Easy Money: Examining Social Disorganization, Urbanization, Healthcare Fraud, and Community Health in America.

Wilmer Alvarez Irizarry
University of Central Florida
EASY MONEY: EXAMINING SOCIAL DISORGANIZATION, URBANIZATION, HEALTHCARE FRAUD, AND COMMUNITY HEALTH IN AMERICA

by

WILMER ALVAREZ
M.B.A. Rutgers University, 2010
M.A. University of Maryland, 2005
B.S. Cornell University, 1999

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Sociology in the College of Sciences at the University of Central Florida Orlando, Florida

Spring Term
2021

Major Professor: Harold Corzine
ABSTRACT

In the past 40 years, the health of citizens in the United States has changed significantly. The population of the United States managed to get sicker and die slower across the prior four decades. Adding to this complexity is the fact that illnesses and health behaviors in the United States are also not equally distributed by race, class, gender, or other social factors. These facts do not only reflect level of the disease and illness in the United States, but also the disparities that exist within them and the sociomedical factors that impact health. Despite costing American taxpayers between $120 billion to $1.32 trillion a year, one sociomedical factor not addressed in the literature is the impact of healthcare fraud on health. Data for US counties and county-equivalents were used to create a custom dataset of secondary data that was used in heat maps, bivariate correlations, and logistic regressions to examine the relationships between social disorganization, urbanization, healthcare fraud, and community health. This study sought to test whether: (1) social disorganization increases healthcare fraud, (2) healthcare fraud decreases community health outcomes, and lastly, (3) Medicare and Medicaid expenditures mediate the effect of healthcare fraud on community health. Results from this analysis showed that counties with high social disorganization are 1.63 times more likely (log odds: 1.6300, p<.05) to have high healthcare fraud rates than counties with low social disorganization when controlling for health insurance and education. The data also showed that healthcare fraud is not a significant predictor (p >.05) of community health when controlling for health insurance and education. Additionally, the results showed that Medicare and Medicaid expenditures did not significantly (p >.05) mediate the effect of social disorganization on healthcare fraud, or of healthcare fraud on community health outcomes. However, the biggest finding of this study was that the size, complexity, invisibility, and trusted nature of the public health insurance system in the United States make it “easy money” for perpetrators.
# TABLE OF CONTENTS

LIST OF FIGURES ............................................................................................................................. vi

LIST OF TABLES ............................................................................................................................. vii

CHAPTER 1: INTRODUCTION ........................................................................................................ 1

CHAPTER 2: WHAT IS HEALTHCARE FRAUD? .............................................................................. 7

Healthcare Fraud and White-Collar Criminality ........................................................................... 8

Healthcare Fraud Statutes, Laws, and the Healthcare Fraud Units ............................................. 9

Industry Enablers of Healthcare Fraud ....................................................................................... 16

Types of Healthcare Fraud ........................................................................................................ 22

Perpetrators of Healthcare Fraud ............................................................................................. 28

Impact of Healthcare Fraud ..................................................................................................... 34

CHAPTER 3: SOCIAL DISORGANIZATION THEORY .................................................................. 37

Origins, Key Concepts, and Application ....................................................................................... 37

Social Disorganization, Medical Fraud, and Health .................................................................. 43

CHAPTER 4: SOCIAL DISORGANIZATION AND THE PRESENT STUDY ................................. 47

CHAPTER 5: DATA AND METHODOLOGY ............................................................................... 51

Data Sources and Study Variables .......................................................................................... 51

Analytical Strategy .................................................................................................................. 61

CHAPTER 6: RESULTS ................................................................................................................... 64
LIST OF FIGURES

Figure 1: Theoretical Framework and Research Questions of the Present Study ......................... 48
Figure 2: US Healthcare Fraud Rates by County, 2014-18 .......................................................... 65
Figure 3: Texas Healthcare Fraud Rates by County, 2014-18 ...................................................... 66
Figure 4: Texas Healthcare Fraud Rates by County and Social Disorganization, 2014-18 .......... 67
Figure 5: Texas Healthcare Fraud Rates by County and County Health Rank, 2014-18 ............ 69
Figure 6: Texas Healthcare Fraud Rates by County and County Health Rank, 2014-18 .......... 71
Figure 7: Texas Healthcare Fraud Rates by County and Urbanization, 2014-18 ......................... 72
LIST OF TABLES

Table 1: Study Variable Descriptions and Sources................................................................. 52
Table 2: Descriptive Statistics of Study Variables ................................................................. 73
Table 3: Bivariate Correlation of Study Variables ............................................................... 75
Table 4: Social Disorganization, Urbanization, and Medicare and Medicaid Expenditures on Healthcare Fraud Rate: US, 2014-18 ........................................................................................................ 78
Table 5: Social Disorganization Indicators, Urbanization, and Medicare and Medicaid Expenditures on Healthcare Fraud Rate: US, 2014-18 ................................................................. 81
Table 6: Healthcare Fraud Rate, Social Disorganization, Urbanization, and Medicare and Medicaid Expenditures on Community Health: US, 2014-18 ................................................................. 84
Table 7: Healthcare Fraud Rate, Social Disorganization Indicators, Urbanization, and Medicare and Medicaid Expenditures on Community Health: US, 2014-18 ................................................................. 87
CHAPTER 1: INTRODUCTION

In the past 40 years, the health of citizens in the United States has changed significantly. Overall death rates have declined, and life expectancy has increased to approximately 78 years (CDC 2020). Sixty-one percent of adults 18 and older are considered to have excellent health (Blackwell et al. 2014), and the probability of death among adults between the ages of 20 and 55 has declined in 31 states and Washington, DC. Despite the decline in death rates and increase in life expectancy, the population of the United States has also experienced worsening health effects and behaviors. Generally, the population experienced increases in hypertension and high body mass index (BMI), and increases in drug and alcohol use (Mokdad et al. 2018). More specifically, however, “11 percent of adults had been told by a doctor or other health professional that they had heart disease, 24 percent had been told on two or more visits that they had hypertension, 9 percent had been told that they had diabetes, and 21 percent had been told that they had some form of arthritis, rheumatoid arthritis, gout, lupus, or fibromyalgia,” (Blackwell et al. 2014). Similarly, 18 percent of adults were current smokers, 21 percent were former smokers, and based on BMI estimates, 35 percent of adults were overweight and 28 percent obese (Blackwell et al. 2014). In short, the population of the United States managed to get sicker and die slower across the prior four decades.

Adding to the complexity of these measures is the fact that the illnesses and healthy behaviors described are also not equally distributed by race, class, gender, or other social factors. For example, 42 percent of women reported being at a healthy weight compared with 29 percent of men. Additionally, while 42 percent of men reported being overweight (but not obese), only 27 percent of women reported the same (Blackwell et al. 2014). Furthermore, 58 percent of Asian
adults reported being at a healthy weight compared with 36 percent of white adults, 28 percent of black adults, and 27 percent of American Indian or Alaska Native adults (Blackwell et al. 2014). Even further, 27 percent of Hispanic adults reported not having a usual place of health care compared with 16 percent of non-Hispanic black adults and 14 percent of non-Hispanic white adults (Blackwell et al. 2014). Aside from race, ethnicity, gender, and economic position, health status within the population of the United States also varies by employment status and type of health insurance. For example, among adults under age 65, those insured by Medicaid had higher percentages of emphysema, asthma, chronic bronchitis, and COPD than those with private insurance or who were uninsured (Blackwell et al. 2014).

Taken together these statistics provide not only additional information on the disease and illness state of the overall United States population, but also on the disparities that exist within it. More importantly, however, these statistics point to additional sociomedical factors within the United States population that impact its health. Moreover, these factors—more commonly now referred to as “social determinants” (Cockerham 2013, Marmot and Wilkinson 2005)—do not only influence common chronic diseases such as diabetes (Blackwell et al. 2014) and hypertension (Le-Scherban et al. 2019), but also mental illness (Lane et al. 2019, Settipani et al. 2018), sexually-transmitted infections (Chesson et al. 2019), alcohol use (Benner et al. 2014), infant mortality (Kim and Saadi 2013), and homicide (Joe and Mollet 2019). Many of these social determinants are not only connected to employment and insurance type (Blackwell et al. 2014), but also the neighborhood where people live and its characteristics (Le-Scherban et al. 2019, Stacy et al. 2019). Two neighborhood characteristics that influence various sociomedical conditions and outcomes are social cohesion and social capital (Kawachi and Berman 2014).

Social cohesion is the ability of a community to come together (Sampson et al. 1997), and social capital refers to the networks, norms, and trust that helps with coordination and cooperation
in communities for mutual benefit (Rosenfeld et al. 2001). Together, social cohesion and social
capital are not only significant predictors of health (Berkman 1986, Yankauer 1952), but also
significant predictors of deviant and criminal behaviors (Sampson 1996, Bursik and Grasmick
1993). Poor social cohesion can lead to poor social capital, and both can lead to not only poor health
outcomes (Kawachi and Berkman 2014), but also (in some neighborhoods) to an increase in crime
(Anderson 1999). In short, “crime and population health may share the same social origins”
(Kawachi et al. 2000), and their interconnectedness worth investigating further.

One research area where crime and health intersect is healthcare fraud. Healthcare fraud is a
type of white-collar crime (Sutherland 1940) that includes intentional acts of false advertising,
identity theft, and misdiagnosis for the purpose of overbilling, among other schemes (Thornton et al.
2015). Financial estimates of healthcare fraud in the US range from 3 to 33 percent of the total
annual US healthcare expenditures (Price Norris 2009, Geyman 2016, Sparrow 2000), or about
$120 billion to $1.32 trillion a year. In Medicare and Medicaid programs, those financial estimates
range from about $12.3 to $135 billion a year (Rice and Cooper 1969, Congress 2019). This is a
staggering amount when considering how reinvesting funds recovered from healthcare fraud cases
into entitlement programs such as Medicare and Medicaid may impact individual health outcomes.
Increased funding in Medicare and Medicaid has been shown to increase access to health insurance
(Germov 1995, Kennedy and Hendricks 2016), and in turn, increased access to health insurance has
shown increases in individual health outcomes (Richard et al. 2000, Levy and Meltzer 2008,
McWilliams et al. 2014). Therefore, the reinvestment of funds recovered from healthcare fraud
schemes can especially be helpful to the most vulnerable segments of the population, and those who
depend on entitlement programs such as Medicare and Medicaid for their survival (Thornton et al.
2015, Geis et al. 1985) as these can lead to an increase in access to health insurance coverage.

While some research has been done on healthcare fraud, most of it focuses on tools used in
healthcare fraud detection and how these tools can be used to uncover fraud in Medicaid and Medicare (Toothman et al. 2011). For example, Ekin at al. proposed that the most cost-effective option for rooting out healthcare fraud was to use existing data and mathematical modeling, including Bayesian co-clustering to identify potentially fraudulent providers and beneficiaries (2013). Berwick and Hackbarth argued that one fraud-detection tool is insufficient to significantly reduce fraud in the US (2012). Instead, they argue that the implementation of numerous cost-reducing “wedges” targeting the most common fraud scheme types (e.g., overtreatment, etc.) would be more effective (Berwick and Hackbarth 2012). Furthermore, few studies have focused on the association of healthcare fraud with community health. Hannigan describes the conflict associated with healthcare fraud whistleblowing and the struggle healthcare providers encounter when deciding between ethical obligations to patients on one the hand and the financial viability of their practice on the other (2006). However, the Hannigan study is limited in focus to individual provider-based decision-making processes that weigh patient benefit against professional benefits and does not look at the impact of healthcare fraud on health outcomes.

Kyriakakis does study the impact of healthcare fraud beyond the individual in his analysis of current healthcare fraud case law and the “missing victims” ignored by the courts (2015). In this study, the “missing victims” include families who have lost loved ones to fraudulent practices, communities that have lost providers to organizational schemes, and individuals who develop mental illnesses from it (Kyriakakis 2015). While Kyriakakis does address some of the community level effects of healthcare fraud, his data is limited to what is found in the case law (2015). Moreover, the data used is qualitative and does not consider changing demographic trends in the population and in the systems designed to care for them. Therefore, while the Kyriakakis study considers the impact of fraud on health outcomes it does not qualitatively study this relationship on a national level. The result is that even within the few studies that analyze the relationship between
healthcare fraud and community health, the focus has not been on quantitative community-based outcomes. Furthermore, these studies (or the studies on healthcare fraud detection and remediation) have not addressed the impact of healthcare fraud on community health at a national level beyond decision-making processes (e.g., whistleblowing, sentencing, etc.) of individuals, and tactics and strategies for industry leaders and policymakers, especially in the context of the existing public health insurance infrastructure that may exist. This is a significant gap in the literature that exits and that the present study will undertake.

Understanding the association between healthcare fraud and community health would provide policymakers, public health officials, health care providers, and patients insight not only on another social factor that influences adverse health outcomes, but also on a possible entry point to minimize them. Within this context, the present study seeks to understand the relationship between healthcare fraud and community health. To achieve this, this study first reviews the extant literature on healthcare fraud in the US, defining what healthcare fraud is and how it impacts society. This review will include the laws and regulations that govern healthcare fraud, who enforces them, and how they are broken. Subsequently, this study will detail the types and schemes most associated with healthcare fraud, its enablers, and its perpetrators (real and perceived) in US society. In addition, the literature review will also explain the impact of healthcare fraud on the US economy, provider and patient interactions, and even on the furtherance of societal stereotypes among recipients of government assistance. To frame the examination of the effect that healthcare fraud may have on community health, this study also reviews the literature on social disorganization theory and its use as a framework for studying crime (including white collar crime), health, and healthcare fraud.

Subsequently, within a social disorganization framework, this study will examine data from various government sources using an analytical framework that includes heat mapping to
understand the scope of healthcare fraud nationally and how it is distributed at the state level by social disorganization, county health rankings, Medicare and Medicaid expenditures, and urbanization. The state of Texas was selected for the state-level heat map analysis because of the similarities of its geographical distribution of healthcare fraud rates to the national sample. The analytical framework also includes descriptive analysis of a national county sample, bivariate correlations, and logistic regressions. Results from these analyses will be used to not only test the effect of the relationship between healthcare fraud and community, but also to test any mediating effects that public health insurance program expenditures may have on that relationship. These results are presented and examined thoroughly in the Discussion section of this manuscript, where additional socio-structural explanations for healthcare fraud and its association with community health are proposed. This study ends with a discussion of its limitations and the policy and research implications of its findings. While the latter discussion will present several additional complex questions on the relationships among healthcare fraud, public health insurance programs, and community health, examining their answers are proposed as worthwhile pursuits for the academic and practice disciplines impacted by them.
CHAPTER 2: WHAT IS HEALTHCARE FRAUD?

Fraud generally describes intentional acts of deception used to cheat a person (Kalb 1999). In healthcare, these intentional acts of deception can include falsely advertising the benefits of a new drug or device, stealing someone’s identity to use their insurance benefits, or misdiagnosing a health condition to bill for a follow-up visit or medically unnecessary exams, among others (Thornton et al. 2015). It can be perpetrated by organizations, providers, and beneficiaries both individually, and as part of integrated networks (Meyers 2017). In some cases, these networks could involve organized crime syndicates, including domestic and international groups such as the Russian mafia (Morris 2009). Furthermore, when discussing fraud in healthcare the terminology used is not only different from non-healthcare fraud, but also instructive of where it occurs within the entire industry. For example, the terms medical fraud and healthcare fraud are not terms that can necessarily be used interchangeably. While medical care can be described as the services that physicians and clinicians provide, healthcare is a much broader term that encompasses larger social factors that impact health care (RWJ 2020). In fact, these broader social factors can actually account for up to 90 percent of all health outcomes in population with the remaining 10 percent being accounted for by medical care (RWJ 2020). Therefore, when describing fraud in healthcare, focusing on the acts committed by physicians, clinicians, and those who employ them, will only cover roughly about 10 percent of the acts committed. Moreover, leaving out acts perpetrated by pharmaceutical companies, medical device wholesalers, insurance companies, and consumers of healthcare in a study of the subject matter, would render that study vastly incomplete. In addition, while differentiating between medical fraud and health care fraud is important, these are not the only characteristics of fraud in the healthcare industry worth elaborating.
Healthcare Fraud and White-Collar Criminality

Healthcare fraud is a type of white-collar crime (Sutherland 1940). White-collar crimes are a generally associated with schemes designed to defraud a person, business, or government of money, property, services or advantage (FBI 2020). However, these schemes are not ordinary, and are at a level beyond what some would consider typical criminal offenses (FBI 2020). For the most part, white-collar crimes do not involve the threat of physical force or violence and have money and power as their main source of motivation (FBI 2020, Sutherland 1940). A key element of white-collar crime that differentiates it from any other crimes is that perpetrators of white-collar crimes are generally charismatic, highly educated individuals with a contempt for rules and the law (Pontell et al. 1982). Besides being smart, these perpetrators can generally weave their deception and deviance in a way that attempts to normalize their behavior, or that at least allows them to justify it (Pontell et al. 1982). For example, some white-collar perpetrators have stated not acting on their personal behalf, but rather on behalf of the company in which they were part (Pontell et al. 1982). While it is difficult to completely validate these types of statements (as criminals rarely act selflessly), white-collar criminals are not like other criminals and not always motivated by money (Coleman 1987). To some, having an advantage over a competitor, or a rival in the same social position is motivation enough to commit a crime (Coleman 1987). Furthermore, white-collar criminals operate within an abstract and complex environment that takes advantage of the unfamiliar and complex nature of societal systems for their gain (Newman 1958). This not only involves the unfamiliar and complicated world of financial securities, but also of the seemingly familiar ones like those in healthcare (Price and Norris 2009). In fact, white-collar criminality is arguably so pervasive across many of the complex social institutions within society, and so “intrinsic to and normative within the value structure of society” that no punishment or treatment program will effectively address it
(Newman 1958). In part, this also makes it extremely difficult to define and to fully understand its origins and causes (Simpson 2010).

While some of its consequences can be clearly understood (including its victims—such as businesses (HBR 2019), shareholders (Schneider 2015), government programs (GAO 2012), and individuals (Moore and Mills 1990)), the complexity of the schemes, the dearth of any program or policy evaluation, and limited access to data make it difficult to arrive at a consensus on anything else (Simpson 2010). The result is almost the perfect criminal opportunity for highly educated and intrinsically motivated individuals operating in social institutions that are incredibly complex and unfamiliar to many. In social systems that are sophisticated and complex, as is the US healthcare system, the specialized knowledge of those who defraud it not only make it a challenge to identify it (Ekin et al. 2013, Jacquelin et al. 2012), but also make it a challenge to address it (Berwick and Hackbarth 2012, Sarwar and Nicolaou 2012). However, these complexities and challenges and even those who perpetrate it are not what makes health fraud illegal. To understand why healthcare fraud is illegal in the US, once must first examine the laws and regulations that govern it.

**Healthcare Fraud Statutes, Laws, and the Healthcare Fraud Units**

One way to understand the laws and regulations that govern healthcare fraud in the US is to examine the layers of government agencies tasked with enforcing them. These government agencies exist at two levels: federal and state. At the federal level, criminal and civil statutes are enforced by the United States’ Department of Justice (DOJ), and administrative measures are pursued by the United States’ Department of Health and Human Services (HHS) (through its Office of the Inspector General). At the state level, licensing and additional regulatory actions are taken by local authorities, including state licensing boards, state or local departments of health, or local law
enforcement officials (Kalb 1999). At the federal level, the criminal and civil statutes include enforcing various sections of the United States Code (U.S.C.). These sections are enforced by more than 70 prosecutors of the Healthcare Fraud Unit at DOJ, and include the following: 18 U.S.C. § 1343 (Wire Fraud); 18 U.S.C. § 1347 (Health Care Fraud); 18 U.S.C. § 1349 and 18 U.S.C. § 371 (Attempt or conspiracy to commit health care fraud, and conspiracy to defraud the United States); 18 U.S.C. §§ 1957 (Money Laundering); 18 U.S.C. §§ 1956 (Money Laundering); 42 U.S.C. § 1320a-7b(b) (Health Care Kickbacks); 18 U.S.C. §§ 1518, 1519 (Obstruction); 18 U.S.C. § 669 (Theft or Embezzlement in Connection with Health Care); 42 U.S.C. § 1320d-6 (Unlawful Use of Health Information); 18 U.S.C. § 1028A (Aggravated Identity Theft); 18 U.S.C. § 1028(a)(7) (Use of Identification Information); 18 U.S.C. § 1028(a)(7) (Use of Identification Information); and U.S.C. § 1035 (False Statements Relating to Health Care Matters) (USDOJ 2020, USHR 2020). In addition to these sections of the U.S.C., the DOJ enforces: the False Claims Act of 1863 (31 U.S.C. § § 3729-3733); the Anti-Kickback Statute (42 U.S.C. § 1320a-7b(b)); and the Physician Self-Referral Law (42 U.S.C. § 1395nn), also known as the “Stark Law”—named after the congressman who sponsored the bill, Congressman Pete Stark, D-CA (Savino and Turvey 2018).

Individually, each of these laws address parts of the transactional system of remuneration in healthcare, but collectively are aimed at minimizing opportunities for deceptive and fraudulent acts. For example, the False Claims Act (FCA) protects the government from being overcharged for the goods or services it procures and is operationalized when claims for payment are submitted to a government agency that is administering a program sponsored by the federal government, such as Medicaid and Medicare. To be charged with a crime under the FCA, it must be proven that an individual submitted, or caused someone to submit a false claim for payment (HHS 2020, Savino and Turvey 2018). Similarly, both the Anti-kickback Statute (AKS) and the Stark Law are aimed at addressing volume-based schemes, the enormous amounts of money that can be generated by them,
and the serious patient harm they can cause. The AKS makes it illegal to offer bribes, rewards, or other inducements in exchange for patient referrals, while the Stark Law makes it illegal for physicians to refer patients to themselves, an entity in which they (or an immediate family member) have an ownership or invested interest in, or an entity with which he or she has a compensation arrangement (HHS 2020, Savino and Turvey 2018).

Both laws are important in combatting healthcare fraud because of the fee-for-service nature of the US healthcare system, where payment is based on the number of patients and procedures performed, and not on a specific health care outcome (Sparrow 2008). One can make the argument that the need for these volume-based laws is changing, or will ultimately change, because of managed care (introduced in the late 1970s to help rein in costs and fraud and increase quality of care (Hoffman 2006)), and the introduction of Affordable Care Organizations (ACOs) through the Affordable Care Act of 2012 (which aims to reduce costs by shifting the focus away from volumes to outcomes (Igelhart 2009)). However, both laws have only achieved mixed results in their intended purposes (Leibenluft 2011, Sparrow 2008), and may have actually paved the way for new types of healthcare fraud, including treatment denials, delayed claim processing, and delivery of substandard care (Thornton 2015, Iglehart 2009, Sparrow 2008, Kalb 1999).

In addition to criminal and civil statutes that are enforced by the DOJ, the federal level of oversight includes the administrative actions that can be pursued by federal agencies administering health care programs. These administrative actions are rooted in laws ratified by Congress that govern how federal programs are administered. For example, in 1965, President Lyndon B. Johnson signed into law Title XIX of the Social Security Act (CMS 2020). This new law required the Secretary of HHS, Anthony Joseph Celebrezze, to establish a medical and hospital insurance for individuals receiving welfare payments and for older Americans (CMS 2020). This new law was built on earlier laws that established medical payments as part of general welfare programs for low-
income families in 1950, and for the indigent elderly five years later (Moore and Smith 2005). The general structure of the program was, and to a large extent still is, to provide states with the opportunity to receive federal funding for medical services needed by certain segments of the population. In return, those medical services needed to be consistent with established federal health care benchmarks (Moore and Smith 2005, CMS 2020). The structure of the programs has been amended significantly, including in 1972 to include the disabled, those with end-stage renal disease, people over 65, and those receiving Supplemental Security Income (SSI), and in 1996 to sever the link between Medicaid and welfare (Moore and Smith 2005, CMS 2020). In 1997, it was amended to cover low-income children above the cut-off for Medicaid (which was 133 percent of the federal poverty line), and again in 2003 to include prescription drug benefits (Moore and Smith 2005, CMS 2020). One of its last major amendments occurred in 2010 when the law was expanded to cover nonelderly adults with income up to 138 percent of the federal poverty line (Moore and Smith 2005, CMS 2020). These changes, along with the initial intent of the program to cover the medical expenses of those Americans who would not otherwise be covered, significantly increased the size of both programs. In fact, in 1967, the first full year Medicaid and Medicare programs were functioning, the US spent approximately $14 billion to administer both programs; that amount increased to approximately $410 billion in 2019 (Rice and Cooper 1969, Congress 2019). The scale and scope of current Medicaid and Medicare programs have not only increased by the number of Americans covered, but also the number of individuals, organizations, and corporations that defraud them. To remedy these criminal acts of theft and fraud, HHS does not only rely on the DOJ to enforce its law enforcement responsibilities under the FCA, AKS, and other statutes, but also relies on its administrative punitive procedures, including its use of exclusions.

Sections 1128 and 1156 of the Social Security Act give the Office of the Inspector General (OIG) at HHS the authority to exclude individuals and entities from federally funded healthcare
programs, and to maintain a list of those exclusions available publicly (HHS 2020). The List of Excluded Individuals/Entities (LEIE) includes the name, address, exclusion violation, and exclusion date of those individuals and entities that have been convicted of criminal conduct, including Medicaid or Medicare fraud, patient abuse or neglect, and the felony unlawful manufacture, distribution, prescription, or dispensing of controlled substances, among others (HHS 2020). By law, exclusions can be mandatory or permissive. This means that while the OIG at HHS has discretion on exclusions with some crimes, it does not with others. Permissive exclusions, or prohibitions resulting from criminal conduct that the law affords the OIG at HHS the discretion to decide whether to exclude an individual or entity from participating in federally-funded healthcare programs, include: misdemeanor convictions related to health care fraud other than Medicare or a state health program; suspension, revocation, or surrender of a license to provide health care for reasons bearing on professional competence, professional performance, or financial integrity; provision of unnecessary or substandard services; defaulting on health education loan or scholarship obligations; among others (HHS 2020). Mandatory exclusions, or prohibitions resulting from criminal conduct where the OIG at HHS must exclude an individual or entity from federally-funded healthcare programs, includes some of the criminal conduct stated earlier (such as patient abuse or neglect, and felony unlawful manufacture, distribution, prescription, or dispensing of controlled substances), but also felony convictions for other health care-related fraud, theft, or other financial misconduct—including crimes specifically aimed at Medicare and Medicaid, and repeat offenses against any federally-funded healthcare program (HHS 2020).

The main effect of exclusions is barring the excluded individual or entity from receiving payment for services rendered to a covered entity, such as a patient (HHS 2020). In addition, these exclusions extend beyond the individual or entity excluded and to the individuals and entities that hire them. In other words, those who hire an individual or entity that has been excluded by the OIG
at HHS from federally funded healthcare programs, could also be subject to civil monetary penalties (HHS 2020). This is even the case when a hiring or servicing entity, like a pharmacy or durable medical equipment (DME) company, are not aware of the exclusion. The law (sub section 1862 of the Social Security Act) places the burden on these entities to check for exclusions using the LEIE (OIG 2013). As such, the effects of an exclusion are expansive across the spectrum of those individual and entities that receive payment for goods and services rendered to covered individuals. However, beyond these primary (financial) effects, exclusions also hamper the movement of an excluded individual or entity within healthcare in other ways. For example, an excluded individual is prohibitive from serving in “an executive or leadership role at a provider that furnishes items or services payable by Federal health care programs” (OIG 2013). They can also be excluded from “providing other types of administrative and management services, such as information technology services and support, strategic planning, billing and accounting, staff training and human resources” (OIG 2013). In short, an exclusion by the OIG at HHS significantly limits the amount of goods and services that an individual or entity can provide within the healthcare industry, and specifically within the federally funded healthcare programs that operate in that space.

The third and final layer of oversight include the state statutes and licensing structures that govern healthcare fraud investigations and prosecutions at the local level. Critical to understanding how healthcare fraud is investigated and prosecuted at this level is understanding how health care is regulated in the United States. Unlike national and global-level treatises and regulations, healthcare law is not made and ratified by national authorities, such as the President and Congress. Instead, the regulatory and administrative purview of healthcare provisions lie with state authorities and their licensing boards. In other words, healthcare in the U.S. is not a centralized service administered by a national public body, but rather a collection of 50 (and more, if you count the territories) different models of health delivery aimed at providing services to diverse and disparate bodies of citizens.
Certainly, some federal standards govern medical training and testing; however, the right to practice medicine is afforded to a physician by the state, and the state is in charge with administering medical licenses and regulating that health care practice (Kocher 2014; Carlson and Thompson 2005). Consequently, this right can also be taken away by the state when licensure requirements are not met, or when other licensing provisions are violated, such as committing health or medical fraud (Post 1991). State licensing boards are made aware of health care and medical fraud convictions by referrals from federal and state prosecutors (Post 1991). These referrals often follow a conviction of healthcare fraud, resulting from an incident reported to the OIG and state law enforcement agencies, or from incidents reported through federal administrative structures located at the state level including those known as Medical Fraud Control Units.

Because Medicare and Medicaid are the largest federally funded healthcare programs, the laws that govern their existence and implementation (Title XIX of the Social Security Act, CMS 2020) require administrators at government agencies that administer these programs to have in place an organizational infrastructure that attempts to control fraud. However, Medicare and Medicaid programs approach fraud control differently. While Medicare divides the country into seven regions and uses zone program integrity contractors (including the use of multi-agency strike force teams) to investigate and prosecute medical fraud claims, Medicaid uses a more state-focused approach with its Medicaid Fraud Control Units (MFCU) (Flasher and Laboy-Ruiz 2019). MFCUs have been established in 50 States, the District of Columbia, Puerto Rico, and the U.S. Virgin Islands, and are a part of the State Attorney General's office (OIG 2020). Each MFCU employs investigators, attorneys, and auditors to probe healthcare fraud claims, and is underwritten jointly by federal and state governments with federal government grants contributing 75 percent of the funding needed and state governments contributing the remaining 25 percent (OIG 2020, Flasher and Laboy-Ruiz 2019). The specific actions taken by MFCUs vary by state as each is required to operate within the
framework of state laws and prosecutorial guidelines (Rehnquist 2001). Using the number of exclusions on the OIG’s LEIE list as a success metric for MFCUs, reports show that approximately 30 percent of the exclusions on the LEIE can be directly attributed to the actions taken by MFCUs (NAMFCU 2020, Flasher and Laboy-Ruiz 2019). However, to further understand the work MFCUs and the type of activities that garner the attention of investigators and prosecutors at the state and federal levels, one must look at the types of medical and healthcare fraud that can be committed.

**Industry Enablers of Healthcare Fraud**

Healthcare fraud exists in many different forms. However, before discussing the most common forms of fraud, it is important to understand the context in which this crime exist. Healthcare fraud exists in a societal structure with ideal conditions that not only contribute to its emergence, but also to its perpetuation and continuance. In fact, one can argue that the healthcare system in the US has been constructed in such a manner that makes it a perfect target for fraud and criminal assault (Sparrow 2008). The principal structural elements of the healthcare infrastructure in the US include: a fee-for-service orientation, private sector involvement, highly automated claims processing systems, focus on claims processing accuracy over verification, and a post-payment audit process that emphasizes medical appropriateness over substantiation (Sparrow 2008). Each of these elements when analyzed individually presents a vivid picture of the pervasive nature of healthcare fraud and of some of its most popular types. For example, the fee-for-payment system allows a healthcare service or goods provider to bill a patient (or their insurer) a fee for the service or good rendered that is set by the provider through a verbal or written agreement with the consumer of the good or service and which becomes the basis for payment. While the fee-for-service is an arrangement that on its own is not fraudulent, it lends itself to misuse because of the number of
goods and service claims that cannot be verified or substantiated (Sparrow 2008). For example, those looking to defraud the system may decide to increase the level of the intervention (e.g., adding an in-office procedure to a claim and “upcoding” the payor), but not provide it. In certain circumstances, the patient (i.e., an elderly patient in pain, or a new dad unsure of suggested recommendations) may be entirely unaware that a procedure was billed and not provided during the visit (Thornton 2015, Flasher and Laboy-Ruiz 2019). Moreover, because the insurance company does not, and because of the volume of claims, cannot follow-up on every claim, and because most fees charged are in line with what has been agreed to for a procedure, it assumes that the procedure was provided, and thus pays the “valid” claim.

Now, it is worth stating that a combination of inter-related system factors are at play in this example, and that the fee-for-service element is not solely at fault for similar perpetrated schemes. However, this example does point to the critical role that fee-for-service arrangements play in a system that facilitates complex transactions that are not only invisible to the patient, but also largely unverifiable by the payor. The invisibility to the patient is an interesting characteristic of healthcare, but one that is certainly not unique to this industry. While consumers are not foreign to the concept of complex services or products and how these work (e.g., smartphones, electric cars, online dating services, etc.), the complexity and unverifiability associated with healthcare is a bit different. At its core, it has a level of deference, respect, and/or trust given to healthcare providers (and physicians specifically) that not only helps perpetuate the risks associated with fraud, but also minimizes the suspicion that a crime can be perpetrated by a provider (Sparrow 2008, Dyer 2018). In short, society gives healthcare providers latitude not found in other industries (except maybe law enforcement), because deviant behavior and criminal wrongdoing are simply antithetical to the mission of the profession (Sparrow 2008, Dyer 2018).

Unsurprisingly, this latitude does not only appear in the fee-for-service system in the
industry, where doctors are able to charge as much as consumers and insurance companies are willing to pay, but also in the systems created to process those claims. The healthcare industry relies on a claims-processing system that is almost exclusively automated and mainly designed to pay claims as fast as possible. Claims are paid based on treatment codes and (mostly) pre-negotiated rates, and their review involve very little human interaction (Sparrow 2008, Flasher Laboy-Ruiz 2019). This level of predictability allows perpetrators to develop payment schemes using provider numbers bought in the black market (and/or the deep and dark web) and used with treatment codes consistent with the practice area of that number (Sparrow 2008, Vito 2008). Because of the level of automation associated with the system, and if perpetrator keeps the charges and treatment numbers within the range of legitimate claims, these will be processed quickly, and payments received readily (Sparrow 2008). Certainly, software and web-based payment systems are upgraded routinely and programmed to detect variances in charges and treatment codes by specialty. However, the response of those systems is also largely automated to minimize the amount of time it takes to process the claim. For example, if a payment system detects that the provider number used for a claim belongs to a provider that has been reported deceased, it sends an automated message to the claimant that an invalid provider number was associated with the claim (Sparrow 2008, Vito 2008). Furthermore, the system does not automatically trigger follow-up by a human being, or even a cursory investigation. Rather, it simply notifies the claimant that the claim will not be processed until the provider number and name are corrected. Therefore, rather than help flag or initiate a response to potential fraud, what the current systems does is clean perpetrator databases of nonproductive numbers, subsequently increasing their value in the markets where they are sold. Further action on claims automatically declined are not taken because claim processing speed and accuracy are valued over verification, and because of some of the other protective industry measures in place, including post-payment audits (PPAs).
PPAs are tools designed by payors to verify the accuracy of a claim (Sparrow 2008). Their purpose is to verify the validity of a claim through documentation and are often implemented through an automated request for medical documentation that supports a claim that has been paid (Sparrow 2008). To clarify, many of the PPAs do not validate the appropriateness of a claim, they only validate the accuracy of claim. The distinction between these two lies in that validating appropriateness requires objective medical judgement, while validating accuracy simply requires documentation that the treatment paid was provided to the patient (even if just written down in their medical record). Both are fraud-reducing efforts, but the latter can easily be overcome by a perpetrator willing and able to generate or falsify medical records to match false claims submitted for payments. In fact, the most successful schemes in healthcare involve perpetrators who keep meticulous records that are doctored as claims are submitted for payment and are readily available during the 90 days given by those conducting PPAs for submission. Moreover, this documentation is not provided to auditors at the site where the treatment took place. Rather, the documentation is required to be mailed-in to the organization conducting the audit to their place of business. In other words, the majority of PPAs are “desk-audits” with no face-to-face interactions (Sparrow 2008).

The question that naturally arises is why these PPAs are not conducted in person, and why they do not occur more often. The answer to that question has at least two parts: (1) as discussed earlier, the latitude given to medical providers by the healthcare industry and the antithetical nature of criminal behavior in it; and (2) the pressures associated with private sector involvement in the industry. Private sector involvement in the healthcare industry is not a new phenomenon and has been around even before the practice was officially regulated (Jones 1993). In fact, prior to the creation of schools of medicine, professional medical associations, and state licensing boards, any individual with an interest and someone willing to pay of their service could practice medicine (Jones 1993). It was a private enterprise in the same way that any other good or service that could
be provided to a consumer for a fee. The professionalization of the private practice of medicine increased with the creation of schools of medicines (followed by professional associations and later medical licensing boards), which also increased the exclusivity of who could practice (based on several factors, including race, gender, class, and education), and subsequently the amount of revenue that could be generated collectively in an area (Jones 1993). To ameliorate the increasing risk associated with the cost of medical practice and hospital costs after the Great Depression, some non-profit hospitals created “voluntary (private) health insurance” programs (Hoffman 2006). Eventually, these non-for-profit insurance services grew -- through employer and labor union involvement – into separate, stand-alone ventures including the first versions of what are today known as Blue Cross and Blue Shield (Hoffman 2006). However, it was not until after the price controls imposed by the Roosevelt administration, the New Deal, and the advent of Medicare that private sector involvement in health care began in earnest with the creation of private insurance (Hoffman 2006).

Initially, for-profit insurance companies covered those individuals the government did not cover through Medicare or Medicaid. However, it was not until later in the 1960s with the rise of copayments and deductibles for some services (including prescription drugs and durable medical equipment) not covered by Medicare that for-profit companies began offering supplemental insurance to Medicare beneficiaries (Hoffman 2006). In turn, this led to rise of for-profit involvement in health care to the point where most health care service providers became private entities. (Sparrow 2008). In addition, while individuals could purchase insurance directly from a non-profit or for-profit provider, most of the healthcare insurance was purchased by large entities, including corporations, unions, associations and other employers that passed some or all the cost down to their employees (Sparrow 2008). This system remains in place today, but the involvement of for-profit entities had a larger effect on healthcare and those looking to defraud it.
The involvement of for-profit entities in healthcare increased the focus on the process of delivering health care, and more specifically, the efficiencies that could be obtained from it to widen the margin between the costs of providing health care and what can be charged from the consumer for it. This is where two cultures in healthcare began to clash as demand for efficient systems that maximized margins was pinned not only against providing goods and services, but also against minimizing theft and abuse. In short, the private sector involvement in health care contributed to the creation of the system-level conditions where healthcare fraud began to take shape even within individual entities (Sparrow 2008). For example, an insurance company can have both a department focusing on maximizing profit margins by maximizing claim processing capacity, and a department focusing on investigating fraudulent incidents to resolution even if that may means slowing down claims processing. The conflict does not necessarily exist with having both departments, and even those priorities. The conflict occurs when one must be deemed more important than the other, and in the case of many of the current for-profit (and even in many non-profit) healthcare entities fraud control is more of a nuisance than a priority (Sparrow 2008). This is true even when potential cost-savings are touted as the reason for an increased focus on healthcare fraud. Because these cost-savings are tied to a crime that is largely invisible, that invisibility renders the potential cost-savings unclear and uncertain—at least when compared to the visible and concrete nature of claims processing. Therefore, the question that arises is why invest in a process from which its benefits are unclear, but potentially damaging to a core business process. The answer to this question is that the investment is often not made to the extent that is possible and needed because senior executives believe that it may embarrass, and simply get in the way of an otherwise smoothly functioning business model and enterprise (Sparrow 2008).

In addition to increasing the focus on the process of delivering care, private sector involvement has also made it easier for perpetrators to justify their fraudulent actions against the
industry. Combining the invisibility associated with the claims process, the lack of transparency around pricing, and the hidden process associated with denial of coverage decisions, the commercialization (if not commodification) of healthcare services by the private sector has engendered a type of apathy that at times can be characterized as antipathy among Americans towards healthcare, and those in charge with administering it (Sparrow 2008, Dorsey and Ritzer 2015). In fact, “segments of the public view stealing from insurers as a natural form of revenge, either against ruthless and heartless businesses, or against wasteful, inefficient, or incompetent government agencies,” (Sparrow 2008). The problem with this perspective is that fraud only marginally impacts insurers, government programs, medical device companies, and service providers. If these entities will continue to address fraud as a sporadic, self-revealing inevitability in their business model, and not as a systematic problem that may hamper the industry, then their reaction will simply be to shift the costs associated with it to consumers by way of higher prices and premiums (Sparrow 2008). This lack of incentive for the industry to deal with fraud systematically, together with the overall apathy, invisibility of highly automated and high-volume environment, and the deference provided by society to its providers, make healthcare fraud an ideal place for all types of perpetrators and a litany of schemes and ruses.

Types of Healthcare Fraud

According to the literature, there are two types of healthcare fraud (Sparrow 2000). The first is referred to as “hit and run” and covers those schemes where the perpetrator submits as many false claims as possible, receives payment, and disappears (Thornton 2013, Sparrow 2000). The second type is referred to “steal a little, all the time” and includes those schemes where the perpetrator will actively work to make sure that the scheme is not discovered by embedding it as part of its business
and operational processes. When researching both types of healthcare fraud, there are at least 18 schemes that can be identified in the literature (Thornton 2015). These include self-referrals (Thornton 2015); doctor shopping (Carlson 2013); identity fraud (Plomp 2011, Duke 2011); false negation, or claiming a false need to induce the government into contracting for a good or service (Doan 2011), among many others. However, the most commonly addressed in the literature include improper coding and upcoding (Agrawal 2013); billing for services not provided (also known as “phantom billing”) (Thornton 2015); kickback schemes (Rabecs 2006, Morris 2009); providing the wrong diagnosis (Ogunbajo 2014, Byrd 2013); and providing unnecessary care (Morris 2009).

Below is a summary of each of these five:

- **Improper Coding and Upcoding:** This scheme runs a spectrum that includes improperly (but mistakenly) coding a diagnosis (e.g., coding an office visit for an adult patient with one chronic but stable disease (#99213) as an office visit for an adult patient with one chronic but not optimally controlled disease (#99214)) on one end, to intentionally coding a service not provided to deceive a payor into providing a higher payment on the other end (Agrawal 2013). In between these extremes is waste (coding for a medically unnecessary service) and abuse (which is coding for a service at a higher degree to which was provided). An example of abuse is coding excising a skin lesion of 2.5 cm (#11403), when the lesion was in fact 1 cm in diameter (#11401). In Maryland, Medicare and Medicaid reimburses the former at a rate of $141.69, and the latter at a rate of $108.78 (MDOH 2020).

- **Phantom Billing:** This scheme entails billing a payor for goods and services not rendered and is perpetrated in different ways. Perpetrators can submit claims for as many patients as one provider can see in one day without seeing the patients (Stanton 2001, Lubao 2008). While these claims may get flagged because time limits the number of patients a provider can see in a day (e.g., a psychiatrist cannot bill for seeing patients over a period of 24 hours
many perpetrators get around these flags by adding additional providers to their practice that do not actually exist (Brooks 2012). Perpetrators also decrease suspicion by adding patients to treatment plans that also do not exist. For example, a mental health therapist may submit a false claim for a group therapy session that only had one patient (Evans 2005). Another version of this scheme includes the use of billing codes from dead providers (Sparrow 2008), or even submitting claims on behalf of dead patients (Stelfox et al. 2003). Because of the highly automated nature of the claims process, some of the schemes involving dead patients or providers can continue for up to a year before they are uncovered (Sparrow 2008, Stelfox et al. 2003).

- **Kickback Schemes**: This type of scheme is one of the most discussed in the literature and one that can take many forms. One form is receiving a kickback payment for writing a prescription that is filled, and later sold illegally on the street or online (Morris 2009). Another version of the scheme could involve a pharmacist filling a prescription with a lower brand of a drug, billing the payor for the most expensive brand of the drug, and pocketing the difference in prices (Morris 2009). Yet another version of the scheme could include informal agreements between providers that include cross-referrals of patients for general, specialty, and follow-up services for a fee (Sparrow 2008, Thornton 2015). The latter is different from self-referrals (which are also not permitted) because referring parties involved in cross-referral schemes do not have ownership stakes in the practice receiving the referral (Thornton 2015).

- **Wrongly Diagnosing**: Wrongly diagnosing for personal gain is a scheme in which a provider will diagnose a patient with a condition but bill the payor for the treatment of a different condition (Sulzle and Wambah 2005). This scheme takes advantage of the asymmetry of information available to patients and physicians concerning specific conditions, and how it
can be used to defraud. In this scheme, a patient could be diagnosed with a disease such as ankylosing spondylitis (a rare chronic inflammatory disease of the spine), but only really suffer from an acute back ache (DOJ 2016). Both conditions require similar treatments initially, but the rates of reimbursement by payors differ dramatically. In 4 years, one perpetrator received approximately $2 million for running this exact scheme in Miami, FL (DOJ 2016).

- **Providing Unnecessary Care:** The scheme of providing unnecessary services is typically performed to maximize the amount for reimbursement that a provider can receive for a patient’s condition (Morris 2009). While the scheme can include ordering additional laboratory services and diagnostic imagery (Thorton et al. 2014), it can also include performing unnecessary surgical procedures (Price and Norris 2009). In one instance, an obstetrician/gynecologist (OB/GYN) was charged with removing patient’s fallopian tubes unnecessarily and without consent and performing an unnecessary hysterectomy on another (DOJ 2020, USA Today 2019). Both procedures were charged to Medicare and Medicaid, as were many others, netting this one provider approximately $2.4 million (DOJ 2020).

These five schemes, and others like them, are just examples of the type of schemes used to defraud Medicare and Medicaid. These schemes when identified and prosecuted often yield an exclusion from being able to bill Medicaid and Medicare. While these exclusions have already been discussed in how they are used to combat healthcare fraud, they have yet to be discussed in the context of how they are operationalized in response to a conviction. As such, one can state that exclusions are part of the punitive actions taken by the OIG at HHS in response to a conviction on a violation of a healthcare fraud statute by a perpetrator. The schemes covered above (and the remaining thirteen not covered) become the basis for the exclusion, which is in turn based on the type of violation committed by the perpetrator (OIG 2020). Some schemes violate one statute, while
others can violate multiple statutes. Therefore, a conviction on healthcare fraud can result in one exclusion, or multiple exclusions based on the scheme (OIG 2020). Furthermore, exclusions can also result from the downstream effect of a conviction for healthcare fraud. For example, a conviction for healthcare fraud may leave a state licensing board to revoke a provider’s license to practice in the state where that conviction occurred. While that revocation may not be directly related to a violation of statute (e.g., a retired physician could have his/her licensed revoked by a state licensing board if it is not renewed on schedule), the revocation on its own can result in an exclusion (i.e., upon receiving notice from a prosecutor or the court, a license that has been revoked will lead to that provider being excluded from the Medicare and Medicaid program). The result is a type of crowding of exclusions across three main categories: license revocation and suspension (violations of section 1128(b)(4) of the Social Security Act), conviction of program-related crimes (violations of section 1128(a)(1) of the Social Security Act), and felony convictions related to healthcare fraud (violations of section 1128(a)(3) of the Social Security Act). Consequently, these three exclusion categories represent the majority (approximately 85 percent) of the exclusions on the LEIE (Flasher and Laboy-Ruiz 2019). The following are more detailed descriptions of these categories:

- **License Revocation and Suspension:** This category can include many schemes, including improper coding (Flasher and Laboy-Ruiz 2019), phantom billing (Flasher and Laboy-Ruiz 2019), providers with lapsed licenses rendering medical care or writing prescriptions (Savino & Turvey 2018), individuals without training pretending to be licensed providers (DOJ 2016, Savino & Turvey 2018), having a lower level or unlicensed staff performing a service that is typically in a physician’s scope of practice (Byrd 2013), and others. As described earlier, while many of these schemes are difficult to identify because of automated claims processing systems, some are identified through whistleblowers (including patients),
or through regulatory processes used to the assess quality (Byrd 2013), and eventually prosecuted (DOJ 2020).

- **Conviction of Program-Related Crimes:** Schemes in this category include the majority of those associated with improper billing, such as unbundling. Unbundling is different from the billing schemes already discussed in that it focuses on necessary services that are in fact provided but billed separately to maximize payment from the payor (Cady 2007). For example, charging a patient for cauterizing a chronic nosebleed (ICD Code #30903) separately from performing a diagnostic nasal endoscopy (i.e., using a lighted video instrument to magnify and examine the nasal cavity billed under code 31221), when the procedures were performed at the same time. The bundling by payors of these procedures when they are performed at the same time is designed to save the provider time in billing and coding, and the payor money in processing the claim (Cady 2007). However, because some of these procedures are paid at higher rates individually, some providers choose to fraudulently bill them separately even when performed at the same time (Cady 2007). To clarify, if the procedures are performed separately at different times, they can be billed separately. However, in order to bill them separately, the provider would have to modify and justify their coding entry with documentation.

- **Felony Convictions Related to Health Care Fraud:** This last category is used for schemes that reach a level a felony, such as those involving willful and intentional acts to deceive and defraud payors, and for repeat offenders (as being convicted of either a misdemeanor or felony more than once leads to a felony charge of fraud) (OIG 2020). The latter become a bit problematic when the scheme is so embedded in the operational process of a clinic that it becomes difficult to differentiate mistakes from fraud. For example, billing for the same procedure more than once on the same patient (double billing) is one those schemes that at
first glance could be seen a mistake (Korcok 1997). With the large amounts of claims that are processed in both the office and hospital settings, submitting a claim twice to payor seems almost inevitable. However, this is when intention and purpose is important. Because repeating a treatment on an individual, and claiming the repeat treatment, requires a documented justification, double billing as a scheme occurs when a provider willfully and intentionally submits the same claim more than once to receive payment for a procedure that has only been performed once (Byrd 2013). In the hospital setting, double billing can happen when a patient is billed for outpatient services that should have been billed as inpatient services when the patient was admitted (Korcok 1997). Even when settled, convictions for these types of schemes (especially at the hospital setting) can generate upwards of $125 million dollars in fines (Korcok 1997).

The last category and the last example highlighting double billing shows that healthcare fraud can occur in both individual provider settings as well as in large healthcare facilities. However, individual providers and hospitals are not the only perpetrators of healthcare fraud. Perpetrators of healthcare fraud vary widely in both size and degree of their crime.

Perpetrators of Healthcare Fraud

Healthcare fraud perpetrators fall into three types or categories: organizations, providers, and individuals. However, when one looks deeper into some of the schemes created to defraud payors, including Medicare and Medicaid, one finds that many of the fraudulent schemes are perpetrated by individuals who are often providers working in certain types of organizations, including those working in hospitals and clinics. Therefore, for simplicity and clarity, in this paper, the terms organization, providers, and individuals will be used very narrowly to describe broad groupings that
depict who has perpetrated these types of crime. Subsequently, in this paper, organizations will refer to for-profit and non-profit entities established in the US to operate as standalone structures. Examples of organizations in this paper, include hospitals, durable medical equipment wholesalers and retailers, pharmaceutical companies, pharmacies, physician group practices (especially those that house multiple specialties), wellness clinics, community health centers, and other entities that represent a collection of providers. Additionally, providers in this paper represent individual physicians, psychologists, primary care providers, or any other provider that individually, in their professional capacity (even if they are unqualified to do so) delivers a health care service. Lastly, individuals in this paper will represent beneficiaries, or those who are eligible for services, but who also may choose to defraud the program that assures them those services. For example, in this paper, an individual would be a Medicare beneficiary who knowingly allows a false claim to be submitted on their behalf in exchange for cash or some other type of payment (DOJ 2017). Given these descriptions, the following is a summary of the type of perpetrator involved with healthcare fraud in the US:

- **Organizations:** Hospital and medical center crimes account for most investigations and convictions for fraud. These include cases associated with double billing, phantom billing, upcoding, and billing for services not rendered (GAO 2012, GAO 2010). In one instance, a medical clinic billed Medicare for an infusion treatment therapy provided by a physician; however, when asked, the physician indicated that he did not provide the treatments, and the beneficiaries could not confirm that they had received it (GAO 2012). The case was pursued and settled with the medical clinic for $17 million (GAO 2012). However, hospital and medical centers are not the only ones at the organizational level engaged in healthcare fraud. Smaller medical practices with a handful of physicians have been involved in healthcare fraud through schemes such as selling prescriptions for controlled substances in large
quantities (e.g., “pill mill” schemes) (Kennedy-Hendricks et al. 2016). These types of schemes do not only cost the payors large amounts of money, but also impact drug misuse and addiction downstream (Kenney-Hendricks et al. 2016, Dyer 2016). Similarly, durable medical equipment companies, pharmaceutical companies, and healthcare device manufacturing companies are also organizations that have been identified, and in many cases charged, with healthcare fraud (Dyer 2016, GAO 2012, OIG 2020). Many of these companies have been charged with perpetrating similar schemes as hospitals and medical centers, such as phantom billing and upcoding (GAO 2012), but others are charged with perpetrating very elaborate schemes to subvert established laws, such as the AKA (Dyer 2016). In one instance, a manufacturing company created an entire division within the company to incentivize physicians to prescribe the “off-label” use of a drug (that is, using an FDA-approved drug in the US for an unapproved use, such as treating a disease that is typically treated with another drug (FDA 2020)) (Dyer 2016). In this case, the drug was approved to treat cancer pain, and the company was collaborating with physicians through an elaborate scheme where they would pay them “speaker fees” for prescribing the drug to patients with pain resulting from other ailments (Dyer 2016). The scheme cost Medicare approximately $16,000 per month per patient, and after the investigation, was linked to the deaths of 63 patients (Dyer 2016). Besides the significant financial burden to the payor, this scheme also highlights the price in lives that healthcare fraud can have when organizations and providers combine their efforts.

- Providers: It probably does not come as a surprise to learn that specialty providers, such as those who treat cancer patients, are not the only types of providers that perpetrate healthcare fraud. Primary care providers (Dyer 2016), surgeons (Price and Norris 2009), and even psychologists (Geis et al. 1985) are also known perpetrators of fraud. For example,
psychologists bill Medicare and Medicaid by the hour of service and not by procedure, and because there is a fixed number of billable hours in a day, these crimes are relatively easier to detect (DOJ 2018). In one case, a Michigan-based psychologist billed Blue Cross and Blue Shield 21 times for performing 24 hours of professional service in one day (DOJ 2018). As discussed earlier, individual providers can also seek (or be sought) by an organization, or other criminal enterprise, to support a larger scheme (Meyers 2017). The advantage of these collaborative schemes for providers is that they can provide a layer of anonymity and/or plausible deniability if it was ever discovered (Meyers 2017). However, these types of collaborations can also be of greater risk because not all organizations involved in the scheme are ran by typical healthcare administrators. Because of the high yield of healthcare fraud schemes, in the past three decades, it has attracted the attention and investment of organized criminal elements, including the Italian and Russian mafia (Meyers 2017, DOJ 2017). These collaborative schemes not only seek to take advantage of the seemingly endless pot of money within healthcare insurance programs, but also the deference and respect afforded to the industry (Meyers 2017, Rossoff 1989, Price and Norris 2009, Sparrow 2008). When a crime is antithetical to an environment generally associated with trust and respect, the suspicion of a crime is minimal (Sparrow 2008). In some cases, the crime is portrayed as being in the best interest of the patient. As result, the crime can proceed without detection and consequence for as long as it does not inadvertently reveal itself to an unsuspecting victim or the authorities (Sparrow 2008, Meyers 2017). This level of secrecy and longevity make it an ideal space for professional criminal enterprises (Meyers 2017, Sparrow 2008). However, even with these types of collaborative schemes, the role of

1 Wynia et al. 2000 discusses how some provers manipulate diagnostic codes to provide patients with better treatment options.
individual beneficiaries cannot be overlooked.

- **Individuals:** Up to now, this paper has focused on providers and organizations being the main perpetrators of healthcare fraud. While this is true (GAO 2012), beneficiaries of healthcare services, including those of Medicare and Medicaid services, can also be perpetrators of healthcare fraud (GAO 2012). In fact, the data suggests that of all the cases identified and referred to prosecution, approximately 10 percent of them involve beneficiaries (GAO 2012, GAO 2010). Beneficiary involvement in healthcare fraud can include lying about eligibility requirements (Champlin 2016), unknowingly agreeing to services that are not rendered (DOJ 2018), and knowingly allowing the use of your benefits for a kickback (DOJ 2017). In one case, several beneficiaries received cash, jewelry, and event luxury household goods as payment for allowing a chain of health care clinics to use their beneficiary policy numbers for false claims to Medicare and Medicaid (DOJ 2017). In other schemes, beneficiaries are unaware of their involvement. In one case, several nursing home residents in Louisiana agreed to receive psychological exams that they neither needed nor understood from a third-party provider (DOJ 2017). The provider continued the scheme in multiple nursing homes and defrauded Medicare for over $25 million (DOH 2017). However, despite their relatively low involvement in perpetrating healthcare fraud schemes, when healthcare fraud is discussed publicly in the context of beneficiaries and needed reforms, those who lie about their eligibility and defraud the programs funded seem to be the image promoted the most (Champlin 2016, Park 2011). One reason for this is the longstanding, American view on the welfare system and its connection to both health care and fraud (Park 2011, Sparrow 2008). In short, the myth of the “welfare queen” (Champlin 2016, Kelly 2010).

A vestige of the late 1970s and early 1980s, the term “welfare queen” was used in describing
the case of Linda Taylor (Champlin 2016, Kohler-Haussman 2007). Linda Taylor was a career con artist who was charged and convicted of using up to 80 aliases to illegally receive welfare, social security, and veteran benefits, including food stamps, healthcare, and cash payments (Champlin 2016, Kohler-Haussman 2007). The term “welfare queen” was used extensively by President Ronald Raegan in 1976 in his campaign for President of the United States to not only refer to the Taylor case, but also as an example of why welfare programs needed reform (Champlin 2016, Kelly 2010). However, the term was not only used to make a statement about welfare fraud, but it was also used to create an image of what welfare fraud looked like (Kelly 2010). The image created and which has long been associated with this term is that of a lazy, hyper-fertile, woman of color (Black woman, specifically), who is not only uneducated and unemployed, but also focused on sitting back collecting checks from government-funded programs (Kelly 2010, Champlin 2016, Monnat 2010, Hancock 2003, Kohler-Haussman 2007). This image did not only persist through the campaigns for President in the late 1970s but has also persisted as a racist dog whistle used ubiquitously when discussing discretionary government spending on social service programs, including welfare and Medicaid (Kelly 2010, Moore and Smith 2005). Furthermore, the image has persisted and was used to influence policy discussions and creation of laws well into the late 1990s (Kelly 2010, Monnat 2010), including work requirements for recipients of social service programs (Gilman 2014), and even through the 2012 Presidential race, when Governor Romney questioned President Obama’s plan to assess the 5-year cap placed on welfare recipients (Gilman 2014). In the past 40 years, the image has taken a cultural significance that in some ways has controlled perceptions of poor women of color (Hill 2000, Monnat 2010) to the point where receiving government services has become an indication of irresponsibility (Kelly 2010) and even criminality (Champlin 2016). The enduring nature of the term and corresponding image has been accredited to structural and colorblind ideologies (Hill 2000, Bonilla Silva 2001, Monnat 2010) in US society, and to the influence of
rugged American individualism and the notion of personal responsibility in America (Park 2011). More importantly, this image has not only influenced policy, but has only perpetuated a narrative of criminality and levels fraud that are not supported by evidence (GOA 2016, NY Time 2019). In fact, of the $150,000 that the original “welfare queen” Linda Taylor was accused of stealing from government-funded programs, several investigations concluded that the figure was closer to $40,000² (NY Times 2019). Even without evidence, this narrative not only promotes an image of poor people of color being associated with social service program fraud schemes that is not true, but also continues to perpetuate a stereotype that can influence and impact who can benefit from those services (Kelly 2010, Park 2011, Hancock 2003).

**Impact of Healthcare Fraud**

The impact of healthcare fraud can be best described as being focused on the economic aspects of the industry. This intuitively makes sense because of the staggering amount of money spent on health care in the US. Healthcare spending in the US has grown to approximately $4 trillion dollars with Medicare and Medicaid accounting for 21 percent ($840 billion) and 16 percent ($640 billion) of that spending respectively (CMS 2020). To provide some context, total US healthcare expenditures are greater that the Gross Domestic Product (GDP) of Canada, Brazil, Italy, France, United Kingdom, India, and Germany (World Bank 2019). Annual US Medicare and Medicaid spending ($1.48 trillion) alone surpasses the GDP of Mexico, Australia, and Spain combined (World Bank 2019). Despite the sheer size and magnitude of the industry, little research has been done on narrowing down the economic impact of healthcare fraud (Sparrow 2000). Estimates in the academic literature range from 3 to 33 percent of total annual US healthcare

---

² Linda Taylor was ultimately only charged with stealing $9,000 (NY Times 2019).
expenditures (Price and Norris 2009, Geyman 2016, Sparrow 2000, Thornton 2015). Public reporting from law enforcement agencies shows that figure to be in the range of 3 to 10 percent of total annual US healthcare expenditures (FBI 2009). That means, that if one uses the estimated $4 trillion projection of total annual US healthcare expenditures, one can estimate that healthcare fraud can cost US taxpayers anywhere between $120 billion to $1.32 trillion a year. Consequently, the focus of the existing healthcare fraud literature has been on identification and fraud prevention (Ekin et al. 2013, Jacquelin et al. 2012), as opposed to the economic impact alone, or any intangible impacts of this crime. However, that is not to say that intangible impacts of healthcare fraud have not been identified and examined, because they have.

For example, there is portion of the healthcare fraud literature, albeit a small portion, that focuses on what healthcare fraud does to the reputation and credibility of those involved. While there is some attention paid to the credibility and reputation of organizations that provide important goods and services to industry, including pharmaceutical and medical device companies (Sparrow 2000), most of the focus of this type of literature has been on providers and what happens to their credibility and reputation when they are involved in healthcare fraud schemes (Price and Norris 2009). Additionally, a specific focus on the literature is patient safety, and especially the effects of misdiagnosis and mistreatment on the mental and physical health of patients, such as those associated with the unnecessary surgeries described earlier (Agrawal et al. 2013, DOJ 2020). Equally addressed in this portion of the literature is the perceived mindset of providers which view patients as revenue for their practice as opposed to patients seeking care for their ailments (Dyer 2018). These studies suggest that this perspective not only leads to increased risk of harm for patients (Dyer 2019, DOJ 2020), but also promotes the perspective that providers are forced into this type of behavior by payors and their onerous reimbursement policies (Sparrow 2008, Wynia et al. 2000). Despite these insights on provider behavior and the motivations for perpetrating fraud, the
focus of this portion of the literature is on trust (Dyer 2018). As discussed earlier, society affords health care providers with a level of deference and trust often not associated with any other profession. At the heart of this regard is the expectation that in spite being in the most vulnerable and helpless state a human can be (that is, the state one may be when sick), providers will never take advantage and betray that trust for personal gain (DOJ 2020). When providers (especially physicians) violate this seemingly solemn expectation, the reputation and credibility of the entire health care profession suffer along with its integrity (Agrawal et al. 2003). The impact of this effect on the profession is difficult to ascertain, but a similar effect of reputation and credibility can also be observed in beneficiaries of Medicare and Medicaid who are charged with healthcare fraud, especially in the lasting stereotypes that may impact health care access (Champlin 2016, Kelley 2010, Monnat 2010). The observation associated with the latter is that healthcare fraud schemes involving certain beneficiaries, including poor women of color, often lead to stereotypes that influence policy (Monnat 2010, Park 2011) and decrease access to health care services such as reproductive health care, primary care, and even routine OBGYN specialty care (Monnat 2010, Kelley 2010, Hancock 2003). Furthermore, the literature suggests that these stereotypes and the potential impact to patient health from healthcare fraud is associated with social structural factors and ideologies (Monnat 2010). To help frame and further understand this association, one can look to social theory to determine if existing theoretical models would help explain not only the social factors that influence healthcare fraud, but whether healthcare fraud influences health care outcomes. One social theory widely used to study crime and deviance in society is social disorganization theory because of its thesis that neighborhood social factors affect criminal behaviors. Given the association of social factors to health, and of health to healthcare fraud, social disorganization may help frame the seeming association between healthcare fraud and health care outcomes.
CHAPTER 3: SOCIAL DISORGANIZATION THEORY

Origins, Key Concepts, and Application

Chicago in the 1920s and 1930s, and the University of Chicago specifically, was the academic home of several sociologists studying urban crime and delinquency. Among these were Robert E. Park and Ernest W. Burgess. Both researchers studied urban ecology and urban growth and used the metaphor of natural ecological communities to study and examine the process of urban expansion (Park, Burgess, and McKenzie 1925). As part of these efforts, Park posited that when commerce and industry expand in communities, they invade spaces reserved for residential areas, pushing residents to the outer edges of the community. To Park, these actions resembled those taken by certain species in the animal communities to seek out dominance over others and the scarce resources of the area (Park 1936).

The concept of a central location within a community where industrious and productive activity occurs, producing a displacement of other type of community activity was further developed and described by Burgess using a series of concentric community zones (1925). The resulting concentric zone theory highlighted urban expansion using a zone-based methodology that identified the innermost zone (Zone I) as the epicenter of economic activity in a community, Zone II as “zone in transition”, Zone III as the “zone of working men’s homes”, and Zones IV and V as the “residential and commuter zone” for many of the white-collar workers of Zone I (Burgess 1925). The use of multiple zones in concentric zone theory underscored the insight that expansion away from the epicenter of community does not just occur to the outer edges (Burgess 1925); rather, it also occurs radially impacting and displacing communities between the epicenter and the outer edges of a neighborhood (Burgess 1925). In short, in concentric zone theory, Burgess sought to
demarcate the process of urban expansions, and the pressure it creates in the communities where it happens.

Following the lead of their professors, Clifford Shaw and Henry McKay used Burgess’ concentric zone theory to examine the distribution of youth delinquency across Chicago. As part of their study, they collected extensive data on boys under the age of 17 who had contact with law enforcement during three distinct periods between 1900 and 1933 (Shaw and McKay 1969). This data included not only subject’s address and type of crime, but data related to community truancy rates, infant mortality, public health disease, mental disorders, among other variables (Shaw and McKay 1969). These were all plotted geographically by hand on a map of Chicago. Shaw and McKay’s most significant finding of this work was that the distribution of delinquents fit a particular pattern (Shaw and McKay 1969). They found that the rates decreased outwardly from the inner-city towards the most affluent areas (Shaw and McKay 1969) of the city. The highest rates of crime and delinquency were concentrated in Zone II, or the area designated as a “zone in transition” (Shaw and McKay 1969). This area was zoned for industry and commerce, and was characterized by physical decay, poor housing, broken families, and a heterogenous population (Shaw and McKay 1969). Residents in these communities were at the bottom end of the social economic ladder, earning minimal income at menial employment and with a low education (Shaw and McKay 1969). Shaw and McKay also found a co-occurrence of youth delinquency with adult crime, infant mortality, high rates of tuberculosis, mental disorders, and population heterogeneity. This finding led Shaw and McKay to theorize that these neighborhood characteristics could be responsible for youth delinquency (1942, 1969). Using this hypothesis, Shaw and McKay developed a theory in which certain community characteristics (collectively interpreted as social disorganization) were found in the areas of highest crime and delinquency (Burgess 1925).

In addition to the concentric zone mapping of youth delinquency across Chicago, Shaw and
McKay also conducted a qualitative study of the areas where crime and delinquency concentrated at higher levels (i.e., Zone II) (Shaw and McKay 1969). The purpose of this data collection was to understand the nature of their quantitative data more fully. In this part of their study, Shaw and McKay found that the youth involved in the highest rates of crime and delinquency “were involved in a conflict between the goals assumed to be attainable in a free society and those actually attainable for a large proportion of the population” (1969). They also found that while youth in neighborhoods with low rates of criminal and delinquent behaviors were homogenous and seemed to uphold conventional norms and values, youth in neighborhoods with high rates of criminal and delinquent behavior operated in “systems of competing and conflicting moral values,” (Shaw and McKay 1969). This additional insight not only provided Shaw and McKay with a deeper understanding of neighborhood effects, but also how these effects set the conditions for crime and delinquency to emerge.

Social disorganization thus emerged as a new pathway for research in the 20th century postulating an impact from neighborhood characteristics (or social disorganization) on crime and deviance. The theory was further expanded and clarified in the early 1980s, when researchers (including Robert Bursik and Harold G. Grasmick) noted that Shaw and McKay did not set out to show that urban expansion caused crime and deviance (Bursik and Grasmick 1988, 1993). Rather, they contended, that Shaw and McKay found that urban expansion prohibited social organization, or the rise of normal, informal social control systems within a community, thus allowing crime and delinquency to emerge (Bursik 1988). According to Bursik and Grasmick, the absence and breakdown of informal social controls was the key finding in Shaw and McKay’s work, and what led to disorganization within neighborhoods (Bursik and Grasmick 1988, 1993). This disorganization, or lack of informal social control, took the form of lack of community supervision of wayward youth, lack of friendship networks, and the minimal participation in formal
organizations (Sampson and Groves 1989). These forms of informal social control could be impacted by population heterogeneity, poverty, and lack of opportunities, and in turn could give rise to crime and deviance (Bursik and Grasmick 1988, 1993, Sampson and Groves 1989). Therefore, it could be argued that the variables that Shaw and McKay theorized leading to social disorganization and crime may also include an element of informal social control. This new concept of informal social control, or the ability of community members to come together to informally police and manage their community was advanced further in the 1990s by Robert Sampson in his theory of collective efficacy (Sampson et al. 1997).

According to Sampson et al., collective efficacy is the “perceived ability of neighborhood residents to activate social control” (1997). This collective efficacy has two main dimensions: (1) social cohesion, or the ability of the community to come together, and (2) shared expectations for social control, or the community’s ability to agree on how to manage their community (Sampson et al. 1997). The idea behind collective efficacy and its impact on crime and deviance is to show that when community members come together and agree on how its members will behave, and detail what the community will accept, crime and deviance does not increase and may in fact decrease. Conversely, when community members cannot come together for various reasons (including language barriers, violent crime, or mistrust), and cannot agree on how their community will behave and detail what it will and will not accept, crime and deviance increases. Additionally, Sampson described the importance of the strength of cohesion and subsequent informal control. Both are dependent on the density of the social network present in the community (Sampson 1997). Thus, weak social networks within a community, produce weak collective efficacy resulting in weak informal social control, while strong social networks within a community, produce strong collective efficacy resulting in strong informal control (Sampson et al. 1997). Sampson’s ideas were supported empirically by his study of “external” factors that impacted selected British communities (1989). In
this study, Sampson and Groves included measures of social disorganization, such as social class, residential mobility, and family disruption among others, and examined their impact on crime victimization (1989). The study showed that social disorganization had an impact on crime victimization and the rates of criminal offenses (Sampson and Groves 1989). Moreover, the work of Sampson showed that collective efficacy was one of the social mechanisms by which social disorganization accounted for varying rates in crime across different communities (Sampson et al. 1997, Sampson 2006). Furthermore, the study of social disorganization and collective efficacy led to the study of social capital as a measure of social disorganization and lack of informal social control.

Social capital refers to the “features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit” (Putnam 1995). In the context of social disorganization theory, it then follows that community characteristics that impact social capital would also impact social organization and the social trust that facilitates coordination and cooperation for mutual benefit (Rosenfeld et al. 2001). Therefore, community characteristics that negatively impact social capital, negatively impact social organization and informal social control, leading to a potential lack of social control and social disorganization. This social disorganization can in turn lead to social conditions where crime and deviance can emerge. However, there is a limitation to using social capital as a measure of collectively efficacy and social organization. While social capital can be linked to lower rates of crime, its association is not as strong and direct as the one found between structural disadvantage (e.g., low income, housing, etc.) and crime (Hawdon and Ryan 2004).

Elijah Anderson utilizes these structural disadvantages and inequalities coupled with social disorganization to develop the concept of the code of the street (1999). The code of the street is a state of “might makes right” mentality that legitimizes and condones the use of violence to acquire
and maintain respect (Anderson 1999, Stewart, and Simmons 2006). Researchers argue that when
the code of the street (or others that emerge from structural disadvantages to assist with
neighborhood survival) is coupled with neighborhood structural characteristics (including physical
decay and poverty), the rate of crime and violence increases in disadvantaged areas (Stewart and
Simmons 2006). The code of the street also gives rise to a subculture where both “street” and
“decent” people in the neighborhood must not only be aware of the code, but also commit to its
violent framework to survive (Anderson 1999). In other words, the rise of the subculture is a type of
informal social control that has both negative and positive impacts on crime in neighborhoods.
However, it is also one that requires the awareness and commitment of those living in the
neighborhood regardless of their direct participation in its criminal outward expression. This
awareness and commitment has been addressed in some studies using social disorganization theory
to examine the impact of social organization on crime (Cantillo et al. 2003). In these studies,
traditional indicators of social disorganization, such as poverty, heterogeneity, and mobility, are
analyzed along with mediating factors such as a sense of community (an alternative indicator of
informal social control) to understand its impact on deviant and criminal behaviors. More
specifically, when sense of community (measured by degree of neighborhood socialization,
belonging, and collaborative problem solving) is considered in examining the impact of social
disorganization on youth deviance and delinquency, it showed that youth in neighborhoods with
higher levels of sense of community were more likely to participate in prosocial activities that led to
high higher grades and less delinquency (Cantillo et al. 2003). These findings are consistent with
studies that have found that certain social ties (an alternative measure of community cohesiveness)
in socially disorganized neighborhoods are more effective in controlling crime that others (Roudtree
and Warner 2006).

For example, in a study of neighborhoods in Seattle, researchers found that female social ties
Social disorganization theory has been tested empirically and used to study segments of the population that exist as disadvantaged classes economically (Wilson 1987). These studies have used several economic variables as indicators for social disorganization and its effect on social problems. For example, some researchers have used economic metrics such as manufacturing decline (White 1999), mortgage foreclosures (Immergluck and Smith 2006), and inflation (Devine et al. 1988) as indicators of social disorganization and as correlates of crime rates. Other researchers have used attitudinal variables including consumer sentiment (Rosenfeld and Fornango 2007) as a correlate of crime rate to study the impact of social disorganization. The conclusion of many of these studies is
that neighborhood factors, such as poverty (Sampson, Raudenbush and Earls 1997) and ethnic
heterogeneity (Shaw & McKay 1969) impact social behaviors. However, the literature is limited on
whether the factor of social disorganization provides the conditions for white-collar crime, and for
healthcare fraud specifically to emerge. While there have been some studies that examined the
impact of social factors, such as poverty, crime, and social mobility on white collar crime
(Gottschalk 2018), studies specifically targeting healthcare fraud either as an intermediary or
outcome variable appear to be a gap in the literature. Turley uses healthcare fraud as an outcome
variable in a qualitative study of beneficiary fraud in national health care systems (2011). However,
while this study presents the concepts of healthcare fraud occurring in “micro-social clusters” and
social ties being a primary driver of organization and of justification for commission of the crime,
the limited scope of the study (Turley 2011) leaves some avenues of inquiry open —particularly, on
the association of healthcare fraud with social disorganization. Another study approached the
connection between healthcare fraud and social disorganization more broadly, using white-collar
criminality as the main factor of analysis (Gottschalk 2018). While this study highlighted the
breakdown of conventional social norms, including conventional relationships of trust, as a
significant factor of white-collar criminality, this study too was qualitative and limited in scope to
just one case (Gottschalk 2018). One quantitative study did find social disorganization to be
associated with white-collar crimes, including healthcare fraud; however, this study was focused on
white-collar crime during disasters and used social disorganization theory to account for some of the
social mobility associated with disasters (Davila et al. 2009).

The Davila et al. study along with the others are examples of the limited literature that exists
in the study of social disorganization and healthcare fraud (2009). However, that is not to say that
social disorganization is entirely divorced from white-collar criminality, because that is certainly not
the case. Seminal work in white-collar criminality by Sutherland (1940) set the course for not only
studying crime beyond the lower social classes, but to understand the impact of social conditions that characterize the manipulation of trust and power in these types of crime (Sutherland 1940). Unfortunately, the opportunity to perform that level of research on white-collar crime has been obviated by the ambiguity, complex, and inaccessible nature of the crime (Simpson 2010). While white-collar crime is seemingly ubiquitous, it suffers from a dearth of data that can be analyzed to understand its causes, solutions, and even structural covariates (Simpson 2010). The result has been attempts to expand the theoretical explanations of white-collar crime by Sutherland (1940) to include routines activities theory (Benson et al. 2009), general strain theory (Langton and Piquero 2007), and life course theory (Benson 2001). Some studies have sought to understand the level of seriousness or concern for the crime in the changing dynamics of society (particularly after the US mortgage crisis of 2008), but these studies did not fully account for the effects of social disorganization (Simpson 2010, Cullen et al. 1982). Grabowsky did highlight the effects of weakening informal institutions of social control (including those that increase social ties, such as families, churches, clubs, etc.), and how they set conditions for criminal activity (including white collar crimes) to emerge (2009). However, the focus of this study was to propose creation of an international body to prosecute transnational white-collar crimes (Grabowsky 2009).

Therefore, the gap in the literature on the association of social disorganization to white-collar criminality presents an opportunity for research as social disorganization is certainly not divorced from studies on health care and health disparities. For example, Berkman and Kawachi found that social cohesion and social capital both impact health significantly (2014). Their observation was that poor social cohesion led to poor social capital which then resulted in poor health (Kawachi and Berkman 2014). Similar results were found in studies examining the relationship between social disorganization and general health (Berkman 1986), prenatal and neonatal health (Yankauer 1952), and even cardiovascular health (Lee and Cubin 2002). Some
studies validated the impact of neighborhood factors of health, and how the poor are limited to health access by both condition and location (Payne 1998), while others furthered the study of social cohesion as a predictor of health and a mediator of structural factors when these are regressed on health (Browning and Cagney 2003). One study in particular used crime as an indicator of well-being to measure the impact of social disorganization and social cohesion on health (Kawachi et al. 2000). The results of this study showed that “areas with high crime rates tend also to exhibit higher mortality rates from all causes, suggesting that crime and population health share the same social origins” (Kawachi et al. 2000). The question not addressed by this study, nor those studies that look at the association between neighborhood factors and their impact on health and crime (including the limited few that look at social disorganization and healthcare fraud, or even social disorganization and white-collar criminality generally), is whether social disorganization creates the conditions under which healthcare fraud can emerge. Additionally, if social disorganization does increase healthcare fraud, then the question that arises is whether that increase in healthcare fraud impacts health. Moreover, if healthcare fraud does impact health, the following question is whether this impact is mediated by other factors, such as the costs of delivering health care in those neighborhoods. These three research questions are the primary focus of this study.
CHAPTER 4: SOCIAL DISORGANIZATION AND THE PRESENT STUDY

While much scholarship has been conducted on social disorganization, neighborhood crime, white collar crime, healthcare fraud, and community health, many of those studies do not quantitatively examine the association between social disorganization, healthcare fraud, and community health. As shown in Figure 1 below, many of these studies focus on the associative relationship in the process between social disorganization and healthcare fraud, but do not follow entirely through to comprehensively understand the impact of these major factors on community health. As described in the review of the literature, all these studies provided an insightful understanding on how neighborhood factors impact social organization (Bursik and Grasmick 1988), social capital (Sampson 1997, Kennedy et al. 1998), and crime (Shaw and McKay 1942, Bursik and Grasmick 1988, Sampson 1997, Kennedy et al. 1998). The studies also provide qualitative insights on how neighborhood effects may impact white-collar criminality (Coleman 1987) and healthcare fraud (Price and Norris 2009), but none use existing quantitative data to understand the nature of that association. Furthermore, while many studies have sought to detail the impact of healthcare fraud on Medicare and Medicaid expenditures, the focus of these studies have been on identification and prevention of fraud (Sparrow 2000, Thornton 2015, FBI 2009) and the effect that it can have on provider trust and credibility (Price and Norris 2009, Dyer 2018), limited attention has been given to the health of individuals in the communities where these crimes occur. Certainly, some of these studies discuss the potential impact of healthcare fraud on health but do so anecdotally and as a consequence of money that is stolen from the program (Sparrow 2000, Thornton 2015, FBI 2009, Price and Norris 2009, Dyer 2018). Moreover, these studies collectively do not connect to existing literature on Medicare and Medicare funding and its downstream impact on health insurance coverage and health (Germov 1995, Kennedy and Hendricks 2016, Richard et
al. 2000, Levy and Meltzer 2008, McWilliams et al. 2004, Franks et al. 1993). In short, there is a gap in the literature and in the current theoretical approach to understanding the impact of social community-level factors on healthcare fraud and in the impact of healthcare fraud on community health.

**Figure 1: Theoretical Framework and Research Questions of the Present Study**

This study seeks to address this limitation through a quantitative analysis of existing secondary data to answer three critical research questions in this area, and which are highlighted in Figure 1. The questions are the following: (1) do neighborhood factors (social disorganization) increase the incidence of healthcare fraud? (2) does healthcare fraud decrease community health? and (3) do Medicare and Medicaid expenditures mediate the effect of healthcare fraud on community health? The answers to these questions have implications at multiple levels. The first is on public policy related to healthcare fraud in Medicare and Medicaid and how it is addressed by
existing laws and administrative regulations. As discussed, existing investigative and enforcement process assume that convictions and recovery of Medicare and Medicaid funding stolen would be incentive enough for program and insurance administrators to focus on identifying and minimizing healthcare fraud (Sparrow 2000, Sparrow 2008). However, the evidence points to this not being the case, largely because of the size and magnitude of the system and the fact that its processes were created and maintained by these same laws (Sparrow 2008). In other words, whatever incentive is produced by a settlement, or recovery directly associated with a successful healthcare fraud prosecution, is outweighed by the amount of money potentially lost by not processing claims at the maximum rate required by the system. The present study seeks to change this calculus by providing the additional incentive of positively impacting community health. More specifically, this study seeks to introduce community health as an incentive that can potentially be ratified in policy to help increase the focus on identifying and prosecuting healthcare fraud not just to save taxpayer money, but to decrease taxpayer morbidity and mortality. Moreover, the result of this study will provide insight on the role that Medicaid and Medicare expenditures play on the relationship between healthcare fraud on community health. The intuitive and mainstream argument is that community health is made worse by healthcare fraud as it makes less money available for community health programs like Medicare and Medicaid (Hannigan 2005, Kyriakakis 2015). This study will provide some insight on that belief.

Secondly, this study seeks to introduce community health as a factor that providers should consider as they engage in billing activities. Again, while the anecdotal belief that healthcare fraud impacts health through community health program expenditure is intuitive to many providers, to quantitatively increase the understanding of the nature of that belief may also be impactful. Providers may no longer see the victim of the fraud as this nameless administrator in an obscure insurance conglomerate, but rather the next patient in their waiting room. Lastly, and perhaps most
reaching, is the implication that answering these critical research questions may have on stereotypes associated with healthcare fraud. While one can argue that providers are more guilty of perpetrating healthcare fraud than beneficiaries, this argument is from a widely held fact. There are many reasons why this is the case, including the invisibility of the innerworkings of the healthcare system among the population; yet stereotypes about both groups within the healthcare system are still pervasive and persistent. Providers are seen as unquestionable paragons of expertise and knowledge, while beneficiaries are seen as the frail elderly on a fixed income, or as lazy, poor women of color taking advantage of the system. As discussed, these stereotypes are not only vestiges of past historical viewpoints, but socially constructed positions that can impact access to health care and overall well-being. Consequently, this study seeks to not only highlight some the demographics most associated with healthcare fraud, but more importantly the structural factors that contribute to its emergence and perpetuates its existence.
CHAPTER 5: DATA AND METHODOLOGY

Data Sources and Study Variables

The data selected for this study were acquired from various sources including the: US Department of Health and Human Services, US Census, Robert Wood Johnson Research Foundation, and the US Department of Agriculture. The data covers the period between 2014 and 2018, which reflects the most recent period where variable-specific data was complete for all study variables. County level data for US counties and county-equivalents (N=3,223) were extracted from datasets at each institution to create a custom dataset of secondary data specifically for this analysis. Not all datasets used for the extraction contained data for all counties—especially, for US counties in Puerto Rico, Alaska, and some covering American Indian reservations. As such, several US counties and county-equivalents were left out of the study. The resulting combined dataset for this analysis thus included 3,139 (n) counties and county-equivalents, or approximately 97 percent of all counties and county-equivalents in the US. Furthermore, the data collected represented variables that served as measures of health, fraud, geographic, and demographic information in this study, and included those shown in Table 1 below.
Table 1  
Study Variable Descriptions and Sources

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Source</th>
<th>Type</th>
<th>Description</th>
<th>Coding</th>
<th>Recoding</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Community Health</td>
<td>The Robert Wood Johnson Foundation, County Health Rankings &amp; Roadmap, <a href="https://www.countyhealthrankings.org/">https://www.countyhealthrankings.org/</a></td>
<td>Ordinal</td>
<td>County in-state quartile health ranking.</td>
<td>1=First Quartile (Healthy)</td>
<td>1=Average in-state quartile rank &lt; 2.4 (High Rank in Community Health)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2=Second Quartile</td>
<td>0= Average in-state quartile rank &gt; 2.5 (Low Rank in Community Health)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3=Third Quartile</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4=Fourth Quartile (Unhealthy)</td>
<td></td>
</tr>
<tr>
<td>Healthcare Fraud Rate</td>
<td>US Department of Health and Human Services, Office of the Inspector General, <a href="https://oig.hhs.gov/exclusions/exclusions_list.asp">https://oig.hhs.gov/exclusions/exclusions_list.asp</a></td>
<td>Continuous</td>
<td>Average county Medicare and Medicaid exclusions on the LEIE as a percentage of the county population. Each exclusion represents one incident of FWA.</td>
<td>0.000 - 9.985</td>
<td>0.000 - 9.985</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social Disorganization</td>
<td>US Census Bureau, American Community Survey, <a href="https://www.census.gov/programs-surveys/acs/data.html">https://www.census.gov/programs-surveys/acs/data.html</a></td>
<td>Continuous</td>
<td>Sum of the average county poverty rate, male rate, Hispanic rate, black rate, and rental vacancy rate.</td>
<td>0.000 - 1.837</td>
<td>0.000 - 1.837</td>
</tr>
<tr>
<td>Poverty Rate</td>
<td>US Census Bureau, American Community Survey, <a href="https://www.census.gov/programs-surveys/acs/data.html">https://www.census.gov/programs-surveys/acs/data.html</a></td>
<td>Continuous</td>
<td>Average number of residents living below the poverty line as a percentage of the total county population.</td>
<td>0.0 - 0.4671</td>
<td>0.000 - 0.4671</td>
</tr>
<tr>
<td>Variable Name</td>
<td>Source</td>
<td>Type</td>
<td>Description</td>
<td>Coding</td>
<td>Recoding</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>-----------------------------------------------------------------------</td>
<td>---------------</td>
<td>-----------------------------------------------------------------------------</td>
<td>----------------------------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Male Population Rate</td>
<td>US Census Bureau, American Community Survey, <a href="https://www.census.gov/programs-surveys/acs/data.html">https://www.census.gov/programs-surveys/acs/data.html</a></td>
<td>Continuous</td>
<td>Average number of residents identifying as male as a percentage of the total count population.</td>
<td>0.000 - 0.7619</td>
<td>0.000 - 0.7620</td>
</tr>
<tr>
<td>Hispanic Population Rate</td>
<td>US Census Bureau, American Community Survey, <a href="https://www.census.gov/programs-surveys/acs/data.html">https://www.census.gov/programs-surveys/acs/data.html</a></td>
<td>Continuous</td>
<td>Average number of residents identifying as Hispanic as a percentage of the total county population.</td>
<td>0.000 - 0.9833</td>
<td>0.000 - 0.9833</td>
</tr>
<tr>
<td>Black Population Rate</td>
<td>US Census Bureau, American Community Survey, <a href="https://www.census.gov/programs-surveys/acs/data.html">https://www.census.gov/programs-surveys/acs/data.html</a></td>
<td>Continuous</td>
<td>Average number of residents identifying as Black as a percentage of the total county population.</td>
<td>0.000 - 0.8607</td>
<td>0.000 - 0.8607</td>
</tr>
<tr>
<td>Rental Vacancy Rate</td>
<td>US Census Bureau, American Community Survey, <a href="https://www.census.gov/programs-surveys/acs/data.html">https://www.census.gov/programs-surveys/acs/data.html</a></td>
<td>Continuous</td>
<td>Average number of vacant rental units as a percentage of the total county population.</td>
<td>0.000 - 42.82</td>
<td>0.000 - 42.82</td>
</tr>
<tr>
<td>County Medicare and Medicare Expenditures</td>
<td>US Department of Health and Human Services, Centers for Medicare and Medicaid Services, <a href="https://data.cms.gov/">https://data.cms.gov/</a></td>
<td>Continuous</td>
<td>Average total Medicaid and Medicare costs per resident in a county.</td>
<td>$2.53 - $3,088,205.96</td>
<td>$2.53 - $3,088,205.96</td>
</tr>
<tr>
<td>Variable Name</td>
<td>Source</td>
<td>Type</td>
<td>Description</td>
<td>Coding</td>
<td>Recoding</td>
</tr>
<tr>
<td>-----------------------------</td>
<td>------------------------------------------------------------------------</td>
<td>---------</td>
<td>-----------------------------------------------------------------------------</td>
<td>--------------</td>
<td>-------------------</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health Insurance Rate</td>
<td>US Census Bureau, American Community Survey, <a href="https://www.census.gov/programs-surveys/acs/data.html">https://www.census.gov/programs-surveys/acs/data.html</a></td>
<td>Continuous</td>
<td>Number of residents reporting having health insurance as a percentage of the total county population.</td>
<td>0.4299 - 0.9724</td>
<td>0.4299 - 0.9724</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>2=Counties in metro areas of 250,000 to 1 million population.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>3=Counties in metro areas of fewer than 250,000 population,</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>4=Urban population of 20,000 or more, adjacent to a metro area.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>5=Urban population of 20,000 or more, not adjacent to a metro area.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>6=Urban population of 2,500 to 19,999, adjacent to a metro area.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>7=Urban population of 2,500 to 19,999, not adjacent to a metro area.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>8=Completely rural or less than 2,500 urban population, adjacent to a metro area.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>9=Completely rural or less than 2,500 urban population, not adjacent to a metro area.</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variable Name</td>
<td>Source</td>
<td>Type</td>
<td>Description</td>
<td>Coding</td>
<td>Recoding</td>
</tr>
<tr>
<td>----------------------------</td>
<td>------------------------------------------------------------------------</td>
<td>----------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------------------</td>
<td>-------------</td>
<td>-------------</td>
</tr>
<tr>
<td>High School Graduate Rate</td>
<td>US Census Bureau, American Community Survey, <a href="https://www.census.gov/programs-surveys/acs/data.html">https://www.census.gov/programs-surveys/acs/data.html</a></td>
<td>Continuous</td>
<td>Average number of high school graduates as a percentage of the total county population.</td>
<td>0.0482 - 0.4460</td>
<td>0.0482 - 0.4460</td>
</tr>
</tbody>
</table>
Additional information about these variables, including additional information on their source can be found below:

- **Community Health:** The community health variable in this study was represented by the health ranking of a county as presented in the County Health Rankings report published by the Robert Wood Johnson Foundation. The County Health Rankings report is the result of a longstanding collaborative relationship between the University of Wisconsin Population Health Institute and the Robert Wood Johnson Foundation. The County Health Rankings report has been published annually for over 20 years, and serves to provide “data, evidence, guidance, and examples to build awareness of the multiple factors that influence health and support community leaders working to improve health and increase health equity,” (RWJF 2020). The rankings take into consideration 73 different measures, including 14 measures of health outcomes, 47 measures of general health factors (such as health behaviors, clinical care, socioeconomic factors, and the physical environment), and 12 measures of demographic factors (such as age, sex, race, and ethnicity). The rankings are used widely in peer-reviewed research on various topics including health disparities (Genusso et al. 2019) and validated as a way to comparatively measure community health (Remington et al. 2015). The rankings order counties within a state using quartiles with counties falling into a 1-4 continuum where 1 represents counties within a state with the healthiest outcomes and 4 represents the counties within the state with the unhealthiest outcomes. For this study, the value of the variable was averaged across the study years and then recoded into a dichotomous variable for the statistical analysis. The recoded variable was a measure where 1 represented the counties with highest health outcome rankings (or with an average in-state health outcomes ranking equal or less than 2.4) and 0 represented the counties with
the lowest health outcomes rankings (or with an average in-state health outcomes ranking equal or greater than 2.5).

- **Healthcare Fraud Rate:** The healthcare fraud measure was created using the 2020 List of Excluded Individuals/Entities (LEIE). This list is maintained by the HHS OIG and is a listing of individuals and entities that have violated a provision of the Social Security Act (and the portions of it that pertain to Medicare and Medicaid), and that were consequently excluded from seeking reimbursement from the programs. The list was collated by county for 2014 through 2018, and the resulting county totals divided by the average population for the county during the same years. The average rate across all counties ranged from 0 to less than 10. The count variable was subsequently recoded into a dichotomous variable where 1 represents the counties reporting at least one incident of healthcare fraud and where 0 represents the counties not reporting at least one incident of healthcare fraud.

In this study, healthcare fraud was also used as an independent variable. It was used as an independent variable to analyze the effect that healthcare fraud had on community health.

Additional independent variables in the analysis included the following:

- **Poverty Rate:** The poverty rate measure was extracted from the American Community Survey (ACS) administered annually by the US Census Bureau, and represents the number of US persons with a household income up to 138% of the poverty line (i.e. the requirement used to determine eligibility for Medicaid). This measure was extracted from the 2014, 2015, 2016, 2017, and the 2018 versions of the ACS and then averaged together. To account for population variation across counties, the averaged poverty amount was then divided by the average county population for the study period. The resulting measure was the rate of the county population living in poverty for the 5-year
period covering 2014 and 2018. The variable was used along with male, Hispanic, Black, and rental vacancy rate to create the social disorganization measure.

- **Male Rate:** Similarly, the male rate measure was extracted from the ACS, and represents the number of US persons in a county that identify as male. This measure was extracted from the 2014, 2015, 2016, 2017, and the 2018 versions of the ACS and then averaged together. To account for population variation across counties, the average number of persons who identify as male was then divided by the average county population for the study period. The resulting measure was the rate of the county population living in poverty for the 5-year period covering 2014 and 2018. The variable was used along with poverty, Hispanic, Black, and rental vacancy rate to create the social disorganization measure.

- **Hispanic Rate:** The Hispanic rate measure was also extracted from the ACS and represents the number of US persons in a county that identify as Hispanic. This measure was extracted from the 2014, 2015, 2016, 2017, and the 2018 versions of the ACS and then averaged together. To account for population variation across counties, the average number of persons who identify as Hispanic was then divided by the average county population for the study period. The resulting measure was the rate of the county population living in poverty for the 5-year period covering 2014 and 2018. The variable was used along with poverty, male, Black, and rental vacancy rate to create the social disorganization measure.

- **Black Rate:** The Black rate measure was also taken from the ACS and represents the number of US persons in a county that identify as Black. This measure was extracted from the 2014, 2015, 2016, 2017, and the 2018 versions of the ACS and then averaged together.
together. To account for population variation across counties, the average number of persons who identify as Black was then divided by the average county population for the study period. The resulting measure was the rate of the county population living in poverty for the 5-year period covering 2014 and 2018. The variable was used along with poverty, male, Hispanic, and rental vacancy rate to create the social disorganization measure.

- **Rental Vacancy Rate:** The rental vacancy measure was also found in the ACS and represents the number of rental properties in a county that are vacant. This measure was extracted from the 2014, 2015, 2016, 2017, and the 2018 versions of the ACS and then averaged together. To account for population variation across counties, the average number of rental vacancies was then divided by the average county population for the study period. The resulting measure was the rate of the county population living in poverty for the 5-year period covering 2014 and 2018. The variable was used along with poverty, male, Hispanic, and Black rate to create the social disorganization measure.

- **Social Disorganization:** The social disorganization variable in this study was a composite measure of the poverty, male, Hispanic, Black, and rental vacancy rates. The measure was created by adding the unweighted continuous variables described above after each was restated to account for multiple years and population. Furthermore, each of these measures were selected because of their consistency with the theoretical underpinnings of social disorganization theory. The theory describes socially disorganized neighborhoods as being heterogenous, mainly poor and male, and transitory (Shaw and McKay 1942). The social disorganization measure covers the 5-year study period and was also used as a continuous variable.
- **Urbanization:** The county urbanization measure was found at the Economic Research Service at the US Department of Agriculture and are generally used to “break county data into finer residential groups, beyond metro and nonmetro, particularly for the analysis of trends in nonmetro areas that are related to population density and metro influence” (USDA 2020). In this study, the measure was used to account for geographical differences in counties, and the impact that location can have on community health and on the emergence of healthcare fraud. The 9-item categorical variable was recoded into a new measure where 1 represents counties in metropolitan areas (initially coded 1-3) and where 0 represents counties in nonmetropolitan areas (initially coded 4-9).

- **County Medicare and Medicaid Expenditures:** The county Medicare and Medicaid expenditure measure was found at the Centers for Medicare and Medicaid (CMS) report on annual program expenditures (CMS 2020). The report details total Medicare and Medicaid expenditures by county and year. This measure was extracted from the 2014, 2015, 2016, 2017, and the 2018 versions of the ACS and then averaged together. To account for population variation across counties, the resulting expenditure average was divided by the average county population for study period. The resulting measure was the County Medicare and Medicaid expenditure amount per resident during the 5-year period covering 2014 and 2018. The variable was used in the analysis as a continuous variable.

In addition to the independent variables, this study included several control variables that were used to qualify the effect that the independent variables had on the dependent variables. The control variables selected for this study included:
• **Health Insurance Rate:** The health insurance variable is a measure also taken from the ACS and represented the number of US persons in a county who identify having health insurance from a public source, including various forms of Medicare and Medicaid. This measure was extracted from the 2014, 2015, 2016, 2017, and the 2018 versions of the ACS and then averaged together. To account for population variation across counties, the average number of persons who identified as having health insurance was then divided by the average county population for the study period. The resulting measure was the County Medicare and Medicaid expenditure amount per resident during the 5-year period covering 2014 and 2018. The variable was used in the analysis as a continuous variable.

• **High School Graduation Rate:** The high school graduation variable is an education measure taken from the ACS and represented the number of US persons in a county who graduated from high school. This measure was extracted from the 2014, 2015, 2016, 2017, and the 2018 versions of the ACS and then averaged together. To account for population variation across counties, the average number of persons who graduated from high school was then divided by the average county population for the study period. The resulting measure was the County Medicare and Medicaid expenditure amount per resident during the 5-year period covering 2014 and 2018. The variable was used in the analysis as a continuous variable.

**Analytical Strategy**

These control variables, along with the independent and dependent variables, were used in an analytical strategy that included spatial, descriptive, and predictive examination of the relationships between social disorganization and healthcare fraud, and between social disorganization and
healthcare fraud on community health. Spatial analysis using ArcMap was used to show the degree to which healthcare fraud was distributed nationally, and to show how key variables were associated with healthcare fraud at the county level. This was done through a focused spatial analysis of a cluster of counties with the highest healthcare fraud rates during the study period, and by highlighting the corresponding spatial associations with the county urbanization, social disorganization, and finally community health. Descriptive analysis of dependent, independent, and control variables was performed using SPSS to determine means, variances, and the range of the data, while bivariate correlations were used to measure the degree of association between variables. Lastly, logistic regression modeling was used to determine the statistical significance of the associative relationships found in the descriptive and spatial analysis.

The logistic models were developed in two sets. The first set included four logistic models that sought to understand the effect of social organization and Medicare and Medicaid expenditures on healthcare fraud. One of the models (Model 1) measured the effects of social disorganization as a composite variable and of urbanization on healthcare fraud while controlling for health insurance and education. The second model sought to measure the impact of Medicaid and Medicare expenditures on this association when controlling for health insurance and education (Model 2). The third (Model 3) and fourth (Model 4) models in the set duplicated the work performed in the first and second model but did so using the individual measures that compose the social disorganization variable. This was done to better understand the social factors driving the effects of social disorganization, especially when those effects were deemed statistically significant. Similarly, the second set of four models sought to understand the effect of healthcare fraud on community health. Consequently, the first model (Model 1) of this set measured the impact of healthcare fraud, social disorganization, and urbanization on community health controlling for health insurance rates and education. Like in the first set, the second model (Model 2) also included Medicare and Medicaid
expenditures in an effort to measure the effect that this variable had on the relationship between the independent variables healthcare fraud, social disorganization, and urbanization, and the dependent variable community health when controlling for health insurance and education. The last two models in this set (Model 3 and Model 4), replicated the efforts of the first models in this set (Model 1 and Model 2), but instead of using the composite measure of social disorganization, they used the individual poverty, male, Hispanic, Black, and rental vacancy rates that composed the social disorganization variable. Like the last two models in the first set, Model 3 and Model 4 sought to understand the social factors driving the effects of social disorganization, especially when those effects were deemed significant both statistically and practically to the association between healthcare fraud community health.

Overall, the hypotheses this analytical strategy sought to test were the following:

- Hypothesis #1: Social disorganization increases healthcare fraud.
- Hypothesis #2: Healthcare fraud decreases community health outcomes.
- Hypothesis #3: Medicare and Medicaid expenditures mediate the effect of healthcare fraud on community health.
CHAPTER 6: RESULTS

Heat Map Analysis: Key Study Variables

The first step in the data analysis was to perform the heat map analysis of key variable data. The results of the analysis are displayed in 6 maps below. Figure 2 below shows the distribution of healthcare fraud rates across counties in the contiguous US. The data show wide areas with very low healthcare fraud rates (<2.5080) (shown in the 2 shades of green) in the west (California), northwest (Oregon and Washington), and in the middle of the country. Clustering of moderate rates (2.5081-4.5065) highlighted in yellow, in the west to southwest the country, but appears alongside a concentration of higher healthcare fraud rates (4.5066-6.9741) can be found in the same area, but these (highlighted in orange) seem to occur at about the same frequency as the clusters of moderate rates and spread widely across the entire territory. Similarly, the counties with the highest healthcare fraud rates (6.9742-9.9850) spread from the northwest across the middle to east of the country relatively evenly, except for some portions of the Midwest that appear to have lower rates (<2.5080) of healthcare fraud.
To further understand the geographic spread of healthcare fraud rates and its potential association with key independent and dependent variables, the state of Texas has been segregated for individual analysis. Texas was chosen because its distribution of healthcare fraud rates appears to mirror that of the nation. There are wide areas of low rates of fraud (<2.5080) in its west and northwest areas, but also a mix of fraud rates from the middle of the state across to the east.

Figure 3 below shows healthcare fraud rates across all 254 counties in the state of Texas. The data in this figure show at least one incident of healthcare fraud in every county across the state with various counties in the north, west, middle, and south with rates below 0.0085. While there is a mixed distribution of moderate (2.2050-4.2171), moderately high (4.2172 – 6.5638), and high (6.5639-9.9247) rates across the north, east, and southeast portion of the states, there appears to be few counties where moderate to high rates of healthcare fraud cluster. The areas
where high rates of healthcare fraud cluster include three contiguous counties in the east, seven contiguous counties in the middle, and three contiguous counties in the south. All three clusters have counties with moderate (2.2050-4.2171) to high (6.5639-9.9247) rates of healthcare fraud. These clusters have also been highlighted in Figure 3.

![Figure 3: Texas Healthcare Fraud Rates by County, 2014-18](image)

The distribution of rates in Figure 3 we subsequently mapped along with other study variables to further understand their relationship at the county community level. Figure 4 shows the healthcare fraud rates mapped with the social disorganization measure. In this map, the data show high levels (1.4681-1.8380) of social disorganization in the south and west of the state among counties bordering Mexico. Moderately high (1.2230-1.4680) to moderate (1.0414-1.2229) social disorganization is also found in the middle west, middle southwest, and north counties of the state. Moderate (1.0414-1.2229), moderately low (0.8777-1.0413), and low
(0.6173-0.8776) social disorganization was found in counties north, middle north, middle northeast, and east of the state. When healthcare fraud rates are analyzed alongside social disorganization, counties with high social disorganization have both high (6.5639-9.9247) and low (0.0000-0.0085) rates of healthcare fraud. The opposite is also true. Counties with low social disorganization have both high (6.5639-9.9247) and low (0.0000-0.0085) rates of healthcare fraud.

When the clusters of highest concentration of healthcare fraud rates found highlighted earlier in Figure 3 were analyzed more closely in Figure 4, the cluster in the north middle of the state showed moderate (1.0414-1.2229) to low (0.6173-0.8776) social disorganization along with the cluster on the east side of the state. Oppositely, the cluster in the south of the state showed moderately high (1.2230-1.4680) to high (1.4681-1.8380) social disorganization.
The same type of spatial analysis was performed on the relationship between healthcare fraud rates and community health. Figure 5 below analyzed the distribution of healthcare fraud rates along with how counties were ranked within the state on its healthcare outcomes. The data in Figure 5 shows that community health in the state of Texas varies widely but relatively evenly. While there are clusters of counties whose health outcomes rank in the lowest quartile (3.51-4.00) of the measure in east, south, and west part of the state, there are also some counties in the north that also fell within that same quartile. Similarly, while some parts in the southeast, southwest, and north show community health rankings in the moderately high (1.26 – 1.75) to high (1.00 - 1.25) quartiles, there were also counties in the same regions that scored lower. When the healthcare fraud rates are analyzed alongside these measures, the data show high levels of healthcare fraud in both counties that rank high (1.000 – 1.5600) or low (3.5201 – 4.000) in health outcomes. Conversely, the data also show low rates of healthcare fraud in both counties that rank that rank high (1.000 – 1.5600) or low (3.5201 – 4.000) in health outcomes.

When the clusters of high rates of healthcare fraud are analyzed, the data show that the cluster in the middle of state has counties that rank in the top two quartiles of the health outcomes rankings. The cluster in the east part of the state has a county in the second quartile of the health outcomes rankings and two that fall in the third quartile of the health outcomes ranking. The southern cluster of counties with high rates of healthcare fraud has counties in the top quartiles of the health outcomes rankings, but also a county in the bottom quartile of the health outcome ranking.
Healthcare fraud rates were also mapped along with Medicare and Medicaid expenditures per resident, and the resulting map is shown in Figure 6. The data in the Figure 6 show low ($3.25 - $15,321.61) to moderate ($56,200.70 - $187,479.96) levels of Medicare and Medicaid expenditures per resident across most of the state. In the north east part of the state, there are five counties that cluster to form an area were the level of Medicare and Medicaid expenditures per resident are moderate ($56,200.70 - $187,479.96)) to moderately high ($187,479.97 - $346,950.11). One county northwest of the state shows a high level ($346,950.12 - $3,088,205.96) of Medicare and Medicaid expenditures per resident. Two counties (one in the northeast part of the state and the other in the southeast part of the state) showed a moderately high ($187,479.97 - $346,950.11) level of Medicare and Medicaid expenditures per resident. The data also show that low or high rates of healthcare fraud can be found in counties with low or
moderately high levels of Medicare and Medicare expenditures per resident.

That is the case when the clusters with highest levels of healthcare fraud are analyzed. The cluster in the middle of the state has counties with low ($3.25 - $15,321.61) levels of Medicare and Medicaid expenditures per resident and counties with moderate ($56,200.70 - $187,479.96)) to moderately high ($187,479.97 - $346,950.11) levels of Medicare and Medicaid expenditures per resident. The cluster in the eastern part of the state has counties with low ($3.25 - $15,321.61) levels of Medicare and Medicaid expenditures per resident and one county with a moderate ($56,200.70 - $187,479.96) level of Medicare and Medicaid expenditures per resident. The same is true of the cluster in the southern part of the state. This cluster has counties with low ($3.25 - $15,321.61) to moderately low ($15,321.62 - $56,200.69) levels of Medicare and Medicaid expenditures per resident. Worth noting is that the county with highest level of Medicare and Medicaid expenditures per resident has a moderately high (4.2172 – 6.5638) rate of healthcare fraud.
The last map created for analysis included healthcare fraud rates and levels of urbanization in the 254 counties in the state of Texas. The resulting data can be found in Figure 7 below. This figure shows high levels of urbanization (1.0000) within the middle southeast, middle northeast, and southeastern parts of the state and clustering in metropolitan areas. The data also shows that these areas (along with the eastern part of the state) also have counties with low levels (0.0000) of urbanization. When healthcare fraud rates were considered, the data showed that low rates of healthcare fraud exist in counties with high (1.0000) or low (0.0000) levels of urbanization. Conversely, the data also showed that high rates of healthcare fraud exist in counties with high (1.0000) to low (0.0000) levels of urbanization. This is the case when analyzing the clusters of counties with the highest rates of healthcare fraud in the state. When the
cluster in the middle of the state is considered it has counties with high (1.0000) levels of urbanization. Similarly, the cluster in the southern portion of the state has counties with high (1.0000) to low (0.0000) levels of urbanization. The cluster in the eastern part of the state appears to be the most consistent with all of its counties at the high (1.000) level of urbanization.

Figure 7: Texas Healthcare Fraud Rates by County and Urbanization, 2014-18

While these maps showed the spatial relationship and trends of healthcare fraud and the key variables of social disorganization, community health, Medicare and Medicaid expenditures per resident, and urbanization, the degree to which these relationships were significant was determined through predictive statistical modeling.
**Descriptive Analysis**

The second step in the data analysis was to conduct a descriptive analysis of the variables used in the study. Descriptive statistics were generated for each of the dependent, independent, and control variables. The results of this analysis can be found in Table 2.

**Table 2**
**Descriptive Statistics of Study Variables**

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Community Health</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.4986</td>
<td>0.5001</td>
</tr>
<tr>
<td>Healthcare Fraud Rate</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.5604</td>
<td>0.4964</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social Disorganization</td>
<td>0.5852</td>
<td>1.8380</td>
<td>0.8815</td>
<td>0.2175</td>
</tr>
<tr>
<td>Poverty Rate</td>
<td>0.0592</td>
<td>0.4671</td>
<td>0.2001</td>
<td>0.0583</td>
</tr>
<tr>
<td>Male Rate</td>
<td>0.4181</td>
<td>0.7619</td>
<td>0.5007</td>
<td>0.0234</td>
</tr>
<tr>
<td>Hispanic Rate</td>
<td>0.0000</td>
<td>0.9833</td>
<td>0.0897</td>
<td>0.1360</td>
</tr>
<tr>
<td>Black Rate</td>
<td>0.0000</td>
<td>0.8607</td>
<td>0.0903</td>
<td>0.1450</td>
</tr>
<tr>
<td>Rental Vacancy Rate</td>
<td>0.0000</td>
<td>0.0648</td>
<td>0.0007</td>
<td>0.0023</td>
</tr>
<tr>
<td>Urbanization</td>
<td>0.0000</td>
<td>1.0000</td>
<td>0.3711</td>
<td>0.4832</td>
</tr>
<tr>
<td>County Medicare and Medicare Expenditures</td>
<td>2.53</td>
<td>3088205.96</td>
<td>5777.62</td>
<td>58213.66</td>
</tr>
<tr>
<td><strong>Control Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health Insurance Rate</td>
<td>0.4299</td>
<td>0.9724</td>
<td>0.8545</td>
<td>0.0640</td>
</tr>
<tr>
<td>High School Graduate Rate</td>
<td>0.0482</td>
<td>0.4460</td>
<td>0.2374</td>
<td>0.0541</td>
</tr>
</tbody>
</table>

The descriptive analysis of the dependent variables show that community health had a mean of 0.5014 indicating that the sample likelihood of high health outcomes were less approximately 50 percent with a standard deviation of 0.5001. The data in Table 2 also show that the sample mean for healthcare fraud rate was 0.5604 indicating that the likelihood of high
healthcare fraud rates was higher than 50 percent with a standard deviation of 0.4964. The composite social disorganization measure in this sample shows that the level of social disorganization among counties ranges from approximately 59 percent in one county to over 183 percent in another. Additionally, the data that within the social disorganization measure: poverty ranged from 6 percent in one county to 47 percent in another; males accounted for 42 percent of the population in one county and 76 percent in another; Hispanics and Blacks represented 0 percent of the population in at least one county, while represented 98 percent and 86 percent of population of another respectively; and that rental units vacant in counties range from 0 percent to approximately 45 percent. Furthermore, the data show urbanization with a mean of 0.3711 indicating that the likelihood that the counties in sample were metropolitan was less that 50 percent with a standard deviation of 0.4832. The data also show that Medicare and Medicaid expenditures in one county was less than $500 per resident, but over $3 million per resident in another. Insurance rates in counties also varied with one county showing that approximately 97 percent of their population was covered by health insurance, while another only shows approximately 43 percent. Lastly, when educational attainment was assessed, the data show that just 5 percent of the population in a county had graduated from high school, while in another county that statistic was closer to 45 percent.

The third step of the data analysis was to understand if the study variables were associated with one another as well as the degree of that association. To that end, bivariate correlations were obtained for all the study variables. The results of those correlations are shown in Table 3 below.
Table 3
Bivariate Correlations of Study Variables

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Community Health</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthcare Fraud Rate</td>
<td>0.0480**</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty Rate</td>
<td>-0.4290**</td>
<td>-0.0230</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male Population Rate</td>
<td>0.0040</td>
<td>-0.1060**</td>
<td>-0.1470**</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic Population Rate</td>
<td>0.0280</td>
<td>-0.0570*</td>
<td>0.0880**</td>
<td>0.1400**</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black Population Rate</td>
<td>-0.1580**</td>
<td>0.1150**</td>
<td>0.4120**</td>
<td>-0.1070**</td>
<td>-0.1070**</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rental Vacancy Rate</td>
<td>-0.0350</td>
<td>-0.0210</td>
<td>0.0450*</td>
<td>0.0750**</td>
<td>0.0450*</td>
<td>0.0220</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urbanization</td>
<td>0.2360**</td>
<td>0.2590**</td>
<td>-0.2490**</td>
<td>-0.1900**</td>
<td>0.0370*</td>
<td>0.1070**</td>
<td>-0.1120**</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>County Medicare and Medicare Expenditures</td>
<td>0.0060</td>
<td>0.0460**</td>
<td>-0.0110</td>
<td>-0.0220</td>
<td>-0.0560**</td>
<td>0.0010</td>
<td>0.0300</td>
<td>0.0680**</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health Insurance Rate</td>
<td>0.1780**</td>
<td>0.0740**</td>
<td>-0.3980**</td>
<td>-0.5110**</td>
<td>-0.3600**</td>
<td>-0.2840*</td>
<td>-0.1230**</td>
<td>0.2030**</td>
<td>0.0020</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>High School Graduate Rate</td>
<td>-0.0247**</td>
<td>-0.0970**</td>
<td>0.1370**</td>
<td>0.1530**</td>
<td>-0.3710**</td>
<td>-0.0420*</td>
<td>-0.0010</td>
<td>-0.3350**</td>
<td>-0.0860**</td>
<td>-0.0560**</td>
<td>1.0000</td>
</tr>
</tbody>
</table>

*p<.05, **p<.001, ***p<.000
The correlations show that there are wide associations between many of the study variables. Focusing the analysis on the key dependent and independent variables of the study, the data show that healthcare fraud is positively and weakly associated with community health ($r=0.048$). The data also show that poverty rate ($r=-0.429$) is negatively and moderately associated with community health. Additionally, the data show that male ($r=0.004$), Hispanic, ($r=0.0280$) and rental vacancy ($r=-0.0490$) rate were not significantly associated with community health, and that Black rate ($r=-0.1580$) negatively and significantly ($p<.01$) associated with community health. However, the latter association was relatively weak. Health insurance rate ($r=0.1780$) and high school graduation rate ($r=-0.0247$) were significantly ($p<.01$) associated with community health, as was urbanization ($r=0.2360$). In contrast, and Medicare and Medicaid expenditures were not significantly associated with community health. However, Medicare and Medicaid expenditures were significantly associated ($p<.01$) with healthcare fraud. While this association was weak ($r=0.0460$), the significant ($p<.01$) association between urbanization and healthcare fraud was stronger ($r=0.2590$). So too were the associations between health insurance rate ($r=0.0740$) and healthcare fraud, and between Black rate ($r=0.1150$) and healthcare fraud. However, while both associations were statistically significant ($p<.01$), both were also moderately weak. The same was true the remaining key variables including male ($r=-.1060$), Hispanic ($r-.0570$), health insurance ($r-.0740$), and high school graduation rate ($r=-.0970$). Though each variable was significantly associated ($p<.01$) with healthcare fraud, the association was relatively weak. The last key variable associations analyzed were between poverty and healthcare fraud, and between rental vacancy rate and healthcare fraud. These correlations yielded non-statistically significant associations.
Predictive Analysis

To understand the nature of the association between the independent and dependent variables in this study, two sets of four logistic regression models were performed. The first set of models is shown in Table 4 and Table 5. In Table 4 below, Model 1 shows that social disorganization is a significant predictor of healthcare fraud when health insurance rate and high school graduation rate are controlled. The model also shows that urbanization is a statistically significant predictor of healthcare fraud when health insurance rate and high school graduation rate are controlled. More specifically, Model 1 shows that counties with high social disorganization are 1.63 times more likely (log odds: 1.6300, p<.05) to have high healthcare fraud rates than counties with low social disorganization when controlling for health insurance and education. In addition, the data show that metropolitan counties are 2.97 more likely (log odds: 2.9760, p<.000) to have high healthcare fraud rates than non-metropolitan counties when health insurance and high school graduation rates are controlled. This model is statistically significant with a chi-square statistic of 224.024 and a p-value of less than 0.000. However, the model is a weak fit for the data with pseudo-R squared measures of 0.0690 (Cox & Snell R Square) and 0.0920 (Nagelkerke R Square) respectively.
Table 4
Social Disorganization, Urbanization, and Medicare and Medicaid Expenditures on Healthcare Fraud Rate: US, 2014-18

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Healthcare Fraud Rate (1=High, 0=Low)</th>
<th>Model #1</th>
<th>CI (95% Exp(B))</th>
<th>Model #2</th>
<th>CI (95% Exp(B))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>SE</td>
<td>Exp(B)</td>
<td>Lower</td>
<td>Upper</td>
</tr>
<tr>
<td>Independent Variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Social Disorganization</td>
<td>0.4890*</td>
<td>0.2190</td>
<td>1.6300*</td>
<td>1.0610</td>
<td>2.5060</td>
</tr>
<tr>
<td>Poverty Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rental Vacancy Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urbanization</td>
<td>1.0910***</td>
<td>0.0860</td>
<td>2.9760***</td>
<td>2.5150</td>
<td>3.5210</td>
</tr>
<tr>
<td>County Medicare and Medicare Expenditures</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control Variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health Insurance Rate</td>
<td>1.7240*</td>
<td>0.7540</td>
<td>5.6090*</td>
<td>1.3190</td>
<td>23.859</td>
</tr>
<tr>
<td>High School Graduate Rate</td>
<td>-0.6700</td>
<td>0.7630</td>
<td>0.9350</td>
<td>0.2100</td>
<td>4.1730</td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.0250*</td>
<td>0.8140</td>
<td>0.1320</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Chi-Square</td>
<td>224.024***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-2 Log likelihood</td>
<td></td>
<td>4081.7</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cox &amp; Snell R Square</td>
<td></td>
<td>0.0690</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nagelkerke R Square</td>
<td></td>
<td>0.0920</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>3139</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p<.05, **p<.001, ***p<.000
Table 4 also shows Model 2 which includes Medicare and Medicaid expenditures as an independent variable. This model shows that social disorganization is a significant predictor of healthcare fraud when controlling for health insurance rates and high school graduation rates. This means that counties with high social disorganization are 1.64 times more likely (log odds: 1.6350, p<.05) to have high healthcare fraud rates than counties with low social disorganization when controlling for health insurance and high school graduation rates. The model also shows that urbanization is a significant predictor of healthcare fraud when health insurance and education are controlled. This means that the metropolitan counties are 2.83 more likely (log odds: 2.8310, p<.000) to have high healthcare fraud rates than non-metropolitan counties when health insurance rates and high school graduation rates are controlled. Additionally, the model shows that Medicare and Medicaid expenditures are a significant predictor of healthcare fraud when health insurance and high school graduation rates are controlled. However, the magnitude of that effect appears marginal. The data show that for every one unit increase in total county Medicare and Medicaid expenditures, the odds of having high healthcare fraud rates is 1.000 (log odds: 1.0000, p<.0000) when health insurance rates and high school graduation rates are controlled. Like Model 1, Model 2 is statistically significant with a chi-square statistic 245.676 and a p-value of less than 0.000. The model also has a weak fit with pseudo-R squared measures of 0.0750 (Cox & Snell R Square) and 0.1010 (Nagelkerke R Square) respectively.

Analyzing the social disorganization factor further, Model 3 in Table 5 shows that the Hispanic and Black rate indicators were significant predictors of healthcare fraud when health insurance and education are controlled. Model 3 shows that for every one unit increase in the county Hispanic rate, the odds of having high county healthcare fraud rates decrease by a factor of 0.37 (log odds: 0.3690, p<.05) when health insurance rates and high school graduation rates are controlled. The opposite is true of Black rates. Model 3 shows that for every one unit increase in the rate of
county’s Black population the odds of that county having high healthcare fraud rates increase by a factor of 3.21 (log odds: 3.2150, p<.000) when controlling for health insurance rates and high school graduation rates. Urbanization in this model is also a statistically significant predictor of healthcare fraud. Model 3 shows that metropolitan counties are 2.88 times more likely (log odds: 2.8810, p<.000) to have high county healthcare fraud rates than non-metropolitan counties when health insurance rates and high school graduation rates are controlled. This model too was statistically significant with a chi-square value of 433.502 and a p-value of less than 0.000. However, it also had weak model fit with a Cox & Snell R square statistic of 0.0810 and a Nagelkerke R square statistic of 0.1080.
Table 5
Social Disorganization Indicators, Urbanization, and Medicare and Medicaid Expenditures on Healthcare Fraud Rate: US, 2014-18

<table>
<thead>
<tr>
<th></th>
<th>Dependent Variable</th>
<th>Model #3 CI (95% Exp(B))</th>
<th>Model #4 CI (95% Exp(B))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Healthcare Fraud Rate (1=High, 0=Low)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Independent Variables</td>
<td></td>
<td>B  SE  Exp(B)  Lower  Upper</td>
<td>B  SE  Exp(B)  Lower  Upper</td>
</tr>
<tr>
<td>Social Disorganization</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty Rate</td>
<td></td>
<td>0.6230  0.8590  1.8640  0.3470  10.031</td>
<td>0.7160  0.8600  2.0450  0.3790  11.038</td>
</tr>
<tr>
<td>Male Population Rate</td>
<td></td>
<td>-2.6580  2.1690  0.0700  0.0010  4.9230</td>
<td>-2.2500  2.1700  0.1050  0.0010  7.4160</td>
</tr>
<tr>
<td>Hispanic Population Rate</td>
<td></td>
<td>-0.9960*  0.3440  0.3690*  0.1880  0.7250</td>
<td>-1.0340*  0.3460  0.3550*  0.1800  0.7010</td>
</tr>
<tr>
<td>Black Population Rate</td>
<td></td>
<td>1.1680***  0.3230  3.2150***  1.7070  6.0540</td>
<td>1.1750***  0.3220  3.2380***  1.7210  6.0930</td>
</tr>
<tr>
<td>Rental Vacancy Rate</td>
<td></td>
<td>0.0060  0.0090  1.0060  0.9880  1.0240</td>
<td>0.0060  0.0090  1.0060  0.9890  1.0240</td>
</tr>
<tr>
<td>Urbanization</td>
<td></td>
<td>1.0580***  0.0910  2.8810***  2.4120  3.4410</td>
<td>1.0100***  0.0910  2.7450***  2.2950  3.2820</td>
</tr>
<tr>
<td>County Medicare and Medicaid Expenditures</td>
<td></td>
<td>0.0000***  0.0000  1.0000***  1.0000  1.0000</td>
<td></td>
</tr>
<tr>
<td>Control Variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health Insurance Rate</td>
<td></td>
<td>0.5420  0.8310  1.7200  0.2900  10.203</td>
<td>0.6310  0.9110  1.8800  0.3150  11.203</td>
</tr>
<tr>
<td>High School Graduate Rate</td>
<td></td>
<td>-1.4170  0.8310  0.2420  0.0480  1.2360</td>
<td>-0.8730  0.8400  0.4180  0.0810  2.1660</td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td>0.8990  1.7730  2.4560</td>
<td>0.4150  1.7780  1.5140</td>
</tr>
<tr>
<td>Chi-Square</td>
<td></td>
<td>263.681***</td>
<td>286.261***</td>
</tr>
<tr>
<td>-2 Log likelihood</td>
<td></td>
<td>4042.0</td>
<td>4019.4</td>
</tr>
<tr>
<td>Cox &amp; Snell R Square</td>
<td></td>
<td>0.0810</td>
<td>0.0870</td>
</tr>
<tr>
<td>Nagelkerke R Square</td>
<td></td>
<td>0.1080</td>
<td>0.1170</td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>3139</td>
<td>3139</td>
</tr>
</tbody>
</table>

*p<.05, **p<.001, ***p<.000
Table 5 also shows that introducing Medicare and Medicaid expenditures to an analysis that utilizes social disorganization indicators does not impact the statistical significance of Hispanic rate, Black rate, and urbanization in predicting the likelihood of healthcare fraud when controlling for health insurance and education. Model 4 shows that for every one unit increase in a county’s Hispanic rate the odds of having high county healthcare fraud rates decrease by a factor of approximately 0.36 (log odds: 0.3550, p<.05) when health insurance rates and high school graduation rates are controlled. The model also shows that for every one unit increase in a county’s Black population the odds of having high county healthcare fraud rates increase by a factor of approximately 3.24 (log odds: 3.2380, p<.000) when controlling for health insurance rates and high school graduation rates. Furthermore, this model also shows that Medicare and Medicaid expenditures were a statistically significant predictor of healthcare fraud rates when health insurance and education are controlled. The model showed that for every one unit increase in county Medicare and Medicaid expenditures the odds of having high healthcare fraud rate increase by a factor of 1.00 (log odds: 1.0000, p<.000) when health insurance rates and high school graduation rates are controlled. However, again, the magnitude of that effect appears marginal. Like the others, Model 4 was statistically significant with a chi-square value of 447.571 and a p-value of less than 0.000, but the model was also a weak fit with a Cox & Snell R square of 0.0870 and a Nagelkerke R square of 0.1080.

The second set of models is shown in Table 6 and Table 7. This set of models was designed to show the effect of healthcare fraud, social disorganization, and urbanization on community health when controlling for health insurance and education. In Table 6, Model 1 shows that healthcare fraud is not a significant predictor of community health when health insurance and education are controlled. The model does show that social disorganization and urbanization are significant predictors of community health when health insurance and education are controlled. The data show
that counties with high social disorganization are approximately 0.05 times less likely (log odds: 0.0480, $p<.000$) at having high community health outcomes than counties with low social disorganization when controlling for health insurance and high school graduation rates. The data also show that metropolitan counties are approximately 2.13 times more likely (log odds: 2.1320, $p<.000$) to have high community health outcomes than non-metropolitan counties when controlling for health insurance rates and high school graduation rates. The data also show that while Model 1 was statistically significant with a chi-square statistic of 513.294 and a $p$-value of less than 0.000, the model was weak fit for the data with pseudo-$R$ square values of 0.1510 (Cox & Snell $R$ square) and 0.2010 (Nagelkerke $R$ square).
Table 6
Healthcare Fraud Rate, Social Disorganization, Urbanization, and Medicare and Medicaid Expenditures on Community Health: US, 2014-18

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Model #1</th>
<th>CI (95% Exp(B))</th>
<th>Model #2</th>
<th>CI (95% Exp(B))</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B</td>
<td>SE</td>
<td>Exp(B)</td>
<td>Lower</td>
</tr>
<tr>
<td>Healthcare Fraud Rate</td>
<td>-0.0500</td>
<td>0.0810</td>
<td>0.9520</td>
<td>0.8120 1.1150</td>
</tr>
<tr>
<td>Social Disorganization</td>
<td>-3.0390***</td>
<td>0.2570</td>
<td>0.0480***</td>
<td>0.0290 0.0790</td>
</tr>
<tr>
<td>Poverty Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Black Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rental Vacancy Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urbanization</td>
<td>0.7570***</td>
<td>0.0890</td>
<td>2.1320***</td>
<td>1.7920 2.5360</td>
</tr>
<tr>
<td>County Medicare and Medicare Expenditures</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>Control Variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Health Insurance Rate</td>
<td>-0.8160</td>
<td>0.8060</td>
<td>0.4420</td>
<td>0.0910 2.1460</td>
</tr>
<tr>
<td>High School Graduate Rate</td>
<td>-11.108***</td>
<td>0.8450</td>
<td>0.0000***</td>
<td>0.0000 0.0000</td>
</tr>
<tr>
<td>Intercept</td>
<td>5.7490***</td>
<td>0.8960</td>
<td>313.89***</td>
<td>513.294***</td>
</tr>
<tr>
<td>Chi-Square</td>
<td>5.7610***</td>
<td>0.8960</td>
<td>317.72***</td>
<td>514.373***</td>
</tr>
<tr>
<td>-2 Log likelihood</td>
<td>3838.3</td>
<td>3837.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cox &amp; Snell R Square</td>
<td>0.1510</td>
<td>0.1510</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nagelkerke R Square</td>
<td>0.2010</td>
<td>0.2020</td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>3139</td>
<td>3139</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*p<.05, **p<.001, ***p<.000
Table 6 also shows the impact of Medicare and Medicaid expenditures on the relationship between healthcare fraud, social disorganization, and community health when controlling for health insurance and education. In Model 2, the data show that Medicare and Medicaid expenditures were not a significant predictor of community health when controlling for health insurance and education. The model also shows that the addition of Medicare Medicaid expenditures did not impact the non-significant effect of healthcare fraud on community health when controlling for health insurance and education. The addition of Medicare and Medicaid expenditures also did not impact the relationship between social disorganization and community health, nor the relationship between urbanization and community health when controlling for health insurance education in both. Subsequently, Model 2 shows that counties with high social disorganization are approximately 0.05 times less likely (log odds: 0.0480, p<.000) to have high community health outcomes than counties with low social disorganization when controlling for health insurance rates and high school graduation. Additionally, Model 2 shows that metropolitan counties are approximately 2.14 times more likely (log odds: 2.1380, p<.000) to have high county health outcomes than non-metropolitan counties when controlling for health insurance rates and high school graduation rates. Like Model 1, Model 2 in Table 6 was statistically significant with a chi-square measure of 514.373 and a p-value less than 0.000. However, Model 2 was also a weak fit for the data as shown by pseudo-R square values of 0.1510 (Cox & Snell R square) and 0.2020 (Nagelkerke R square).
The third model in this set is shown in Table 7 and sought to understand the social factors that drove the significant relationship between social disorganization and community health when controlling for health insurance and education. Model 3 shows that healthcare fraud is not a significant predictor of community health when controlling for health insurance and education. The data in Model 3 also show that poverty rate was a significant predictor of community health when controlling for health insurance and education. The data show that for every one unit increase in a county’s poverty rate, the odds of having high community health outcomes was approximately 0.00 (log odds: 0.0000, p<.000) when controlling for health insurance rates and high school graduation rates. This means that while poverty was significant predictor of community health its impact was marginal for every one unit increase at the county level when controlling for health insurance and education. Additionally, Model 3 shows that urbanization remained a significant predictor of community health when controlling for health insurance and education. This means that metropolitan counties are approximately 1.58 times more likely (log odds: 1.5790, p<.000) to have high community health outcomes than non-metropolitan counties when controlling for health insurance and education. Furthermore, the data show that like previous models in this set, Model 3 in Table 7 was statistically significant with a chi-square measure of 821.322 and a p-value less than 0.000. The model was a better fit for the data than the previous models, but still was weak fit for the data with pseudo-R square values of 0.2310 (Cox & Snell R square) and 0.3070 (Nagelkerke R square).
Table 7
Healthcare Fraud Rate, Social Disorganization Indicators, Urbanization, and Medicare and Medicaid Expenditures on Community Health: US, 2014-18

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Community Health (1=High, 0=Low)</th>
<th>Model #3</th>
<th>CI (95% Exp(B))</th>
<th>Model #4</th>
<th>CI (95% Exp(B))</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Healthcare Fraud Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>0.0210</td>
<td>0.0860</td>
<td>1.0210</td>
<td>0.8630</td>
<td>1.2080</td>
</tr>
<tr>
<td>SE</td>
<td>0.0860</td>
<td></td>
<td></td>
<td>0.0860</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>1.0210</td>
<td></td>
<td>1.0240</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>0.8630</td>
<td></td>
<td>0.8660</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>1.2080</td>
<td></td>
<td>1.2110</td>
<td></td>
</tr>
<tr>
<td>Social Disorganization</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Poverty Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-18.095***</td>
<td>1.0880</td>
<td>0.0000***</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>SE</td>
<td>1.0880</td>
<td></td>
<td></td>
<td>1.0870</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>0.0000***</td>
<td></td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>0.0000</td>
<td></td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>0.0000</td>
<td></td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Male Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-4.0530</td>
<td>2.4000</td>
<td>0.0170</td>
<td>0.0000</td>
<td>1.9180</td>
</tr>
<tr>
<td>SE</td>
<td>2.4000</td>
<td></td>
<td></td>
<td>2.4010</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>0.0170</td>
<td></td>
<td>0.0170</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>0.0000</td>
<td></td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>1.9180</td>
<td></td>
<td>1.8840</td>
<td></td>
</tr>
<tr>
<td>Hispanic Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-0.2910</td>
<td>0.3840</td>
<td>0.7470</td>
<td>0.3520</td>
<td>1.5860</td>
</tr>
<tr>
<td>SE</td>
<td>0.3840</td>
<td></td>
<td></td>
<td>0.3840</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>0.7470</td>
<td></td>
<td>0.7560</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>0.3520</td>
<td></td>
<td>0.3560</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>1.5860</td>
<td></td>
<td>1.6040</td>
<td></td>
</tr>
<tr>
<td>Black Population Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-0.6790</td>
<td>0.3910</td>
<td>0.5070</td>
<td>0.2350</td>
<td>1.0920</td>
</tr>
<tr>
<td>SE</td>
<td>0.3910</td>
<td></td>
<td></td>
<td>0.3910</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>0.5070</td>
<td></td>
<td>0.5050</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>0.2350</td>
<td></td>
<td>0.2340</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>1.0920</td>
<td></td>
<td>1.0870</td>
<td></td>
</tr>
<tr>
<td>Rental Vacancy Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-0.0050</td>
<td>0.0100</td>
<td>0.9950</td>
<td>0.9760</td>
<td>1.0140</td>
</tr>
<tr>
<td>SE</td>
<td>0.0100</td>
<td></td>
<td></td>
<td>0.0100</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>0.9950</td>
<td></td>
<td>0.9950</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>0.9760</td>
<td></td>
<td>0.9760</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>1.0140</td>
<td></td>
<td>1.0140</td>
<td></td>
</tr>
<tr>
<td>Urbanization</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>0.4570***</td>
<td>0.0960</td>
<td>1.5790***</td>
<td>1.3070</td>
<td>1.9070</td>
</tr>
<tr>
<td>SE</td>
<td>0.0960</td>
<td></td>
<td></td>
<td>1.9180</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>1.5790***</td>
<td></td>
<td>1.586***</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>1.3070</td>
<td></td>
<td>1.3120</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>1.9070</td>
<td></td>
<td>1.9150</td>
<td></td>
</tr>
<tr>
<td>Control Variables</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>County Medicare and Medicare Expenditures</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>0.0000</td>
<td>0.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>SE</td>
<td>0.0000</td>
<td></td>
<td></td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>1.0000</td>
<td></td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>1.0000</td>
<td></td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>1.0000</td>
<td></td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Health Insurance Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-1.6810</td>
<td>1.0280</td>
<td>0.1860</td>
<td>0.0250</td>
<td>1.3970</td>
</tr>
<tr>
<td>SE</td>
<td>1.0280</td>
<td></td>
<td></td>
<td>1.0280</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>0.1860</td>
<td></td>
<td>0.1860</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>0.0250</td>
<td></td>
<td>0.0250</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>1.3970</td>
<td></td>
<td>1.3940</td>
<td></td>
</tr>
<tr>
<td>High School Graduate Rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>-7.9870***</td>
<td>0.9340</td>
<td>0.0000***</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>SE</td>
<td>0.9340</td>
<td></td>
<td></td>
<td>0.9350</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>0.0000***</td>
<td></td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td>0.0000</td>
<td></td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td>0.0000</td>
<td></td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>8.9070***</td>
<td>2.0050</td>
<td>7385.5***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SE</td>
<td>2.0050</td>
<td></td>
<td></td>
<td>2.0060</td>
<td></td>
</tr>
<tr>
<td>Exp(B)</td>
<td></td>
<td>7385.5***</td>
<td></td>
<td>7560.8</td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td></td>
<td></td>
<td></td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Upper</td>
<td></td>
<td></td>
<td></td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Chi-Square</td>
<td></td>
<td>821.322***</td>
<td></td>
<td>822.507***</td>
<td></td>
</tr>
<tr>
<td>-2 Log likelihood</td>
<td></td>
<td>3530.2</td>
<td></td>
<td>3529</td>
<td></td>
</tr>
<tr>
<td>Cox &amp; Snell R Square</td>
<td></td>
<td>0.2300</td>
<td></td>
<td>0.2310</td>
<td></td>
</tr>
<tr>
<td>Nagelkerke R Square</td>
<td></td>
<td>0.3070</td>
<td></td>
<td>0.3070</td>
<td></td>
</tr>
<tr>
<td>N</td>
<td></td>
<td>3139</td>
<td></td>
<td>3139</td>
<td></td>
</tr>
</tbody>
</table>

*p<.05, **p<.001, ***p<.000
The last model in this set (Model 4) shows the impact of Medicare and Medicaid expenditures on the relationship between the individual social disorganization variables, urbanization, healthcare fraud, and community health when controlling for health insurance and education. Similar to Model 3 in this set, Model 4 shows that healthcare fraud is not a significant predictor of community health when controlling for health insurance and education. The data also show that Medicare and Medicaid expenditures did not have significant effect on community health, nor on the relationship between the individual social disorganization measures, urbanization, and community health when controlling for health insurance and education. Poverty rate was again a significant predictor of community health in Model 4 when controlling for health insurance and education. This model showed that for every one unit increase in a county’s poverty rate, the odds of having high community health outcomes was approximately 0.00 (log odds: 0.0000, p<.000) when controlling for health insurance rates and high school graduation rates. Urbanization in this model also remained a significant predictor of community health when controlling for health insurance and education. The data show that metropolitan counties are approximately 1.59 more likely (log odds: 1.5860, p<.000) to have high community health outcomes than non-metropolitan counties when controlling for health insurance and education. Lastly, and as the other models in this set, Model 4 was statistically significant with a chi-square measure of 827.507 and a p-value less than 0.000. The model was still a weak fit for the data with pseudo-R square values of 0.2310 (Cox & Snell R square) and 0.3070 (Nagelkerke R square).
CHAPTER 7: DISCUSSION

The data analysis performed in this study resulted in several findings that provide insights into the relationship among social disorganization, healthcare fraud, and community health. These insights were evident across the entire analysis and collectively provide a more accurate picture of healthcare fraud in the US, the social factors that set the conditions for its emergence, and the impact it can have on community health. The first of these insights is that social disorganization is a significant predictor of healthcare fraud when controlling for health insurance and education. This finding was first evident in the spatial analysis which showed that while some healthcare fraud occurs in socially organized counties, some of the highest rates of healthcare fraud were found in moderately to highly socially disorganized counties. This finding suggests that an association between social disorganization was evident and that the association would have to be validated by the statistical analysis. The statistical analysis confirmed this assertion and showed that being in a socially disorganized community does increase the likelihood of experiencing healthcare fraud. This finding further suggests that healthcare fraud is significantly impacted by social cohesion (Sampson 1996) and social capital (Bursik and Grasmick 1988) when controlled for health insurance and education (at least not at the community level). This also suggests that because neighborhood factors may be a positive predictor of healthcare fraud, the individual factors that compose it in a more targeted population group (specifically providers) may show a similar outcome. This line of reasoning and inquiry draws on the literature describing subcultures (Anderson 1999), and their ability to create opportunities for control of social structures that benefit communities where they exist. It also follows extant findings in the literature that point to a healthcare culture that reveres healthcare providers (Meyers 2017, Rossoff 1989, Price and Norris 2009), and perpetuates a complex and opaque system designed to address a public need but one that
is also rife with fraud (Sparrow 1996). In short, because social disorganization did impact healthcare fraud as it has been theorized to impact other crimes (Shaw and McKay 1942), further research can be done to determine if social disorganization in the context of a subculture further impacts healthcare fraud.

The significant effects between social disorganization and healthcare fraud when controlling for health insurance and education remained when Medicare and Medicaid expenditures were added to the relationship. Additionally, adding the public insurance expenditures variables showed both that Medicare and Medicaid on its own was a significant predictor of healthcare fraud when controlled for health insurance and education, and that it may not mediated the effect of social disorganization on healthcare fraud when controlling for health insurance and education. The association between Medicare and Medicaid expenditures and healthcare fraud was also evident but unclear in the geographic analysis because of seemingly contradictory results. The map shows that while the highest levels of healthcare fraud may occur in counties with low levels of public insurance program expenditures, moderate to high levels of healthcare fraud can also occur in counties with high levels of public health program expenditures. This finding is confirmed by the odds ratio value of 1.0000 (p<.000) and suggests that the level of Medicare and Medicaid expenditures may not only be associated with different levels of healthcare fraud, but also serve as a stable source of revenue for fraudulent schemes regardless of the level of expense in the county. In short, Medicare and Medicaid may simply be a source of opportunities for fraudulent activities across US counties irrespective of the public health needs these programs are intended and funded to address. It is as if Medicare and Medicaid are so ubiquitous and pervasive in American society that its impact of healthcare fraud is not mediated by the amount of expenditures in a particular county. Furthermore, this finding is significant because of its policy implications, including suggesting that increases or decreases in government program funding will only have a marginal
impact on healthcare fraud. In other words, the quintessential government strategy at combatting fraud in a program by modifying its funding, may not be an effective tool for addressing this problem. The problem may be too big and too invisible to be addressed in this manner. Therefore, an alternative strategy, such as one aimed at providers and the invisibility in the system, may be more effective.

This concept of invisibility was also evident throughout this analysis. While it was not entirely clear in the spatial analysis, it was made clear in the statistical analysis when examining the effect of urbanization on healthcare fraud. This analysis showed that healthcare fraud may be more prevalent in non-metropolitan counties than in metropolitan counties and suggests that urbanization permits social organization and increases the incidence of crime and deviance. This finding is slightly antithetical to the established position that urbanization creates the conditions in which crime may emerge (Shaw and McKay 1942), but it also may not provide the entire picture of the relationship between urbanization and healthcare fraud. For example, this finding does not consider the factor of invisibility (through process, jargon, and complexity) of healthcare fraud. In other words, while one can make the argument that urbanization leads to additional resources for identifying and combatting healthcare fraud, including law enforcement and administrative assets that may prevent fraud from emerging in high numbers, the likely explanation is that urbanization may simply make it harder for fraud to be identified. The volume and financial incentives associated with health care and healthcare fraud in population centers may drive claims processing capacity to such high levels that a focus on healthcare fraud is just a complete nuisance (Cady 2007, Sparrow 2008). One can certainly argue that accounting for population differences in metropolitan and non-metropolitan areas may minimize the potential impact of volume on healthcare fraud rates. While that may be possible, it may still not be enough to understand the added complexity in examining these schemes in urban centers because of the additional resources that perpetrators can also bring to
bear on their schemes. In short, additional research should be conducted on the variation of healthcare fraud in metropolitan and non-metropolitan areas to better understand how geographic location impacts healthcare fraud rates.

Before discussing the impact of healthcare fraud on community health, and the impact that Medicare and Medicaid expenditures may have on this relationship, it is worth noting that several social disorganization indicators were also significant predictors of healthcare fraud. Parsing out these effects, the analysis showed that increases in the percentage of the population who identified as Black increased the likelihood of high healthcare fraud rates in the counties when controlling for health insurance and education. The analysis also showed that increasing the percentage of the Hispanic population showed the opposite effect on healthcare fraud when controlling for the same variables. Further, while the effects of these variables were marginal, their significance may be an indication of the racial and ethnic differences associated with healthcare fraud. While it is far from accurate to say that being a Black county increases the likelihood of high rates of healthcare fraud when controlling for health insurance and education, or that being a Hispanic county decreases the likelihood of high rates of healthcare fraud when controlling for health insurance and education, these significant relationships to healthcare fraud may point to race-specific and ethnicity-specific factors that should be explored further. For example, the effect of race in the relationship could be mediated by other factors such as housing, transportation, or utility of healthcare services. Likewise, the effect of ethnicity in the relationship with healthcare fraud may be mediated by geographic location, social mobility, or even immigration status. Thus, while significant, these individual variables need to be explored further to understand their nuanced relationship with healthcare fraud. Nonetheless, their results are significant not only because of the additional lines of research that they provide, but also because of the additional insight they can provide on the public narratives pertaining to Medicare, Medicaid, and welfare payments, which conflate race and ethnicity as part

Additionally, this study revealed that healthcare fraud is not a significant predictor of community health when controlling for health insurance and education. This finding indicates that the association between healthcare fraud and community health is one not directly observable and may require looking at additional mediating and moderating relationships to determine if an association even exists. One of the mediating relationships was the one undertaken in this study, which examined the mediating effects of Medicare and Medicaid expenditures on the relationship between healthcare fraud and community health when controlling for health insurance and education. This study not only revealed that Medicare and Medicaid expenditures are not a significant predictor of community health when controlling for health insurance and education, but also that these expenditures do not mediate the effects of the relationship between healthcare fraud and community health when controlling for health insurance and education. This finding is significant because it opposes the prevailing and anecdotal understanding of the relationship among healthcare fraud, Medicare and Medicaid expenditures, and community health. While it makes sense intuitively to believe that healthcare fraud decreases community health by not making available funds, especially Medicare and Medicaid funding, that could otherwise be used for healthcare services, this finding suggests that this may not be the case. This is not to say that lack of funding does not lead to decreases in community health; the existing literature clearly outlines that it does (Kawachi and Berkman 2014). However, what this finding proposes is that Medicare and Medicaid healthcare fraud recoveries may not be as important to community health as once thought. It is not because recovering stolen funding may not be important, especially from the legal and fiduciary standpoint of government agencies (OIG 2020); but because the comparatively small amounts of the recoveries and the overall size of healthcare, may simply overshadow the effects that these
recoveries may have on community health. This assertion will require further study, but at the very least shows that the moderating effect that Medicare and Medicaid expenditures may have had on the relationship between healthcare fraud and community health may not be as direct as anticipated.

This study also revealed that social disorganization decreases community health when controlling for health insurance and high school graduation rates. This finding is significant because it not only validates the findings in the geographical analysis that showed an association between social disorganization and community health, but more importantly because it quantitatively supports several findings in the literature pertaining to social cohesion, social capital, and community health (Kawachi and Berkman 2014). More specifically, this finding suggests that as social disorganization increases, social cohesion and social capital may also decrease, and thereby influence a decrease in community health when controlling for health insurance and education. Subsequently, this means that community health outcomes may not only be tied to social determinants, such as poverty, housing, and gender, but also to the social ties linked with these factors. While a connection between these social ties, community health, and healthcare fraud is outside the scope of this study, one can argue that it does present and opportunity for further research. A focused examination of these social ties can show how these contribute to changes in community health, including those between patients and providers who genuinely seek to address the healthcare needs of the community, but also those between patients and providers who look to help themselves (Roudtree and Warner 2006).

Before discussing the effects that individual social disorganization variables had on community health and their impact on the relationship of healthcare fraud and community health, it is worth noting that this study also showed that urbanization was a significant predictor of community health when controlling for health insurance and education. This finding supports the
idea that metropolitan areas may have additional health care resources that impact community health, compared to non-metropolitan areas. The finding also shows that the effect of urbanization on community health is significant when controlling for health insurance and education. The data show that when county social disorganization increases the likelihood of high community health outcomes decreases when controlling for health insurance and high school graduation rates. Therefore, urbanization, while a significant predictor of community health when controlling for health insurance and education, only slightly impacts community health outcomes.

In contrast, when individual social disorganization variables were examined for effects on community health, one of these showed significant and important effects on community health when controlling for health insurance and education. This study showed that poverty was a significant predictor of community health when controlling for health insurance rates and high school graduation rates. The study showed that increasing poverty slightly decreased the likelihood of high community health outcomes when controlling for health insurance and education. This finding is significant because first it shows how poverty was a driver of social disorganization in the set of models that showed the effects of healthcare fraud on community health when controlling for health insurance and education, but secondly because it highlights the importance of community factors on community health outcomes. Furthermore, they highlight the role that social cohesion and social capital can play on these (Kawachi and Berkman 2014), through the social ties that can be lost (Roudtree and Warner 2006) or gained (Anderson 1999) to social disorganization.

Furthermore, when analyzing the effect of Medicare and Medicaid expenditures on the relationship between healthcare fraud and community health, the data showed that these expenditures did not impact the significance of the relationship when controlling for health insurance and education. Adding Medicare and Medicaid expenditures to the analysis only had a marginal mediating effect on the significant relationships between poverty, urbanization, and
community health when controlling for health insurance and education. This finding is consistent not only with the analysis performed on community health with the composite social disorganization measure, but also with the analysis performed on the impact of social disorganization on healthcare fraud.

It is also worth mentioning that replacing the composite social disorganization measure in the analysis of the relationship between healthcare fraud and community health and in the relationship between social disorganization and healthcare fraud may have changed the interaction of the data. Adding variables to the analysis increased the degrees of freedom in the model, and as result the model fit. In short, the individual social disorganization indicators may have shown significant relationships worthy of further study (e.g., the positive significant effect of poverty on community health when controlling for health insurance and education, etc.), but attempting to interpret them here are outside the scope of this study. This does not mean that pursuing to understand the effects of these factors on community health and healthcare fraud are not worthwhile efforts, they are. They are just not the focus of this study. The focus of this study was to understand the relationship among social disorganization, healthcare fraud, and community health. The analysis was performed with that purpose, and with the following hypotheses in mind for testing:

- Hypothesis #1: Social disorganization increases healthcare fraud.
- Hypothesis #2: Healthcare fraud decreases community health outcomes.
- Hypothesis #3: Medicare and Medicaid expenditures mediate the effect of healthcare fraud on community health.

The results and subsequent interpretation of those results showed that social disorganization as a composite measure does marginally increase healthcare fraud when controlling for health insurance and education. The data also showed that some of the individual social disorganization
indicators (e.g., ethnicity, race, etc.) decreased healthcare fraud when controlling for health insurance and education. Secondly, the results of this study showed that healthcare fraud does not decrease community health outcomes when controlling for health insurance and education. This is a new finding currently not present in the literature. As discussed earlier, the existing literature largely addresses the strategies needed to identify and combat healthcare fraud (Ekin et al. 2013, Berwick and Hackbarth 2013), few have focused on how healthcare fraud may impact health outcomes (Hannigan 2006, Kyriakakis 2015). The present study adds to the literature that examines how healthcare fraud impacts health outcomes, and uniquely details the qualitative nature of that impact. In fact, the data in this study showed that healthcare fraud may not impact health community outcomes at all when controlling for health insurance and education.

Lastly, and related to the finding just described, the results of this study showed that Medicare and Medicaid expenditures do not mediate the effect of healthcare fraud on community health when controlling for health insurance and education. Indeed, the study showed that the relationship between Medicare and Medicaid expenditures and community health may be more unclear than currently addressed in the literature. One reason may be the increasing number of sociomedical factors that impact individual and community health outcomes, including (as were shown in this study) urbanization and social disorganization. In other words, having health insurance is important (Germov 1995, Kennedy and Hendricks 2016), but it is not enough for high health outcomes.
CHAPTER 8: CONCLUSION

After describing what healthcare fraud is and how it has emerged in the US healthcare system, this study sought to understand the relationship between healthcare fraud and community health using social disorganization as its theoretical framework. Not only did the study produced concrete answers to the hypotheses tested, but it also produced several additional findings that have policy implications and present opportunities for additional research. The biggest finding of this study is that the public health insurance system in the US is “easy money” for perpetrators. The size, complexity, invisibility, and its trusted nature make it the perfect target for perpetrators focused on high-margin schemes. Above all, the lack of transparency of the US system and the deference given by society to its providers, make it an ideal system to settle and run long-term schemes that are embedded in complicated processes and activities aimed at increasing the volume of claims and the payments that result from it.

More so, this study has shown that the impact of healthcare fraud on community health is minimal, and certainly not as valuable as the sum generated from maintaining a system that processes claims that would otherwise stop it. Therefore, effects on community health may not be as valuable as this study originally anticipated and may on its own not change the calculus on the importance of addressing healthcare fraud. Because healthcare fraud has been shown to not have a significant effect on community health, then it may not be an effective motivating factor in reducing healthcare fraud in the system. Instead, this study has shown that larger factors beyond the size and scope of social disorganization may impact healthcare fraud and community health. These may include institutional and systemic issues that have created a healthcare system that may be unaffected by community factors, and as such are not only too big to fail, but too valuable to be allowed to fail. On the one hand the healthcare system serves the basic health needs of Americans,
but on the other hand it also serves the insatiable needs of those who seek to defraud it.

This finding and those detailed in this study have significant implications for policymakers and those who administer public health insurance programs. First, increasing the amount of taxpayer money spent on these programs, while needed to provide services to an increasing patient base, will not improve community health nor decrease fraudulent activities. The system appears to be too large for an increase in funding to have a significant impact on both measures. Furthermore, because of the lack of impact on community health, the motivation to combat healthcare fraud beyond those ratified by laws and regulations does not exist. Therefore, perpetrators may be free to continue defrauding a system that the public already suspects and dislikes. Consequently, rather than increasing funding to combat healthcare fraud, policymakers and administrators should focus on transparency and on simplifying the system. While measures such as price controls and universal insurance may be unachievable for political reasons, initiatives aimed at simplifying healthcare pricing and at improving quality of care provided (as opposed to quantity of care provided) may be worthwhile places to start.

Secondly, and related to the first implication, this study also has policy implications for providers and their billing practices. While this study anticipated finding a significant relationship between healthcare fraud and community health, and one that showed how decreases in healthcare fraud would increase healthcare outcomes, such a finding did not materialize. Therefore, it cannot be used to motivate providers who skirt the rules and defraud the system. However, the study did find that absent a community health incentive for providers willing to place their economic interest above the well-being of patients, policymakers should instead consider measures aimed at increasing the transparency in provider billing practices, including making “charge masters” publicly available and free of jargon than can confuse and intimidate patients and their families. In short, policymakers should ensure that patients understand their providers and intention. The
evidence shows that without such an intervention, providers will not provide this transparency as it may impact many lucrative (and some illegal) practices.

Lastly, in validating some of the social factors that influence community health and healthcare fraud, including poverty, race, ethnicity, gender, housing, and urbanization, this study may have provided greater insight on why these issues conflate and form social stereotypes. The interplay between poverty, race, ethnicity, urbanization, welfare, health, and crime, is so intricate that it can easily lead to misunderstandings and misinformation on how and why they exist. Moreover, because of the challenges that exist in disentangling these relationships to acquire a clearer understanding, many choose not to, and proceed with the first observation that reinforces existing value-system judgements. This study saw evidence of these relationships and showed that these relationships exist in particular ways and highlight structural patterns already present in society. More importantly, this study showed that while race and ethnicity may be associated with healthcare fraud when controlling for health insurance and education, this association is marginal and most likely the result of larger structural disparities in the American health system.

Beyond policy implications, this study also showed that there is much research left to pursue in healthcare fraud and community health. This study has shown that there may be connection between larger socio-structural factors, healthcare fraud, and community health through the potential availability of resources. While the connection between socio-structural factors and community health is not new, their connection to healthcare fraud certainly is. Thus, research on the racial and ethnic differences associated with healthcare fraud rates and community health are worthy avenues of pursuit. However, beyond analyzing these differences in the context of structural inequalities, these should be studied while considering the role of social ties and social capital. While this study did not test the influence of social ties and social capital on healthcare fraud and community health, it highlighted certain relationships that make examining these relationships
worthwhile—especially in communities of color. This study also showed that urbanization influences both healthcare fraud and community health. While it is unclear why variations on healthcare fraud rates and community health exist in both metropolitan and non-metropolitan areas when controlling for health insurance and education, further research is warranted. Especially important is research that highlights the difference in healthcare fraud identification and enforcement mechanisms across the urbanization spectrum. The results of such research can increase the current understanding on why healthcare fraud rates vary by geographic location.

Similarly, this study has added some understanding to the use of social disorganization theory to examine healthcare fraud. While using social disorganization theory in this study did produce an insightful understanding of how community factors impact healthcare fraud and community health, and of larger socio-structural elements that may be impacting the same, the theory had its limitations. The most evident limitation was that the theory was unable to address some of the characteristics that define the system in which fraud takes place. To be fair, these characteristics became more evident as the analysis showed marginal results on the impact of social disorganization on both healthcare fraud and community health. However, the findings did show how other factors not considered may influence the dependent variables. Because of the emphasis found in the literature on motivated and highly educated offenders, a suitable monolithic target, and the absence of capable and engaged guardians, routines activities theory (Cohen and Felson 1979) may be the most logical choice to use as a theoretical framework for a subsequent analysis on healthcare fraud and community health. Pursuing this avenue of research would not only continue to inform this area at the micro level (e.g., examining individual cases of fraud and their impact of community health), but also at the macro level (e.g., examining the systemic deficiencies and their impact on community health). Knowledge created at both levels would be of great value to multiple fields of study and practice.
Additional limitations of the study also included the use of secondary data and dearth of literature that could be used to further frame the study. For example, this study relied heavily of secondary data, and the many disadvantages associated with that type of data, including that it was collected mainly by government agencies with another purpose (i.e., demographics, exclusions, etc.) in mind. As a result, the data may not be as precise as they perhaps could be at capturing social behaviors including the intent to commit a deviant or fraudulent act. Furthermore, this study suffered from a lack of literature that connected various areas of study already explored. For example, the literature on identifying and combatting fraud is readily available, but literature on how it impacts health or how it is impacted by other social factors is not. While this presents an opportunity for original research, the lack of information also did not provide clear direction on how to take advantage of this opportunity. Lastly, this study attempted to examine complicated situations and behaviors within a complicated social structure. Healthcare systems research is complicated because it crosses and transcends multiple fields of study, practice, and policy. The competing and often contradictory studies make it difficult to establish a framework from which to launch an examination of a targeted subject such as healthcare fraud. Despite these difficulties, and having healthcare fraud exist awkwardly between the traditional disciplines of health economics, health policy, crime policy, anomaly detection, and pattern recognition (Sparrow 2008), understanding it—as this study has attempted to do—is a meaningful pursuit. Furthermore, and more importantly, additional studies should consider overcoming the limitations of the present study—namely, the limitations in data collected solely for the study of the impact of healthcare fraud on community health outcomes. An investment in strategic data collection and analysis that focuses on healthcare fraud and connecting them to existing measures of health outcomes will not only allow for a closer examination of the relationship between these variables, but also a springboard to revising existing narratives about healthcare fraud and understanding new factors that impact community health.
NOT HUMAN RESEARCH DETERMINATION

July 23, 2020

Dear Wilmer Alvarezzirizarry:

On 7/23/2020, the IRB reviewed the following protocol:

<table>
<thead>
<tr>
<th>Type of Review:</th>
<th>Initial Study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Title of Study:</td>
<td>Medical Fraud in the US: Revisiting Welfare Queens, Social Disorganization, and their Impact on Community Health.</td>
</tr>
<tr>
<td>Investigator:</td>
<td>Wilmer Alvarezzirizarry</td>
</tr>
<tr>
<td>IRB ID:</td>
<td>STUDY00002027</td>
</tr>
<tr>
<td>Funding:</td>
<td>None</td>
</tr>
<tr>
<td>Grant ID:</td>
<td>None</td>
</tr>
<tr>
<td>Documents Reviewed:</td>
<td></td>
</tr>
<tr>
<td>- HRP-251 - FORM - Faculty Advisor Scientific-Scholarly Review_vPE07162020.pdf, Category: Faculty Research Approval;</td>
<td></td>
</tr>
<tr>
<td>- IRB Alvarezzirizarry 2027 HRP-250 - FORM - Request for NHSR[35788]_vAlvarezzirizarryW-05312020 (1)UPDATE.docx, Category: IRB Protocol;</td>
<td></td>
</tr>
<tr>
<td>- Study Variables_Source_vWA07162020.pdf, Category: Other</td>
<td></td>
</tr>
</tbody>
</table>

The IRB determined that the proposed activity is not research involving human subjects as defined by DHHS and FDA regulations.

IRB review and approval by this organization is not required. This determination applies only to the activities described in the IRB submission and does not apply should any changes be made. If changes are made and there are questions about whether these activities are research involving human in which the organization is engaged, please submit a new request to the IRB for a determination. You can create a modification by clicking Create Modification / CR within the study.

If you have any questions, please contact the UCF IRB at 407-823-2901 or irb@ucf.edu. Please include your project title and IRB number in all correspondence with this office.

Page 1 of 2
Due to current COVID-19 restrictions, in-person research is not permitted to begin until you receive further correspondence from the Office of Research stating that the restrictions have been lifted.

Sincerely,

Kamille C. Birkbeck
Designated Reviewer
REFERENCES


Government Accountability Officer. (2012). Health Care Fraud: Types of Providers Involved in Medicare Cases, and CMS Efforts to Reduce Fraud. GAO-13-213T

Government Accountability Officer. (2010). Health Care Fraud: Types of Providers Involved in Medicare, Medicaid, and the Children’s Health Insurance Program Cases. GAO-12-820

Hancock, AM. (2003). Contemporary Welfare Reform and the Public Identity of the "Welfare Queen". Race, Gender & Class, 10(1), 31-59


Lane, SD., Rubinstein, R., Reichert Schimpff, T., Keefe, RH., Jennings-Bey, T., Russell Leed, S., Iles, B., Cuff, PA., and Lynn Beth Satterly. (2019). Bringing in the Community: A University-Community Endeavor to Teach Marital and Family Therapy Students About Community-Based Violence and Trauma. *Contemporary Family Therapy*, 41, 147–156.


Containment Strategy. Health Affairs, 28(5), 1351-1356


116
Forces, 80, 283-310.


Sarwar, U., and Marios Nicolaou. (2012). Fraud and Deceit in Medical Research. *Journal of Research and Medical Sciences*, 17(11), 1077-81


Shaw, C. and Henry McKay. (1942). *Juvenile Delinquency and Urban Areas*. Chicago:
University of Chicago Press.


*Medicaid Fraud Control Units (MFCUs).* Retrieved from https://oig.hhs.gov/fraud/medicaid-fraud-control-units-mfcu/


*Exclusions Programs.* Retrieved from https://oig.hhs.gov/exclusions/index.asp


*Special Advisory Bulletin on the Effect of Exclusion from Participation in Federal Health Care Programs,* Issued May 8, 2013


