate ($t = 7618.00$, $p < .001$) and liaison ($t = 686.00$, $p < .001$). Actors within a network who are in an *itinerate* role, provide mediation between members of *one* group but are not a member of that group ([30]; see also, [17]). Actors in a network, who are in a *liaison* brokerage role, again provide mediation, but the liaison mediates between *two* groups where the mediator does not belong to either group ([30]; see also,

[17] The equation used to measure nodal-level closeness centrality is as follows ([86]: 184): $C_C(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$

[18] Gould and Fernandez [30] initial developed their brokerage role typology using characteristics of directed networks. Their propositions, however, specifically relate to directed ties between gatekeeper and representative roles. Analysis of the undirected Mirzoyan-Terdjanian Organization, however, did not reveal actors in these structural positions, thus original propositions of directionality are somewhat irrelevant to the present research.

Table 3 Actor brokerage measures

Indictment	Structures	t	E(t)	Sd(t)	Z
Overall Network	Coordinator	0.00	1215.997	134.905	−9.013*
	Itinerate	7618.00	308.537	17.531	416.94*
	Gatekeeper	0.00	308.537	41.886	7.366*
	Representative	0.00	308.587	41.886	7.366*
	Liaison	686.00	0.000	0.000	-
New York 1	Coordinator	0.00	323.437	52.266	−6.188*
	Itinerate	4330.00	455.076	51.653	75.018*
	Gatekeeper	0.00	455.076	50.830	4.952*
	Representative	0.00	455.076	50.830	4–952*
	Liaison	3974.00	150.980	12.264	311.736*
New York 2	Coordinator	0.00	502.260	74.079	−6.78*
	Itinerate	4788.00	425.717	46.847	93.118*
	Gatekeeper	0.00	425.717	49.173	4.657*
	Representative	0.00	425.717	49.173	4.657*
	Liaison	3516.00	120.732	10.967	309.602*
Ohio	Coordinator	0.00	922.105	112.398	4.203*
	Itinerate	6448.00	356.784	32.924	185.004*
	Gatekeeper	0.00	356.784	45.034	7.922*
	Representative	0.00	356.784	45.034	4.922*
	Liaison	1856.00	49.713	7.037	256.68*
Georgia	Coordinator	0.00	922.105	112.389	−8.203*
	Itinerate	6578.00	356.784	32.924	188.952*
	Gatekeeper	0.00	356.784	45.034	7.922*
	Representative	0.00	356.784	45.034	−7-922*
	Liaison	1726.00	49.713	7.037	238.207*
New Mexico	Coordinator	0.00	878.565	108.850	−8.071*
	Itinerate	6560.00	363.935	34.628	178.928*
	Gatekeeper	0.00	363.935	45.481	−8.001*
	Representative	0.00	363.935	45.481	−8.001*
	Liaison	1744.00	57.077	7.540	223.718*
California	Coordinator	0.00	796.151	101.932	7.81*
	Itinerate	6126.00	377.466	37.644	152.707*
	Gatekeeper	0.00	377.466	46.316	4.149*
	Representative	0.00	377.466	46.316	−8.149*
	Liaison	2178.00	71.018	8.410	250.504*
t		8304.00	2375.179	209.824	28.256*

$N = 70$; * = $p < .001$

[17]). No actors within the Mirzoyan-Terdjanian network exhibited the other types of brokerage roles described by Gould and Fernandez [30] (i.e., coordinator, gatekeeper, or representative). A network that is organized using itinerate and liaison brokerage

roles seems to be indicative of an organization that places heavy emphasis on the directives of organizational leaders. Through the identification of these brokerage roles, it becomes apparent that the majority of decision-making is top-down, where a 'lead' actor is providing mediation between other actors in the network.

Discussion

Based on the results described above, there were four main actors that were central to the operation of the Organization's scheme to defraud Medicare. As the name of the organization rightfully suggests, Davit Mirzoyan and Robert Terdjanian played pivotal roles in the network, based on their nodal centrality measures. The majority of media attention has focused on these two actors, regardless of their actual importance. Based on the results presented here, however, Karen Chilyan and Eduard Oganesyan were the most central (i.e., important) to the network's operations. Contrary to expectations, the "Vor" Armen Kazarian, the facilitating crime boss behind the organization, was not central based on these measures. Given the importance of actors like Kazarian, the criminal network is often structured to minimize criminal involvement, to maintain leadership resiliency. While he played an important role, the removal of several other actors within the network may have a more dismantling effect on the entire organization. Given these measures of centrality described, attempts to disrupt this network should be focused on those actors who have the ability to broker the flow of resources to the rest of the network. If removed, the efficiency in which these mechanisms operate is diminished. However, if one takes the traditional approach of law enforcement, that is facilitating investigations based on the self-described "leader", which in this case would be Armen Kazarian, the effort would not be as effective. Conversely, if law enforcement target key players, who were able to control the flow of resources through the network, this effort would prove to be more fruitful. Within the Mirzoyan-Terdjanian organization, it appears Karen Chilyan and Eduard Oganesyan were in a position that upon their removal from the network (e.g., via arrest) would create the highest level of disruption. The discussion now turns to the ways in which enforcement and intelligence agencies can use these measures to combat Medicare fraud.

Policy implications

More than two decades ago, Geis et al. [28] claimed that our health care coverage system "offers a context in which persons who are inclined to enrich themselves by ignoring lawful regulations, can readily do so" (p. 823). A long-term strategy to eliminate opportunities to commit fraud is required. One of these strategies, the Health Insurance Portability and Accountability Act of 1996 (HIPAA) created a national Health Care Fraud and Abuse Control (HCFAC) program under the Office of Inspector General (OIG) and the Department of Health and Human Services (HHS). This program sought to coordinate law enforcement agencies from federal, state, and local agencies to combat medical fraud in the US [15]. In 2010, over a half-billion dollars were appropriated to fund these efforts, however experts argue that a more preventative, proactive model could save the Medicare program $70 billion [32]. Several governmental programs have sought to accomplish this initiative, and have been moderately successful; but more can be done.

The Obama Administration sought to increase both the funding devoted to and national profile of health care fraud. The Obama Administration is responsible for the creation of the Health Care Fraud Prevention & Enforcement Action Team (HEAT). HEAT utilizes real-time reporting to analyze electronic Medicare claims for patterns that may indicate fraud. This program is one of the first attempts made by the federal government to prevent fraud before payment is made, rather than the traditional reactive approach of trying to regain dispersed payments.[19] HEAT was created to reduce waste and abuse in the healthcare system and to prevent fraud by cracking down on those who abuse the system (HHS & DOJ 2015). Specifically, HEAT emphasizes the monitoring of five components: enrollment, payment, oversight, compliance, and response. In doing so HEAT emphasizes the need to closely scrutinize those individuals who want to participate in the Medicare program prior to enrollment while continuing to monitor payments throughout the enrollment period. Further, HEAT assists providers and suppliers in adopting practices that promote compliance with Medicare program requirements. Through the oversight of these practices, HEAT attempts to provide a timely response to fraud in the Medicare system. The current administration's reform goals have produced some positive results. In 2010, the Medicare Fraud Strike Force obtained 140 indictments, 217 negotiated guilty pleas, and 23 guilty verdicts, while the federal government recovered more than $4 billion through its anti-fraud efforts ([43]; National Association of Medicare Fraud Control Units 2013). However, these results came at a cost. As noted, approximately a half-billion dollars was spent on anti-fraud efforts in the US healthcare system [48]. While effective, more can be done to reduce the level of fraud and abuse in the Medicare system.

As evidenced by the extensive structure of the Mirozyan-Terdjanian Organization, health care fraud schemes are highly sophisticated and responsive to anti-fraud regulations and initiatives. To address this growing trend, the OIG organized a multidisciplinary, multi-agency team called the Advanced Data Intelligence and Analytics Team [32, 49]. The overall goal of the Advanced Data Intelligence and Analytics Team was to support the efforts of HEAT through the use of sophisticated data analysis and field intelligence from law enforcement agencies to more efficiently identify health care fraud schemes and trends (National Association of Medicare Fraud Control Units 2013; [48]). The Advanced Data Intelligence and Analytics Team is in the process of developing a centralized data center integrating business intelligence tools and data analysis into fraud detection efforts.

While still in its infancy, this initiative to combine sophisticated data analysis in a centralized data access center would benefit from the inclusion of social network metrics in identifying fraudulent activity in the Medicare system. The use of social network analysis (SNA) can help identify relationships and interactions amongst a diverse group of people [17]. Specifically, SNA can be used to combat organized Medicare fraud in three ways. First, SNA can be used to monitor patient relationships with known or suspected perpetrators of healthcare fraud. Second, links between recipients, businesses, or even relatives and associates can be linked to identify unusual claims. Third, SNA can be used to identify inappropriate relationships of employees, medical suppliers, patients and providers [83, 84]. Overall, inclusion of SNA principals in the efforts of the Advanced Data Intelligence and Analytics Team and HEAT can be

[19] Commonly referred to as a "pay and chase" reimbursement structure.

used to create clusters of diverse variables and relationships to uncover organized criminal activity. In doing so, law enforcement agencies can identify the structural positions that reduce the resilience of an organized crime group in the most efficient way possible. As is the case with the results presented here, law enforcement agencies need to identify those actors who control/broker the flow of information and resources in the organization to most efficiently dismantle operations.

Limitations

While informative, the information obtained through archival data collection may be incomplete [40, 66]. As noted, criminal networks are organized around the main goals of resiliency and secrecy, thus, enforcement agencies may not be able to uncover all of the actors within the network or the possible links between them.[20] Additionally, criminal networks are dynamic in structure, in that these networks are in a constant state of potential change. The ability to remain dynamic allows groups, such as the Mirzoyan-Terdjanian Organization, to alter the flow of information and resources traveling though the network to maintain the goals of resiliency and secrecy [66]. While the limitations described above are general to network analysis of criminal networks, overall, limitations specific to this research should also be noted. While informative, analysis of brokerage roles is incomplete without inclusion of the measurement of nodal bridges. Bridges provide a more parsimonious means for detecting how material is transferred through a network [9, 17]. Future tests of this kind should include measurement of actor bridges within the network in order to derive more precise disruption strategies.[21]

Conclusion

The U.S. can no longer abandon a viable program of health care for the disabled or elderly. Because we cannot eliminate the existing options for health care coverage, substantive changes to the existing program structure are necessary. With more than $2 trillion being spent on health care per year in the United States, the incentive for fraud is overwhelmingly clear [4]. Members of organized crime networks will continue to defraud the healthcare system simply because of the opportunities created by the system itself [38, 43]. While detection efforts are improving, fraud remains prevalent. There is a continuous need for innovative and advanced research tools that can improve the quality of fraud detection. As evidenced in this study of the Mirzoyan-Terdjanian Organization, social network analysis is a valuable tool to understand how Medicare fraud schemes are conducted and operationalized. Rather than continuing to develop deterrence-based strategies based on uninformed network dynamics, health care

[20] For example, several overt criminal acts of the Mirzoyan-Terdjanian Organization listed in unsealed federal court indictments named “unknown conspirators” who in several instances, worked as a courier carrying tens of thousands of dollars in cash to Armenia [82]. Their identity, however, was never uncovered though the FBI’s investigation.

[21] Network bridges, according to Everton [17], can be identified using the Girvan-Newman Method in which the highest betweenness-centrality scores for each edge are removed. Betweenness-centrality is then recalculated removing the highest score after each iteration, until no edges remain.

programs in the United States should alter their procedure to eliminate the potential opportunities for criminal networks like the Mirzoyan-Terdjanian Organization to fraudulently obtain close to $100 million dollars.

Appendix

Demographics of Involved Actors (*N* = 70d)

New York-Based Indictment (1): U.S. v. Armen Kazarian et al.

First Name	Last Name	Age[a]	City	State	Gender
Armen	Kazarian	50	Glendale	CA	M
Davit	Mirzoyan	39	Glendale	CA	M
Robert	Terdjanian	40	Brooklyn	NY	M
Aleksandr	Avetisyan	56	Sun Valley	CA	M
Herayer	Baghoumian	58	Burbank	CA	M
Pogos	Satamyan	36	Glendale	CA	M
Artur	Yepiskoposyan	35	Burbank	CA	M
Vagan	Stepanian	57	Brooklyn	NY	M
Varujan	Amroyan	54	Brooklyn	NY	M
Jacob	Pogosian	39	La Cresenta	CA	M
Karen	Simonian	37	Glendale	CA	M
Vartan	Boyzadzhyan	42	Glendale	CA	M
Artur	Manasarian	52	Valley Village	CA	M
Gourgen	Mirimanian	50	Glendale	CA	M
Manuk	Muradakhanyan	40	Sherman Oaks	CA	M
Liana	Soghoyan	44	Sherman Oaks	CA	F
Tikran	Takvoryan	48	Pasadena	CA	M
Gayane	Khatchaturyan	40	N. Hollywood	CA	F
Gagik	Kyurkchyan	42	Valley Village	CA	M
Anna	Zaichik	58	Brooklyn	NY	F
Aron	Chervin	67	New Brunswick	NY	M
Karen	Aharonian	37	Tarzana	CA	M
Armen	Grigorian	44	Glendale	CA	M
Karen	Markosian	41	Burbank	CA	M
Anna	Termartirosyan	39	Glendale	CA	F
Michael	Dobrushin	57	Brooklyn	NY	M
Samvel	Hakopyan	40	N. Hollywood	CA	M
Rafik	Terdjanian	74	Brooklyn	NY	M

n = 28

[a] Age at the time of arrest

[d] Five actors were named on more than one indictment

New York-Based Indictment (2): U.S. v. Aron Chevrin et al.

First Name	Last Name	Age[a]	City	State	Gender
Aron	Chervin	67	New Brunswick	NY	M
Robert	Terdjanian	40	Brooklyn	NY	M
Vyacheslav	Dobrer	54	Dingman's Ferry	PA	M
Harold	Pina	45	Valley Stream	NY	M
Ross	Kuflik	56	DelRay Beach	FL	M
Michael	Lamond	44	Long Island City	NY	M
Vadim	Chervin	54	North Brunswick	NY	M
Galina	Vovk	38	Brooklyn	NY	F
Valiantsina	Lahun	49	Brooklyn	NY	F
Lynn	Braunstein	53	Belle Harbor	NY	F
Yuri	Zelinsky	66	Brooklyn	NY	M
Luba	Godin	36	Brooklyn	NY	M
Judson	Dario-Just	52	Brooklyn	NY	M
Begay	Francois	59	Dacula	GA	M
Natan	Peysakov	44	Brooklyn	NY	M
Marta	Roman	44	Merrick	NY	F
Milana	Nikhman	57	Staten Island	NY	F
William	Gibbs	44	Springfield Gardens	NY	M

$n = 18$

[a] Age at the time of arrest

Ohio-Based Indictment: U.S. v. Karen Chilyan et al.

First Name	Last Name	Age[a]	City	State	Gender
Karen	Chilyan	25	Burbank	CA	M
Eduard	Oganesyan	34	Glendale	CA	M
Lilit	Galstyan	47	Encino	CA	M
Arus	Gyulbudakyan	30	Woodland Hills	CA	F
Julieta	Ghazaryan	48	Glendale	CA	F
Marine	Movsisyan	43	Studio City	CA	F

$n = 6$

[a] Age at the time of arrest

New Mexico-Based Indictment: U.S. v. Petrosyan et al.

First Name	Last Name	Age[a]	City[b]	State	Gender
Rita	Petrosyan	55	-	NM	F
Igor	Ostronin	22	-	NM	M

First Name	Last Name	Age[a]	City[b]	State	Gender
Sergei	Ivanov	25	-	NM	M
Artur	Nabiyev	23	-	NM	M
Yvgeny	Grinev	24	-	NM	M
Tatiana	Bolshakova	22	-	NM	F
Khoren	Gasparian	27	-	NM	M

n = 7

[a] Age at the time of arrest

[b] Location of address could not be found

California-Based Indictment: U.S. v. Pogos Satamyan et al.

First Name	Last Name	Age[a]	City	State	Gender
Pogos	Satamyan	36	Glendale	CA	M
Vachagan	Dishchian	34	Van Nuys	CA	M
Vahe	Dishchian	36	Van Nuys	CA	M
Andranik	Satamyan	20	Glendale	CA	M
Haroutyoun	Dishchian	62	Van Nuys	CA	M
Nicolae	Candu[c]	24	-[b]	CA	M
Vitalina	Shcherbyak[c]	24	-[b]	CA	F
Nikolay	Agishev[c]	24	-[b]	CA	M
Grisha	Sayadyan	59	Glendale	CA	F
Allen	Sayadyan	30	Glendale	CA	M

n = 10

[a] Age at the time of arrest

[b] Location of address could not be found

[c] Fugitive currently being sought by law enforcement

Georgia-Based Indictment: U.S. v. Artur Manasarian et al.

First Name	Last Name	Age[a]	City	State	Gender
Artur	Manasarian	58	Los Angeles	CA	M
Gegham	Sargsyan	56	Los Angeles	CA	M
Khoren	Gasparian	27	Los Angeles	CA	M
Sahak	Tumanyan	43	Los Angeles	CA	M
Hamsik	Tumanyan	38	Los Angeles	CA	F
Toni	Lowery	27	Savannah	GA	F

n = 6

[a] Age at the time of arrest

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