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Federal Offices of Inspectors General: The Relationship Between Per Capita Staffing Levels and Performance Results

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Nova Southeastern University
Abraham S. Fischler College of Education and School of Criminal Justice

Federal Offices of Inspectors General:
The Relationship Between Per Capita Staffing Levels and Performance Results


by
Craig Yuen
A Dissertation Presented to the
Abraham S. Fischler College of Education and School of Criminal Justice
of Nova Southeastern University
in Partial Fulfillment of the Requirements for the Degree of
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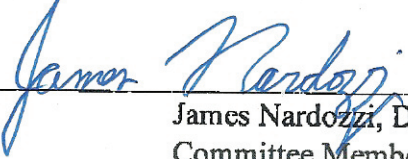
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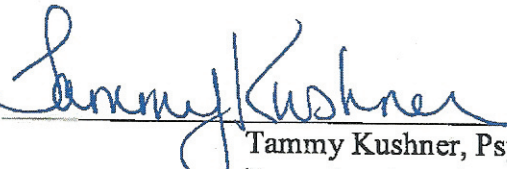
Approval Page

This dissertation was submitted by Craig Yuen, under the direction of the persons listed below. It was submitted to the School of Criminal Justice, Abraham S. Fischler College of Education, and approved in partial fulfillment of the requirements for the degree of Doctor of Philosophy at Nova Southeastern University.

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Abstract

Federal Offices of Inspectors General: The Relationship Between Per Capita Staffing Levels and Performance Results. Craig Yuen, 2019: Dissertation, Nova Southeastern University, Abraham S. Fischler College of Education and School of Criminal Justice. Descriptors: Office of Inspector General, Organizational Performance, Staffing, Personnel.

Each year, the federal government spends trillions of dollars on operations and in awarding contracts, grants, loans, and other forms of financial assistance. Federal Offices of Inspectors General (OIGs) are charged with auditing and investigating fraud, waste, abuse, and misconduct affecting the government. There are 73 such OIGs – 40 of which have law enforcement authority and oversight responsibilities for a parent agency – and each is a separate organization with varying staffing levels and performance results. This study examined, on a per capita level, the relationship between staffing levels and performance results (criminal charges filed, financial recoveries, and questioned costs) at these 40 OIGs. Using data envelopment analysis, this study also examined whether there is an optimal per capita staffing level beyond which performance results start to decrease. Additionally, this study examined the relationship between audit-related and investigative-related performance results.

No relationship was found between per capita staffing levels and charges filed or questioned costs. However, a potential correlation was found between per capita staffing levels and financial recoveries. No relationship was found between the audit-related performance outcome of questioned costs per capita and the investigative-related performance outcomes of charges filed per capita and financial recoveries per capita. An optimally efficient OIG staffing level range was identified as being 0.00137 to 0.02738 full-time equivalents for every million dollars of the OIG parent agency's budget. OIGs having staffing levels within this range were 1.089 to 1,000 times more efficient than OIGs with staffing levels outside the range. However, this range should be viewed as one within which maximum performance can be achieved as opposed to a target range that OIGs should strive to attain. OIGs with per capita staffing levels higher than the optimally efficient range did not have higher efficiency. Additionally, among the sample, no correlation was found between efficiency and either financial recoveries per capita or questioned costs per capita; however, a correlation was found between efficiency and charges filed per capita. This demonstrates that among the sample, OIGs with higher charges filed per capita had higher efficiency scores, but OIGs with higher financial recoveries per capita or questioned costs per capita did not have higher efficiency scores.

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Chapter 1: Introduction

Nature of the Research Problem

Each year, the federal government spends vast sums of money. In fiscal year 2017, this amount was approximately \$4 trillion (Congressional Budget Office, n.d.). Of this amount, over \$3.1 trillion was spent on contracts, grants, loans, and other forms of financial assistance. Specifically, in fiscal year 2017, the federal government spent over \$508 billion on contracts, over \$719 billion on grants, over \$2.8 billion on loans, and over \$1.9 trillion on other forms of financial assistance (USAspending.gov, 2018). With the term “government” often associated or even viewed as synonymous with “bureaucracy,” there is a palpable existence of fraud, waste, and abuse associated with federal spending.

Fortunately, there are federal oversight agencies whose mission is to detect, audit, investigate, and prevent such fraud, waste, and abuse. These agencies are called Offices of Inspector General (OIGs). There are 73 federal OIGs – generally, one for each cabinet department and each independent agency (Council of the Inspectors General on Integrity and Efficiency, n.d.a). Each OIG is independent from one another and has its own authorities, budget, staffing levels, and priorities. However, all OIGs are part of the statutorily created Council of the Inspectors General on Integrity and Efficiency (CIGIE), a governing body that sets general standards and coordinates peer reviews (Council of the Inspectors General on Integrity and Efficiency, n.d.b). All 73 OIGs have personnel who conduct or manage audits, and 42 of the OIGs also have law enforcement authority with federal agents conducting criminal investigations (Ginsberg, 2014). On a semiannual basis, each OIG reports data relating to their performance, including investigative-related

arrests, indictments, convictions, and monetary recoveries, as well as audit-related questioned costs. Annually, each OIG must also report its budget and related data, such as its number of employees. Each federal cabinet-level department and independent agency – to which OIGs are embedded – must also report their budget and staffing levels. Additionally, the U.S. Office of Personnel Management publishes some staffing-related data on its website.

This data, along with the relatively high number of OIGs, presented an important research opportunity: determining whether correlations exist between performance outcomes and staffing levels, which are critical factors in law enforcement organizations across the United States (Wilson and Heinonen, 2011) and are top considerations of law enforcement leaders (Mendel, Fyfe, and Den Heyer, 2017). These correlations – or the lack thereof – are needed to inform the criminal justice field of the ideal staffing ratios, particularly with respect to OIGs, many of which are small in size, lack resources for mission-related work, and lack the time and resources to conduct such research. Additionally, the existence and direction of any correlation between investigative- and audit-related performance outcomes can inform the field on the potential relationship between the investigative and audit functions of OIGs.

Furthermore, there is an important gap in the field’s understanding concerning the nature of the contributions of staffing-related factors and per capita performance outcomes of federal OIGs. Data envelopment analysis was used to determine the optimal number of personnel relative to the OIG parent agency’s budget (termed “coverage ratio” in the remainder of this paper). Data envelopment analysis is a technique that calculates the relative efficiency of organizations by comparing their inputs and outputs, and prior

research supports the use of this technique in assessing police performance (Alda, 2014).

Background and Significance

The federal government is a complex organization with numerous agencies that have seemingly overlapping missions. To illustrate, the federal government has three branches – the executive branch, the judicial branch, and the legislative branch (USA.gov, n.d.a). The executive branch alone has 15 departments, collectively known as the cabinet: the Department of Agriculture, Department of Commerce, Department of Defense, Department of Education, Department of Energy, Department of Health and Human Services, Department of Homeland Security, Department of Housing and Urban Development, Department of the Interior, Department of Justice, Department of Labor, Department of State, Department of Transportation, Department of the Treasury, and Department of Veterans Affairs. Each department contains numerous bureaus – for example, the Internal Revenue Service falls within the Department of the Treasury. Within each of these components are numerous sub-bureaus – for example, the Internal Revenue Service has a criminal investigation organization employing law enforcement special agents who investigate tax fraud (Internal Revenue Service, 2016). Outside of the 15 departments, there are numerous independent agencies, such as the Securities and Exchange Commission (SEC) and the Central Intelligence Agency (CIA) (USA.gov, n.d.b).

Generally, each of the 15 departments and many of the various independent agencies has an OIG that provides objective oversight. Although OIGs are components of the larger organization to which they oversee, they enjoy a significant degree of independence (Council of the Inspectors General on Integrity and Efficiency, n.d.a). For

example, the heads of many OIGs – known as Inspectors General –are appointed by the President of the United States and can only be removed by the President. The Inspector General has a dual-reporting line to both the head of the organization he or she oversees and to Congress. Additionally, some OIGs have their own budget, human resources, and information technology personnel and processes. Furthermore, federal statutes known as the Inspector General Act of 1978 (Council of the Inspectors General on Integrity and Efficiency, n.d.c) and the Inspector General Empowerment Act of 2016 (Congress.gov, 2016) provide OIGs with, among other authorities, direct access to the records of the agencies they oversee.

Charged with the responsibility of auditing and investigating activities associated with the trillions of dollars the federal government spends each year on contracts, grants, loans, and other financial assistance, the OIGs play a significant role in protecting the American fisc. However, the role, work, and results of the OIGs are often overshadowed by the federal government’s much larger law enforcement agencies, such as the Federal Bureau of Investigation, which in fiscal year 2017 had an individual annual budget of over \$8.7 billion and over 35,000 employees (Department of Justice, n.d.). This notion is reflected in the apparent lack of criminal justice research related to OIGs. For example, a search of the ProQuest Criminal Justice Database for peer-reviewed articles containing “Inspector General” returned very few results. Many of the results were not scholarly articles. In some of the articles, “Inspector General” was referenced, and sometimes its work was mentioned, but it was not the focus of the material. The few remaining studies focused on more conceptual issues: whether OIGs should have law enforcement authority, before such legislation was passed (Kaiser, 1992); a narrative on whether, from

a conceptual sense, the CIA OIG is able to keep CIA operatives honest (Check & Radsan, 2010); and a narrative on whether the Department of Justice (DOJ) OIG should have the authority to investigate DOJ attorneys for prosecutorial misconduct (Sullivan & Possley, 2015).

Therefore, further criminal justice research on the OIG community is needed. The purpose of this study was to examine the organizational effectiveness of the OIGs. Specifically, this study compared the number of personnel each OIG has, expressed in proportion to the budget dollars of the OIG's parent agency (the "coverage ratio"), with the number of per capita performance outcomes (investigative-related criminal charges filed and financial recoveries, as well as audit-related questioned costs) attributable to the OIG's work. As audits and investigations are the two primary but distinct functions of OIGs, this study also examined the nature of the relationship between the investigative- and audit-related performance outcomes.

The emphasis of this study was "per capita"; this means that each OIG's performance was analyzed relative to the number of personnel it had. This enabled the identification of any tipping points in the coverage ratio that mark the beginning of decreased performance results. That is, there may be an optimal threshold of personnel with respect to per capita performance outcomes. For example, due to division of labor, the existence of specialized units with a niche expertise, and sufficient numbers of personnel to allow for the shifting of resources, an organization with a large number of personnel may have better per capita performance than an organization with a small number of personnel. However, there may come a tipping point where adding more personnel lowers the agency's overall per capita performance due to the relative

bureaucracy and inflexibility that can be associated with large organizations.

Prior research on general law enforcement organizations support the use of staffing levels in analyzing performance. For example, Ferrandino (2012b) examined a performance measure that is used in some police departments – the number of stop-and-frisks performed by police personnel. The study analyzed data from the New York Police Department in particular. During a six-year period, the department conducted approximately 3.4 million stops, 1.7 million of which involved frisks. Given the results of the stop-and-frisks, the research found the activities to be inefficient in general; there should have been approximately one million fewer frisks and 180,000 more arrests by the New York Police Department as a whole. Using a technique called data envelopment analysis, these figures were calculated by determining the most efficient precinct in the department based on the number of frisks the precinct conducted and the resulting number of arrests, using that precinct as a benchmark, and comparing the remaining precincts' frisks and arrests to that benchmark.

Additionally, Alda (2014) examined the efficiency of police departments in Guatemala in combating crime. The research involved the use of data envelopment analysis, a technique for determining the efficiency of institutions. As was the case in the Ferrandino (2012b) study, this technique involved the comparison of inputs with outputs across a number of similarly situated institutions, identifying the most efficient institution as a benchmark, and comparing it against the remaining institutions. The inputs used in the study were the number of police officers, number of police cars, and cost of labor. The outputs were the homicide clearance rate and the robbery clearance rate. The study found that the average efficiency score of the 22 police departments studied was 62%,

with only four departments meeting the threshold for being deemed efficient. The study further found that many of the inefficient departments could achieve efficiency through a 139% increase in outputs coupled with a decrease in inputs.

Furthermore, Bonkiewicz (2016) examined how the crime rate and staffing levels of a particular patrol area affected officer productivity. Both the number of reported violent crimes per officer and the number of reported property crimes per officer were analyzed as independent variables. The number of citations, warrants, and arrests were analyzed as dependent variables. The research concluded that the property crimes ratio is correlated with a decrease in citations and arrests, while the violent crimes ratio is correlated with a decrease in citations and an increase in arrests.

Also, Zhao, Zhang, and Thurman (2011) examined the effect of federal grant dollars on officer productivity, as measured by the number of arrests. The researchers examined arrest data from nearly 6,000 cities during a seven-year time frame, during which federal grants for community policing were at an all-time high. The findings suggest that the federal grants were positively correlated with the number of police arrests even though the grants accounted for a small percentage of a department's total budget. The study concluded that additional resources did indeed appear to have a positive correlation with the number of arrests.

Purpose Statement

The overall purpose of this study was to determine whether correlations exist between staffing levels and performance outcomes of federal OIGs. Specifically, this study determined whether statistically significant correlations exist between the staffing-related *coverage ratio* and the performance outcomes of *charges filed per capita*,

financial recoveries per capita, and *questioned costs per capita*; whether a correlation exists between the audit-related performance outcome of *questioned costs per capita* and the investigative-related performance outcomes of *charges filed per capita* and *financial recoveries per capita*; and the optimal *coverage ratio* beyond which performance outcomes start to decrease. These terms are defined below.

Definition of Terms

The following terms were used for this study and were calculated from the raw data that was collected:

1. Performance outcomes:

a. *Charges filed per capita*: The number of criminal charges (criminal complaints, indictments, and informations) resulting from the OIG's work, divided by the number of full-time equivalents in the OIG

b. *Financial recoveries per capita*: The dollar value of all restitution, forfeitures, civil settlements, and administrative recoveries resulting from the OIG's work, divided by the number of full-time equivalents in the OIG

c. *Questioned costs per capita*: The dollar value of questioned costs resulting from the OIG's work, divided by the number of full-time equivalents in the OIG

2. Staffing-related factor:

a. *Coverage ratio*: The number of full-time equivalents in the OIG divided by the budget dollars (expressed in millions) of the OIG's parent agency; the aforementioned budget dollars of the OIG's parent agency excludes the OIG's budget dollars

Chapter 2: Review of the Literature

There appeared to be a significant shortage of research on OIGs specifically. As a result, the time scope for the research discussed in this literature review was expanded so that Inspector General-specific material could be examined. However, even with the expanded time scope, there was a shortage of research. Therefore, research studies for broader but relevant topics were also found. These studies involve police departments in general, as opposed to OIGs in particular. Three themes emerged from the literature view. The first theme is that there are varying perspectives in measuring police performance. The second theme is the importance of staffing levels. The third theme is the importance of investigative quality. These themes are described in more detail below.

Varying Perspectives in Measuring Performance

Newcomer (1998) conducted a study into the accountability of the OIG community. At the time of the study, the various agencies of the federal government were experiencing a push to move away from focusing on procedural guidelines and to move toward focusing on results. Two initiatives contributed to this push – the White House’s National Performance Review of 1993 and Congress’s Government Performance and Results Act of 1993. Together, these two initiatives mandated that federal agencies do more with less, maintain performance plans, and track performance metrics. The various OIGs, like all other federal agencies, were subject to these initiatives. Unlike other federal agencies, however, OIGs enjoy substantial independence from both the legislative branch and the executive branch. The heads of many OIGs – the Inspectors General – are appointed by the President, confirmed by the Senate, and responsible for keeping Congress informed of their work.

Newcomer (1998) surveyed and conducted interviews with 53 OIGs. The research study found that the OIGs were being expected to do more work with fewer resources. Specifically, their workloads had increased, but their budgets and personnel had not. Performance results were being measured in part by the monetary savings and recoveries attributable to the audits, investigations, and recommendations of the OIGs. Calculating and achieving these monetary figures in light of stagnant resources was a top challenge for these offices.

Over a decade later, Johnston (2010a) found that both performance results and a lack of resources continued to be an issue across the OIG community. In a study of various local and federal OIGs, Johnston (2010a) found a lack of major increases in the budget and personnel of those offices, as well as a lack of consensus on what an OIG should do to be successful. The powers, responsibilities, resources, and accountability of these offices vary greatly, and necessarily so, given the fact that their oversight areas vary greatly. One of the major focus areas of these offices – corruption – is secretive in nature and therefore difficult to measure. It follows that measuring anti-corruption performance would also be difficult to measure.

Johnston (2010b) built upon this foundation with a study into the ways OIGs approach anti-corruption efforts. Specifically, there are two general approaches: targeting the “big fish” and targeting the “low-hanging fruit.” Targeting the “big fish” may garner media attention, have a major deterrent effect, and enhance the public’s perception of government integrity. On the other hand, this approach consumes a very significant amount of resources and may yield a relatively low amount of monetary recoveries and convictions, in the sense of performance metrics. Meanwhile, targeting

the “low-hanging fruit” allows OIGs to cast a wider net that encompasses more areas of the government, expend fewer resources, and generate relatively higher performance metrics by way of monetary recoveries and convictions. OIGs are split as to their approaches.

Barlage, Van Den Born, Van Witteloostuijn, and Graham (2014) recognized the difficulty in measuring the performance of public sector organizations. Because developing objective performance measures is a complicated task, subjective performance measures are sometimes used as a substitute. The researchers used a multi-trait/multi-method model to determine the validity of subjective performance measures and the extent of biases in those measures. The model was used in analyzing the police forces in 26 different countries in Europe that use subjective performance measures. The study found that the subjective performance measures had significant biases and were not reliable estimates of police performance.

Despite the perceived difficulty of developing objective performance measures, there are ways of doing so. Jaaskelainen and Lonnqvist (2011) examined how productivity in public sector organizations is measured objectively. Even when an organization produces outputs that are complex or otherwise difficult to measure, they can be divided into tangible and intangible components that can individually be measured. Tangible components include the quantity and magnitude of outputs, the availability and location of services provided, and the results of the services provided. The intangible components include the atmosphere in which services are provided, the satisfaction of direct customers, the satisfaction of indirect customers, and the organizational image that has developed as a result of providing the services.

It follows that the performance measures of a particular law enforcement agency should not be a one-size-fits-all metric, but instead be individualized based on the constituents the agency serves. Ferrandino (2012a) conducted a study comparing the efficiency of university police departments in Florida with traditional municipal police departments in Florida. The university police departments were modeled after the municipal departments. However, the university departments had a substantially different function – they performed more security-related, order maintenance functions than did the traditional departments they were modeled after.

Ferrandino's (2012a) study found that based on the traditional metrics of writing citations, handling crimes, making arrests, and clearing investigations, the university departments were much less efficient than their municipal counterparts. In order to be equivalent in efficiency, the university departments would have had to write 258% more citations, handle 165% more crimes, make 281% more arrests, and have a 9% increase in their investigations clearance rate. Such increases, however, are not necessarily desirable or feasible, as despite being modeled after municipal departments, university departments fulfill a different function and serve a different constituency.

In a similar vein, Davis, Ortiz, Euler, and Kuykendall (2015) took a critical look at traditional measures of police performance, which include response time, arrests, and crime clearance rates. They found that these measures do not encompass the ever-evolving complexity of the police role, which includes police-community relations, successfully dealing with mentally ill persons, and the need to be viewed with confidence by the public. Based on field tests, the researchers determined that standardized performance measures developed by the Commission on Accreditation for Law

Enforcement Agencies appear to be feasible performance measures. These measures include the traditional metrics of crime rates and response times combined with emerging metrics such as police absenteeism, courteous dealings with citizens, and success in obtaining government grants.

As previously indicated, there have been several emerging methods for measuring police performance objectively across a variety of dimensions. One emerging method for measuring police productivity – patrol officers, in particular – is through the use of "sabermetrics" (Bonkiewicz, 2015). The sabermetrics model involves the use of multiple productivity measures, as opposed to the traditional counts of calls and arrests.

Additionally, each of the productivity measures is weighted to give importance to some over the others, depending on the particular department's priorities. One of the measures is unique in that it assesses how much time officers have available for self-initiated activities, which would otherwise be seen as unproductive time under the traditional metrics of calls and arrests. Twelve patrol activities in particular were examined and calculated into a single comprehensive performance metric, and this metric was found to have strong indicators of validity.

Rosenbaum, et al. (2017) also examined an emerging metric for measuring police performance. This metric differed from the traditional performance measure of arrests and citations and instead focused on the quality of police-citizen interactions, which had been garnering public interest. The metric was an instrument called the Police-Community Interaction Survey. Using a quantitative analysis of data from 53 police departments across the United States, the research study found that the Police-Community Interaction Survey possesses the characteristics of reliability and validity.

The study concluded that the quality of police interactions with citizens is important in the criminal justice arena, and agencies should consider using the survey as a performance metric.

That being said, traditional metrics can still serve a valuable role in painting a picture of police efficiency. Ferrandino (2012b) examined a performance measure that is used in some police departments – the number of stop-and-frisks performed by police personnel. The study analyzed data from the New York Police Department in particular. During a six-year period, the department conducted approximately 3.4 million stops, 1.7 million of which involved frisks. Given the results of the stop-and-frisks, the research found the activities to be inefficient in general; there should have been approximately one million fewer frisks and 180,000 more arrests. Using a technique called data envelopment analysis, these figures were calculated by determining the most efficient precinct in the department based on the number of frisks the precinct conducted and the resulting number of arrests, using that precinct as a benchmark, and comparing the remaining precincts' frisks and arrests to that benchmark.

Measuring police performance is a concern that affects other countries as well. Alda (2014) examined the efficiency of police departments in Guatemala in combating crime. The research involved the use of data envelopment analysis, a technique for determining the efficiency of institutions. As was the case in the Ferrandino (2012b) study, this technique involved the comparison of inputs with outputs across a number of similarly situated institutions, identifying the most efficient institution as a benchmark, and comparing it against the remaining institutions. The inputs used in the study were the number of police officers, number of police cars, and cost of labor. The outputs were the

homicide clearance rate and the robbery clearance rate. The study found that the average efficiency score of the 22 police departments studied was 62%, with only four departments meeting the threshold for being deemed efficient. The study further found that many of the inefficient departments could achieve efficiency through a 139% increase in outputs coupled with a decrease in inputs.

Verman and Gavirneni (2006) also used data envelopment analysis to measure the efficiency of policing activities in India. For all 25 states in India, the researchers analyzed four inputs and four outputs (performance outcomes). The inputs were dollar expenditures, number of police officers, number of investigating officers, and number of cases investigated. The outputs were the number of arrests, number of charges, number of convictions, and number of trials completed. The conclusion was that 11 states were operating at the most efficient level, while the remaining 14 states were operating below that level.

Wu, Chen, and Yeh (2010) is another study that used data envelopment analysis. In this study, the researchers examined the efficiency of policing activities in 22 administrative districts of Taiwan. The inputs were labor costs, general operating costs, and equipment purchasing costs. The outputs were the number of burglary crimes cleared, number of violent crimes cleared, number of other crimes cleared, number of traffic accidents resulting in death or serious injury, number of services provided in response to resident requests, and residents' satisfaction with the security of their community. Eight of the administrative districts were found to be operating at the most efficient level, while the remaining 14 were operating below that level.

Akdogan (2012) is yet another study involving data envelopment analysis. This study examined the efficiency of 19 police precincts in the Turkish city of Ankara. The inputs were the number of police personnel, number of police vehicles, population of the area covered by the precinct, square meters covered by the precinct, number of critical entities such as schools and hospitals, number of incoming judicial and managerial documents, and number of crime and traffic incidents. The outputs were the number of processed documents, number of outgoing documents, and number of solved incidents. Ten of the 19 precincts were found to be operating at the most efficient level, while the remaining 9 were found to be operating below that level.

Chen, Lee, Chen, and Tsai (2014) analyzed the perceptions and satisfaction levels between citizens and police officers in a rural area of Taiwan. The research found support for five dimensions and 25 sub-dimensions as indicators of police service quality. The five dimensions are tangibility, reliability, responsiveness, assurance, and empathy. An example of tangibility is the equipment of police agencies. An example of reliability is the expertise of the police personnel. An example of responsiveness is the response time to a citizen's request for help. An example of assurance is the popularity of reform projects. An example of empathy is the police personnel's knowledge of the citizens.

Continuing with the international theme, Bruce (2011) studied the performance indicators used to evaluate the performance of the national police department in South Africa. He recognized that it is difficult to measure the achievements of an organization, which is distinct from mere outputs, such as arrests. The outputs that the police department has traditionally used include the number of reported crimes, with decreased levels being desirable. These types of measures can incentivize police personnel to

misreport data and not investigate crimes. The research found that external audits should be conducted to validate output data and to examine the qualitative questions of whether a police department is in fact achieving its mission of providing quality service and reducing crime.

An example demonstrating questionable data is Velikonja's (2016) study into the enforcement statistics reported by the Securities and Exchange Commission, which has a large role in enforcing the various securities-related laws. Each year, the Commission produces a report detailing their enforcement statistics, which are viewed as performance measures. This study examined the validity of those statistics. Using a mixed methods approach by examining the publicly reported statistics and synthesizing existing research, the research study concluded that many enforcement actions were double- or triple-counted, lacked construct validity, and were inconsistent in how they were counted. The conclusion was that the enforcement-related metrics are flawed and not accurate measures of the Commission's work.

Importance of Staffing Levels

Regardless of how performance is measured, one input factor that is continually referenced is the number of personnel. Mendel, Fyfe, and Den Heyer (2017) conducted a meta-analysis of studies into the effect of personnel size on performance outcomes in police agencies. The researchers found that the size of an agency, as well as the structure, is one of the top concerns for the agency's leadership. However, there appears to be no simple cause-and-effect relationship between the number of personnel and performance outcomes. This applies whether the police agency's mission is focused on traditional policing services or on protection-based services.

Although there appears to be no simple cause-and-effect relationship, there have been studies into how police agencies vary in staffing levels based on the communities they serve. Hollis and Wilson (2015) conducted such a study. The researchers classified all of the counties in the United States based on three factors: the region in which they are located, the population size of the county, and the category of the county; the latter is based on the following twelve characteristics: income, race, immigration, religion, housing, population density, distance to a major city, education, migration, consumer expenditures, property taxes, and charitable donations. The study found that the size and category of the county had a statistically significant relationship with staffing levels (the ratio of officers to citizens) but that the region of the county had no statistically significant relationship. In nearly every region, a u-shaped parabola represented the relationship between staffing levels and crime rates and between staffing levels and community size (in other words, communities with low or high crime rates had greater staffing levels than communities with medium crime rates, and small and large communities had greater staffing levels than medium-sized communities).

Wilson and Heinonen (2011) found that personnel planning is an often overlooked but very critical challenge in police organizations across the United States, particularly in times of economic downturn. Despite this challenge, police managers have few resources to use data- and evidence-based practices to optimize the use of their personnel. This is particularly so in light of the ever-changing nature of the workforce. As there is no single approach to resolving the situation, the staffing challenge is dynamic in nature. A survey was sent to every municipal police department in the United States with at least 300 officers. Approximately 25% of departments did not respond to the

survey, and no distinguishing characteristics for the non-responsive departments could be identified. Personnel data is critical, but is often difficult to assemble, especially in light of police departments' themselves not always having the data available.

Wilson (2012) furthered the research on the dynamic staffing issue by studying how changing circumstances affect police recruitment and retention. The research involved the synthesis of over 150 prior works on the topic. According to the research, there are three challenges in staffing. First, attrition is increasing due to baby-boomer retirements, military deployments, and new generational expectations for careers. Second, the supply of new recruits is decreasing due to a lack of qualified applicants, increased competition among departments, and new generational preferences for other careers. Third, police responsibilities are expanding due to terrorism and other security concerns, new types of crime, and the increased focus on community policing.

McCarty, Ren, and Zhao (2012) studied the factors that determined police strength in large cities in the United States in the 1990s, which saw a significant decrease in crime. The researchers made three findings in particular. First, police strength is determined more by the perception of danger than by actual measures of danger (such as crime rates). Second, police strength depends in large part on the extent of available resources, including federal hiring grants for community-oriented policing initiatives. Third, police strength is positively correlated with population density.

Srinivasan, Sorrell, Brooks, and Edwards (2013) also examined the staffing levels of police departments, realizing that such levels are a constant concern across the industry. The research study examined quantitative methods for determining staffing levels and justifying the desired staffing levels to approving officials. Using a discrete-

event simulation model, the number of officers needed to meet specific benchmark goals was estimated. The research concluded that as long as the input data is reliable, agencies should consider using the simulation model to determine the number of officers needed to meet the department's objectives.

Although there is no simple cause-and-effect relationship between staffing and productivity, there does appear to be a correlation between the two. Bonkiewicz (2016) examined how the crime rate and staffing levels of a particular patrol area affect officer productivity. Both the number of reported violent crimes per officer and the number of reported property crimes per officer were analyzed as independent variables. The number of citations, warrants, and arrests were analyzed as dependent variables. The research concluded that the number of reported property crimes per office is correlated with a decrease in citations and arrests, while the number of reported violent crimes per officer is correlated with a decrease in citations and an increase in arrests.

Staffing affects productivity in investigations as well. Lane (2010) studied the impact of fraud investigations conducted by police agencies at the local and national level in England. The study was conducted after a previous report was released suggesting that local agencies were not as well-equipped to investigate fraud as the national agencies based in part on their organizational staffing structures. Using a quantitative analysis based on data from interviews and surveys sent to local and national agencies, the research concluded that the type of fraud cases worked by local and national agencies and the amount of financial recoveries were comparable, indicating that the organizational staffing structures of local and national agencies are equally equipped to handle fraud investigations.

Wilson and Weiss (2014) examined how different police departments determine their staffing needs. Some methods used by the departments are per capita, minimum ground levels, authorized maximum levels, and workload-based. The researchers studied 20 different police agencies to identify current trends and experiences. The researchers also consulted with 21 staffing experts. They concluded that the most effective and most efficient method for determining staffing needs is one that considers a department's individual performance objectives and workload.

A concept related to the issue of staffing is budget allocation, which ultimately determines how many personnel an agency can hire. Zhao, Ren, and Lovrich (2010) examined the factors that determined changes to the budget allocations of municipal police departments over time. Previous research suggested that there are three factors in particular. The first factor is the local political culture. The second factor is socioeconomic conditions. The third factor is the extent incremental decision-making was used in budget matters. By analyzing data from 188 municipal governments, the research study found that incremental decision-making largely explained differences in police departments' budget allocations, and that the other two factors (political culture and socioeconomic conditions) were weak effects.

Zhao, Zhang, and Thurman (2011) created a research study to determine the effect of federal hiring grants – which translates to increased personnel – on police department performance, as measured by the number of arrests. The researchers examined arrest data from nearly 6,000 cities during a seven-year time frame, during which federal grants for community policing were at an all-time high. The findings suggest that the federal hiring grants were positively correlated with the number of police arrests even though the

grants accounted for a small percentage of a department's total budget. The study concluded that the grants did indeed appear to have a positive correlation with the number of arrests.

Importance of Investigative Quality

Given the nature of law enforcement investigations, emphasis needs to be placed on the quality of investigative work. Miller (2010) conducted a study of existing police literature to identify the various qualities associated with a good internal affairs investigation, which is part of the work that OIGs perform. Miller (2010) found the following qualities: competence of investigators; resilience of investigators; independence of investigators; lawfulness and ethical nature of the investigation; compatibility with the public interest; consideration of organizational priorities; open-mindedness of investigators; planning; thorough review of all information and evidence; comprehensive recording and preservation of all information and evidence; security of all information and evidence; respect for the rights of victims; respect for the rights of witnesses; respect for the rights of subjects; careful use of covert tactics; proper management of informants; efficient and effective use of resources; communication with stakeholders; timeliness; professional approach to the presentation of evidence; accountability; and continuous improvement.

Many of these qualities relate to police supervision, which has been found to be important with respect to organizational performance. According to Cronin, McDevitt, and Cordner (2017), the presence and effectiveness of supervisors is required to implement an organization's performance objectives. Also, Keel, Jarvis, and Muirhead (2009) discovered that murder clearance rates are affected by the oversight and

accountability provided by supervisors. Additionally, Famega, Frank, and Mazerolle (2005) found that supervisory directives affect the productivity of patrol officers during the times they were not assigned to a call and instead expected to be proactive. Specifically, by conducting field observations, this study examined the use of unassigned patrol officer time in the Baltimore Police Department – this is time during which officers were not dispatched to respond to a particular situation. The study found that how officers use this unassigned time was affected, in part, by supervisory instructions – and the lack thereof – as to the type and location of proactive enforcement activities to engage in.

Although no research was found that directly examines supervisor-to-subordinate ratios in the law enforcement context, Iammartino, Bischoff, and Willy (2016) studied the effect of supervisor ratio (supervisors to employees) on the turnover of federal government employees working as engineers. In this study, the researchers examined data from 17 large independent federal agencies across multiple years. Through a hierarchical multiple regression analysis, the researchers found a negative correlation between supervisor ratio and engineer turnover, suggesting that a sufficiently high supervisor ratio is beneficial to organizational performance.

On the other hand, Konarg, Wollersheim, and Welppe (2017) found a negative correlation between the supervisor ratio and the individual performance of doctoral and post-doctoral candidates at German business and economic academic institutions. Using a sample of 594 individuals, the researchers found that higher supervisor ratios were associated with lower levels of individual performance. Performance was measured by the number of journal and conference publications.

Further supporting the need for optimal supervision is the notion that organizations such as OIGs that have a responsibility to reduce waste must ensure that they themselves are not contributing to government inefficiency. Apaza (2015) conducted a case study into the Department of Homeland Security OIG's effectiveness in reducing fraud, waste, and abuse. The study analyzed five investigations involving contracts awarded by the Department of Homeland Security. The conclusion was that the OIG did not fit the profile of an ineffective agency, and the investigations resulted in recommendations to the department for improving its management of contracts.

Check and Radsan (2010) conducted another case study into the effectiveness of the Central Intelligence Agency (CIA) OIG. The researchers focused on the question of whether the OIG kept CIA officers honest and competent. The CIA OIG was found to have many tools at its disposal to oversee CIA operations. These include the statutory designation to receive and investigate complaints or other information from any person, as well as statutory whistleblower protection to individuals who report wrongdoing. The statutory investigative authority and whistleblower protections were found to be significant oversight mechanisms for the CIA. Additionally, several major investigations were analyzed. The OIG was found to have sufficient independence to perform its work, although the quality of the work depended on the individuals holding the leadership and line-level positions at the agency.

The importance of independence is not to be understated, as this affects the quality of internal affairs investigations. Sullivan and Possley (2015) were concerned with the need to investigate prosecutorial misconduct in an objective and transparent manner. At the federal level, prosecutors are employees of the Department of Justice.

For misconduct involving their prosecutorial powers, however, they are not investigated by the OIG. Rather, there is a statutory carve-out that gives such investigative authority to the Office of Professional Responsibility, a division within the Department of Justice that reports, in regular fashion, to the Attorney General. Through synthesizing existing research, the research study concluded that the current method of investigating prosecutorial misconduct is inadequate, and there should be reformatory measures that transfer the investigative authority to the OIG.

Such independent oversight bodies contribute to the quality of internal investigations. Terrill and Ingram (2016) examined citizen complaints against the police in eight cities in the United States. In doing so, they also examined various models for investigating such complaints, which include internal affairs departments, management inquiries, and independent external oversight bodies, and the models' effect on the rate at which complaints were found to have merit. A great variation in the number and types of complaints were found across the eight cities. However, the research found that departments with independent external oversight bodies were the most likely to find merit in citizen complaints against the police.

Management-related decisions also have an impact on the quality of internal investigations by way of its effect on the investigative personnel. Kisil (2014) studied professional degradation as it affects officers performing internal affairs functions. Degradation is characterized by factors such as bias in favor of or against the subjects under investigation and an arbitrary or subjective interpretation of the rules and laws. The research study found that some of the causes of degradation are frequent rotations in personnel, disorganization within the internal affairs unit, and the lack of a training

apparatus for both new and existing internal affairs officers. The research study further found that prevention of degradation is achieved by having professional guidance in place, sufficient supervisory oversight of investigations, and continual training and development of officers.

Touching on the topic of the relationship between training (which is affected by management decisions) and performance, Caro (2011) examined the effect of initial training on a police academy graduate's performance in the field. The research study involved an analysis of a sample of officers located in the southeastern area of the United States. The research study found that performance at the training academy only accounted for 10% of the graduates' performance in the field during the field training officer phase. The research concluded that the curriculum of training programs should be aligned with any desired performance measures.

Finally, touching on the importance of organizational structure (which is ultimately affected by management decisions), Eitle, D'Alessio, and Stolzenberg (2014) studied the association between organizational and environmental factors and the extent of police misconduct. The study involved data from 497 municipal police departments and found that with respect to environmental factors, the only predictor of police misconduct was the violent crime rate. With respect to organizational factors, the organization's size, the extent of in-service training, and the presence of a dedicated internal affairs unit all had a significant impact on police misconduct.

Summary

In summary, there was a lack of studies that directly examine OIGs. However, the literature showed three themes with respect to the performance of law enforcement

agencies in general. First, there are varying perspectives on how performance should be measured. In some situations, traditional metrics such as arrests and citations are appropriate. In other situations, more complex, multi-factor metrics are appropriate. The common theme is that there is no one-size-fits-all approach for every type of law enforcement agency; metrics must be tailored to the mission type. Given the fact that OIGs have the mission of investigating fraud, waste, abuse, and misconduct and OIGs must report related performance outcomes, there is support for using charges filed per capita, financial recoveries per capita, and questioned costs per capita as performance measures in the present study. The second theme is that staffing levels are important, regardless of the performance metric used. Investigations and other police activities are not performed by machines, but rather by human beings. Therefore, the number and per capita rate of personnel is a crucial factor in how well an organization performs. Finally, the third theme is that quality measures are important additions to any performance metrics that are used. These quality measures include strong organizational structures that have sufficient investigative authority, independence, and training and development apparatuses for their personnel. These measures relate to resource allocation decisions and therefore lend support for examining the relationship between investigative- and audit-related performance outcomes, as investigations and audits are the two primary but distinct functions of an OIG.

Research Questions

This study involved the research questions listed below. The referenced terms were described in a preceding section of this paper.

1. What is the relationship between the coverage ratio and the per capita

performance outcomes of charges filed per capita, financial recoveries per capita, and questioned costs per capita?

2. What is the relationship between the audit-related performance outcome of questioned costs per capita and the investigative-related performance outcomes of charges filed per capita and financial recoveries per capita?

3. What is the optimal coverage ratio beyond which the per capita performance outcomes of charges filed per capita, financial recoveries per capita, and questioned costs per capita begin to decrease?

Chapter 3: Methodology

As the purpose of this study was to analyze correlations using existing numerical data, this study employed a quantitative methodology using non-experimental research, a correlational approach, and a predictive design. The coverage ratio (as defined above) was the predictor variable, while charges filed per capita, financial recoveries per capita, and questioned costs per capita (also as defined above) were the outcome variables. In a separate analysis (for research question two only), questioned costs per capita (the audit-related performance outcome) was the predictor variable, while charges filed per capita and financial recoveries per capita (the investigative-related performance outcomes) were the outcome variables. Datasets for each of three federal fiscal years (2016, 2017, and 2018) were analyzed; this was done to determine whether results replicated year-to-year. Also analyzed was a dataset containing the average figures across 2016, 2017, and 2018. Each federal fiscal year ran from October 1 through September 30. Fiscal year 2016 ran from October 1, 2015, through September 30, 2016; fiscal year 2017 ran from October 1, 2016, through September 30, 2017; and fiscal year 2018 ran from October 1, 2017,

through September 30, 2018.

Archival Research

This study was an archival research project based on existing data sources. The study examined all federal OIGs that have law enforcement authority and oversight responsibilities for a parent agency. There was a total of 73 federal OIGs, but only 42 had law enforcement authority (Ginsberg, 2014). Two of the OIGs with law enforcement authority did not have a parent agency and were not included in the study; these two OIGs were the Office of the Special Inspector General for Afghanistan Reconstruction and the Office of the Special Inspector General for the Troubled Assets Relief Program. Therefore, there were 40 OIGs that were examined:

1. Board of Governors of the Federal Reserve System (FRS) OIG
2. Corporation for National and Community Service (CNCS) OIG
3. Export-Import Bank of the United States (EXIM) OIG
4. Federal Deposit Insurance Corporation (FDIC) OIG
5. Federal Housing Finance Agency (FHFA) OIG
6. Library of Congress (LOC) OIG
7. National Aeronautics and Space Administration (NASA) OIG
8. National Archives and Records Administration (NARA) OIG
9. National Railroad Passenger Corporation (Amtrak) OIG
10. National Science Foundation (NSF) OIG
11. Peace Corps (PC) OIG
12. Smithsonian Institution (Smithsonian) OIG
13. Social Security Administration (SSA) OIG

14. Tennessee Valley Authority (TVA) OIG
15. Treasury Inspector General for Tax Administration (TIGTA)
16. U.S. Agency for International Development (USAID) OIG
17. U.S. Department of Agriculture (USDA) OIG
18. U.S. Department of Commerce (DOC) OIG
19. U.S. Department of Defense (DOD) OIG
20. U.S. Department of Education (Education) OIG
21. U.S. Department of Energy (DOE) OIG
22. U.S. Department of Health and Human Services (HHS) OIG
23. U.S. Department of Homeland Security (DHS) OIG
24. U.S. Department of Housing and Urban Development (HUD) OIG
25. U.S. Department of Justice (DOJ) OIG
26. U.S. Department of Labor (DOL) OIG
27. U.S. Department of State (State) OIG
28. U.S. Department of the Interior (DOI) OIG
29. U.S. Department of the Treasury (Treasury) OIG
30. U.S. Department of Transportation (DOT) OIG
31. U.S. Department of Veterans Affairs (VA) OIG
32. U.S. Environmental Protection Agency (EPA) OIG
33. U.S. General Services Administration (GSA) OIG
34. U.S. Government Publishing Office (GPO) OIG
35. U.S. Nuclear Regulatory Commission (NRC) OIG
36. U.S. Office of Personnel Management (OPM) OIG

- 37. U.S. Postal Service (USPS) OIG
- 38. U.S. Railroad Retirement Board (RRB) OIG
- 39. U.S. Securities and Exchange Commission (SEC) OIG
- 40. U.S. Small Business Administration (SBA) OIG

Instruments

Each year, all agencies must prepare and submit a budget justification detailing their request for the coming year and their actual budget figures for the previous year. Additionally, every six months, each OIG is required to prepare and submit to Congress a detailed report describing the work completed and the number of arrests, charges filed, and monetary recoveries, among other data. Furthermore, the U.S. Office of Personnel Management publishes some staffing-related data on its website. All of the aforementioned budget and staffing data and reports to Congress – which contained all of the data necessary for this study – were publicly available on government websites. Reports and proposals covering federal fiscal years 2016, 2017, and 2018 (as described above) were obtained directly from each OIG’s website, the OIG parent agency’s website, the U.S. Office of Personnel Management’s website, or Congress’s website.

Procedures

The following steps were followed:

1. Data, as discussed in the *Instruments* section above, was collected.

Specifically, the semiannual reports to Congress were retrieved from the website of each individual OIG. The annual budget proposals were retrieved from the website of the OIG or the OIG’s parent agency. Some staffing-related data was obtained from the website of the U.S. Office of Personnel Management. In total, nearly 500 distinct documents were

obtained and reviewed.

2. A very small number of data points were estimated due to the data not being available:

a. For fiscal year 2018, the number of OIG full-time equivalents (FTEs) for the U.S. Government Publishing Office OIG was calculated by computing the average 2016-2017 ratio of OIG FTEs to parent agency budget dollars and then multiplying this ratio by the 2018 parent agency budget dollars (thereby retaining the same ratio of OIG FTEs to parent agency budget dollars for 2018 as for 2016-2017). Additionally, the OIG FTE data for the Board of Governors of the Federal Reserve System OIG, Library of Congress OIG, National Aeronautics and Space Administration OIG, National Railroad Passenger Corporation (Amtrak) OIG, and U.S. Department of State OIG is the number of FTEs requested for 2018, as contained in Congressional budget justifications. Furthermore, the budget dollars for the Library of Congress OIG (for the purpose of excluding these dollars from the parent agency's budget) was calculated by multiplying the 2018 parent agency budget dollars by the average 2016-2017 ratio of OIG budget dollars to parent agency budget dollars (thereby retaining the same ratio of OIG budget dollars to parent agency budget dollars for 2018 as for 2016-2017).

b. For fiscal year 2017, the number of OIG FTEs for the Corporation for National and Community Service OIG, Export-Import Bank of the United States OIG, and U.S. Agency for International Development OIG was calculated by dividing the 2017 OIG budget by the 2018 OIG budget and then multiplying that quotient by the number of 2018 OIG FTEs (thereby retaining the same ratio of OIG FTEs to OIG budget dollars for 2017 as for 2018).

c. For fiscal year 2016, the number of OIG FTEs for the Corporation for National and Community Service OIG, Export-Import Bank of the United States OIG, and U.S. Agency for International Development OIG was calculated by dividing the 2016 OIG budget by the 2017 OIG budget and then multiplying that quotient by the number of 2017 OIG FTEs (thereby retaining the same ratio of OIG FTEs to OIG budget dollars for 2016 as for 2017). Additionally, the budget dollars for the Federal Deposit Insurance Corporation OIG (for the purpose of excluding these dollars from the parent agency's budget) was calculated by multiplying the 2016 parent agency budget dollars by the average 2017-2018 ratio of OIG budget dollars to parent agency budget dollars (thereby retaining the same ratio of OIG budget dollars to parent agency budget dollars for 2016 as for 2017-2018).

3. The data was compiled into a spreadsheet. Specifically, the spreadsheet consisted of four worksheets – one for each of the three fiscal years examined (2016, 2017, and 2018), and one that contained the averages across all three fiscal years. On each worksheet, each OIG was listed vertically, from top to bottom, in alphabetical order. Horizontally, from left to right, the predictor and outcome variables were listed (coverage ratio, charges filed per capita, financial recoveries per capita, and questioned costs per capita), followed by the additional pieces of data needed to calculate the variables: number of criminal charges resulting from the OIG's work; dollar value of all restitution, forfeitures, civil settlements, and administrative recoveries resulting from the OIG's work; dollar value of questioned costs resulting from the OIG's work; budget dollars of the OIG's parent agency; budget dollars of the OIG; and number of full-time equivalents in the OIG.

4. Data analysis, as discussed in the *Data Analysis* section below, was conducted.

Data Analysis

Research questions one and two were addressed using regression, which is appropriate for determining whether, and to what extent, a relationship exists between two continuous variables. The regression analysis resulted in the calculation of Pearson's r , which denotes whether the relationship between the two variables is positive or negative and how strong the relationship is. The regression analysis also resulted in the calculation of a probability value (p), which represents the chance that the relationship occurred due to random chance. Pursuant to social science convention, p values of less than or equal to .05 indicated statistical significance (because the probability that the relationship is due to chance was relatively small). Using IBM SPSS Statistics Version 25, the following statistical analyses were conducted for each of the three fiscal year datasets and for an additional dataset containing the averages across all three fiscal years:

Research question 1.

1. Curve estimation using the linear and quadratic models was performed to determine the best-fitting shape of the regression line between predictor variable coverage ratio and outcome variable charges filed per capita.

2. Curve estimation using the linear and quadratic models was performed to determine the best-fitting shape of the regression line between predictor variable coverage ratio and outcome variable financial recoveries per capita.

3. Curve estimation using the linear and quadratic models was performed to determine the best-fitting shape of the regression line between predictor variable coverage ratio and outcome variable questioned costs per capita.

4. The resultant equations, Pearson's r , and probability value (p) indicated the nature of the relationship between the coverage ratio and each of the three per capita performance outcomes (charges filed per capita, financial recoveries per capita, and questioned costs per capita).

The relationship between the coverage ratio and each of the three performance outcomes (charges filed per capita, financial recoveries per capita, and questioned costs per capita) was predicted to be quadratic and represented by an n-shaped parabola, indicating an optimal coverage ratio beyond which the performance outcomes begin to decrease. In the alternative, the relationship between coverage ratio and each of the three performance outcomes was predicted to be linear and represented by a positive-sloped line, indicating there is no optimal coverage ratio and that increasing the coverage ratio at any level will also increase the performance outcomes.

Research question 2.

1. Curve estimation using the linear and quadratic models was performed to determine the best-fitting shape of the regression line between predictor variable questioned costs per capita and outcome variable charges filed per capita

2. Curve estimation using the linear and quadratic models was performed to determine the best-fitting shape of the regression line between predictor variable questioned costs per capita and outcome variable financial recoveries per capita

3. The resultant equations, Pearson's r , and probability value (p) indicated the nature of the relationship between the questioned costs per capita (the audit-related performance outcome) and each of the two investigative-related performance outcomes (charges filed per capita and financial recoveries per capita).

The relationship between the audit-related questioned costs per capita and each of the two investigative-related performance outcomes (charges filed per capita and financial recoveries per capita) was predicted to be linear and represented by a negative-sloped line, indicating that as the audit-related performance outcome (questioned costs per capita) increases, the investigative-related performance outcomes (charges filed per capita and financial recoveries per capita) decrease, and vice versa. In the alternative, the relationship between questioned costs per capita and each of the investigative-related performance outcomes was predicted to be quadratic and represented by an u-shaped parabola, indicating that low levels of the audit-related performance outcome is correlated with high levels of investigative-related performance outcomes or vice versa (potentially indicating that resources are allocated to one operating unit at the expense of the other), and that high-levels of the audit-related performance outcome is correlated with high levels of investigative-related performance outcomes or vice versa (potentially indicating a symbiotic relationship between the two operating units).

Research question 3. Research question three was addressed using the data envelopment analysis technique. As Wu et al. (2010) discuss, data envelopment analysis is a non-parametric linear programming technique that evaluates how efficient similarly-situated entities (also referred to as “decision making units”) are to one another, based on the inputs these entities use and the outputs they produce. For each entity, a single efficiency score is calculated, with 1.000 representing the most efficient entity and scores of less than 1.000 representing the degree of efficiency relative to the most efficient entity. A score of 1.000 means that the entity had the highest output-to-input ratio (in other words, that entity produced the most output for each unit of input). When multiple

inputs and outputs are involved, each input and output is weighted so that a single efficiency score is calculated; the weights vary for each entity, and data envelopment analysis calculates the weights so as to provide the highest possible score for each entity. This data envelopment analysis technique has been used to compare the performance of banks, schools, restaurants, hospitals, police departments, and other entities having a similar mission to one another (Wu et al., 2010; Verma & Gavirneni, 2006). For example, in comparing the performance of police departments in a particular country, one study calculated an efficiency score for each department based on four inputs and four outputs (Verma & Gavirneni, 2006). The inputs were dollar expenditures, number of police officers, number of investigating officers, and number of cases investigated. The outputs were the number of persons arrested, number of persons charged, number of persons convicted, and number of trials completed.

The present study expanded the use of data envelopment analysis to federal OIGs. This study involved one input and three outputs. The input was the coverage ratio, while the outputs were charges filed per capita, financial recoveries per capita, and questioned costs per capita. Data envelopment analysis resulted in the identification of the most efficient OIG and the calculation of the relative efficiency scores of the remaining OIGs. The most efficient OIG indicated, for the sample, the optimally efficient coverage ratio beyond which per capita performance outcomes begin to decrease. Using Win4Deap 2 data envelopment analysis software (Deslieries, 2015), the following statistical analyses were conducted for each of the three fiscal year datasets and for an additional dataset containing the averages across all three fiscal years:

1. The input and output data for each OIG in the sample was entered into

Win4Deap 2, with coverage ratio as the input, and charges filed per capita, financial recoveries per capita, and questioned costs per capita as the outputs.

2. Using multi-stage, input-oriented, constant-returns-to-scale data envelopment analysis, the relative efficiency score was computed for each OIG in the sample. The OIGs with the highest efficiency score indicated that they had the optimally efficient coverage ratio among all OIGs in the sample.

3. Using the regression equations produced in research question one, the optimally efficient coverage ratio identified by data envelopment analysis was used to calculate the expected performance outcomes (charges filed per capita, financial recoveries per capita, and questioned costs per capita) that have a statistically significant relationship with the coverage ratio.

Changes from Original Methodology

Originally, this study included a second predictor variable – the number of non-supervisors divided by the number of supervisors (termed the *supervisor ratio*) – as a measure of investigative quality and the impact of management decisions, the third theme identified in the literature review. Also, only the staffing levels and performance outcomes for the OIGs’ investigative function alone were contemplated; the audit-related questioned costs per capita was not an outcome variable. Additionally, the original study included a fourth performance outcome – the number of employee disciplinary actions per capita. The data necessary for the original study – specifically, the number of employee disciplinary actions and the number of supervisors and other personnel in each OIG’s investigations division – relied on the use of Freedom of Information Act requests that were to be sent to each of the federal agencies involved in the study. The data

necessary for the original study also relied on the assumption that each federal agency would have the requested data readily available in an existing record and be responsive to the Freedom of Information Act requests. Unfortunately, during the proposal phase of this dissertation, the federal government experienced a 35-day shutdown – the longest in history at that point – affecting Freedom of Information Act operations, among many other areas of government. It was unknown when such operations would return to normal, and there remained the possibility of additional shutdowns. Therefore, it became infeasible to rely on Freedom of Information Act requests and to conduct the study as originally designed.

The current study only used data that was generally known to be publicly and readily accessible – the aforementioned performance outcomes (charges filed per capita, financial recoveries per capita, and questioned costs per capita) and the number of people employed by an OIG as a whole. To account for investigative quality and the impact of management decisions (in place of the supervisor ratio), this study examined the correlation between the two primary but distinct functions of an OIG – audits and investigations, to which OIG executives must allocate resources from the same overall OIG budget. Specifically, this study examined the correlation between the two investigative-related performance outcomes (charges filed per capita and financial recoveries per capita) and the one audit-related performance outcome (questioned costs per capita); a negative correlation would potentially indicate that as attention or resources are allocated to one function instead of another, that function’s performance increases at the expense of the other’s, while a positive correlation would potentially indicate a symbiotic relationship between the two functions, whereby one’s performance aids in the

other's.

Chapter 4: Results

The results of the data analysis for each of the three research questions are described below.

Research Question 1

The first research question asked, “What is the relationship between the coverage ratio and the per capita performance outcomes of charges filed per capita, financial recoveries per capita, and questioned costs per capita?” Data analysis was performed on four data sets: fiscal year 2016 (October 1, 2015, through September 30, 2016), fiscal year 2017 (October 1, 2016, through September 30, 2017), fiscal year 2018 (October 1, 2017, through September 30, 2018), and the average across fiscal years 2016, 2017, and 2018.

Fiscal year 2016. The coverage ratio ranged from 0.00141 to 0.65796 ($N = 40$, $M = 0.06941$, $SD = 0.12918$). Charges filed per capita ranged from 0 to 1.6648 ($N = 40$, $M = 0.30851$, $SD = 0.39611$). Financial recoveries per capita ranged from 0 to 66,640,403 ($N = 40$, $M = 4,198,488.93$, $SD = 14,595,851.485$). Questioned costs per capita ranged from 0 to 12,694,699 ($N = 40$, $M = 773,711.28$, $SD = 2,117,791.235$).

Regarding the regression of coverage ratio on charges filed per capita, neither the linear nor quadratic model showed a statistically significant relationship between coverage ratio and charges filed per capita (linear: $r = .226$, $r^2 = .051$, $p = .162$; quadratic: $r = .342$, $r^2 = .117$, $p = .099$). The data points are shown in Figure 1.

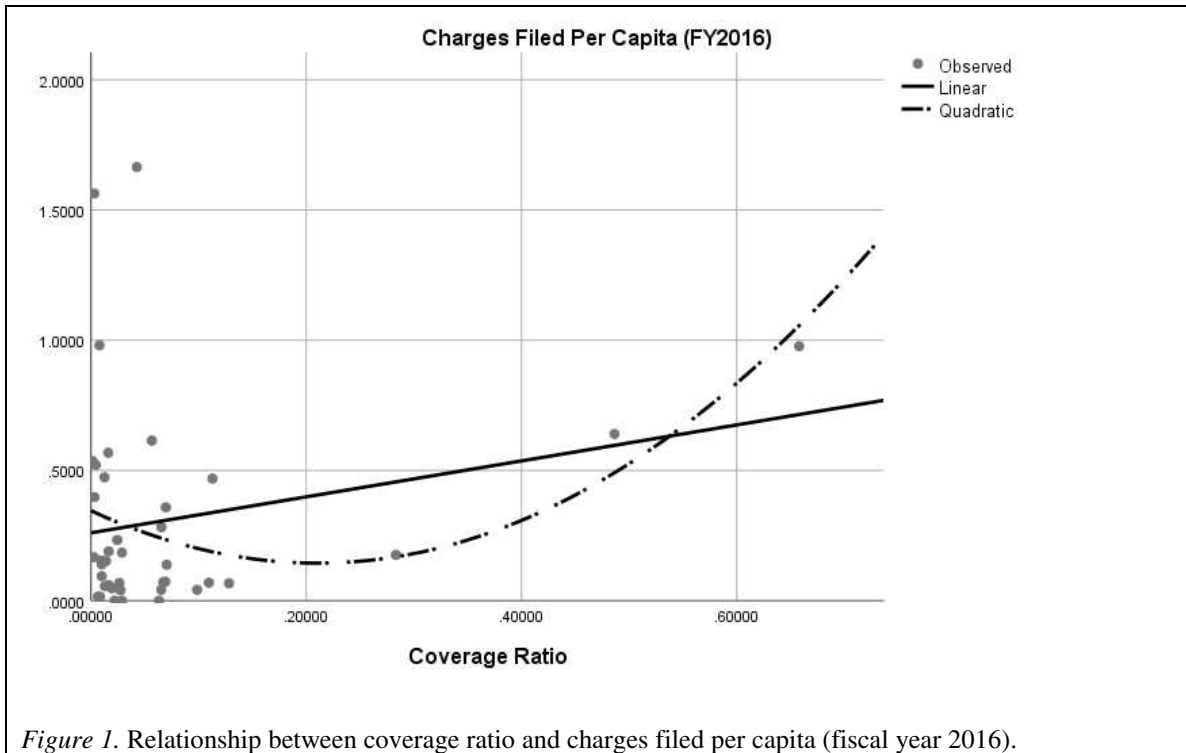


Figure 1. Relationship between coverage ratio and charges filed per capita (fiscal year 2016).

Regarding the regression of coverage ratio on financial recoveries per capita, both the linear and quadratic model showed a statistically significant relationship between coverage ratio and financial recoveries per capita (linear: $r = .500$, $r^2 = .250$, $p < .001$; quadratic: $r = .624$, $r^2 = .389$, $p < .001$). However, at coverage ratios between 0.07483 and 0.26440 (which represent 29% of the range), the quadratic model results in negative financial recoveries per capita, which is impossible. The linear model is depicted by the following equation: (Financial Recoveries Per Capita) = 279,040.194 + [56,466,849.606 * (Coverage Ratio)]. The quadratic model is depicted by the following equation: (Financial Recoveries Per Capita) = 4,793,762.248 + [-82,192,664.677 * (Coverage Ratio)] + [242,294,481.135 * (Coverage Ratio)²]. The data points are shown in Figure 2.

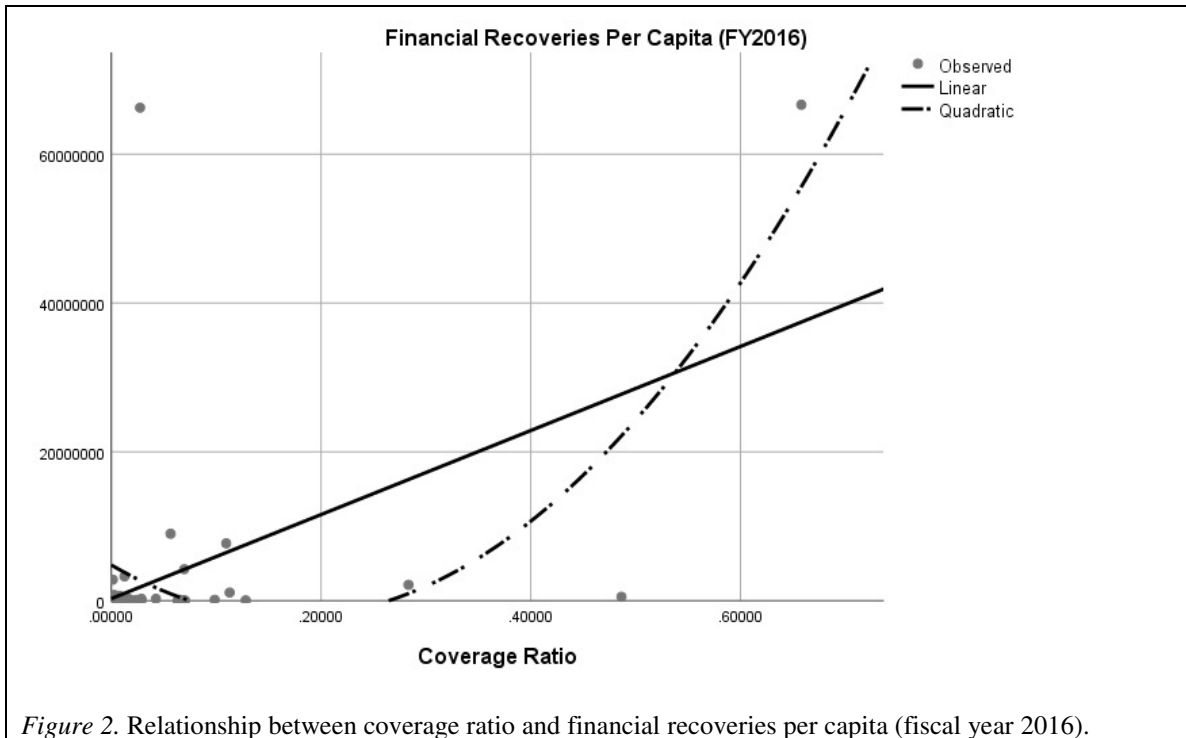


Figure 2. Relationship between coverage ratio and financial recoveries per capita (fiscal year 2016).

Regarding the regression of coverage ratio on questioned costs per capita, both the linear and quadratic model showed a statistically significant relationship between coverage ratio and questioned costs per capita (linear: $r = .446$, $r^2 = .199$, $p = .004$; quadratic: $r = .456$, $r^2 = .208$, $p = .013$). The linear model is depicted by the following equation: (Questioned Costs Per Capita) = 266,005.387 + [7,314,434.761 * (Coverage Ratio)]. The quadratic model is depicted by the following equation: (Questioned Costs Per Capita) = 99,455.735 + [12,429,632 * (Coverage Ratio)] + [-8,938,326.860 * (Coverage Ratio)²]. The data points are shown in Figure 3.

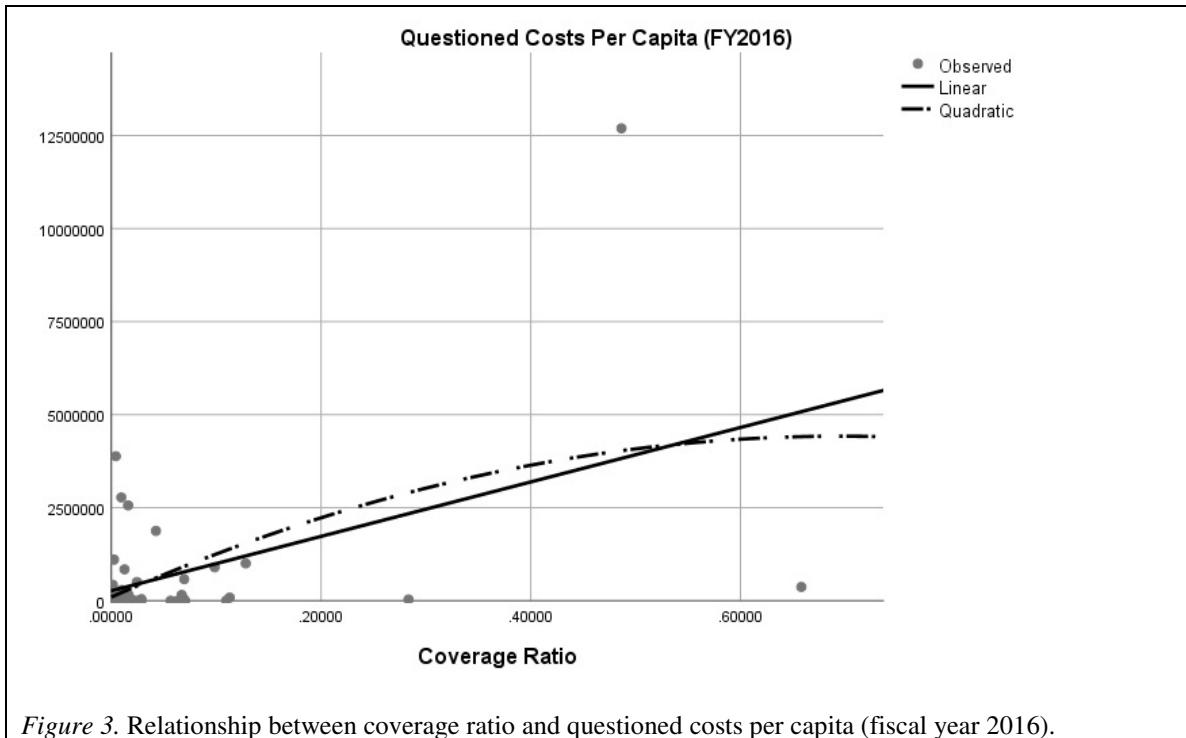


Figure 3. Relationship between coverage ratio and questioned costs per capita (fiscal year 2016).

Fiscal year 2017. The coverage ratio ranged from 0.00141 to 0.68170 ($N = 40$, $M = 0.06807$, $SD = 0.12562$). Charges filed per capita ranged from 0 to 1.3333 ($N = 40$, $M = 0.30006$, $SD = 0.32652$). Financial recoveries per capita ranged from 0 to 93,090,413 ($N = 40$, $M = 3,127,711.50$, $SD = 14,661,368.117$). Questioned costs per capita ranged from 0 to 6,487,719 ($N = 40$, $M = 548,282.95$, $SD = 1,179,677.798$).

Regarding the regression of coverage ratio on charges filed per capita, neither the linear nor quadratic model showed a statistically significant relationship between coverage ratio and charges filed per capita (linear: $r = .298$, $r^2 = .089$, $p = .062$; quadratic: $r = .333$, $r^2 = .111$, $p = .114$). The data points are shown in Figure 4.

Regarding the regression of coverage ratio on financial recoveries per capita, both the linear and quadratic model showed a statistically significant relationship between coverage ratio and financial recoveries per capita (linear: $r = .809$, $r^2 = .655$, $p < .001$; quadratic: $r = .964$, $r^2 = .929$, $p < .001$). However, at coverage ratios between 0.03765

and 0.23621 (which represent 20% of the range), the quadratic model results in negative financial recoveries per capita, which is impossible. The linear model also results in negative financial recoveries per capita at coverage ratios less than 0.03497 (which represent 5% of the range). The linear model is depicted by the following equation: (Financial Recoveries Per Capita) = -3,304,453.391 + [94,496,858.138 * (Coverage Ratio)]. The quadratic model is depicted by the following equation: (Financial Recoveries Per Capita) = 2,708,253.522 + [-83,400,111.073 * (Coverage Ratio)] + [304,541,057.751 * (Coverage Ratio)²]. The data points are shown in Figure 5.

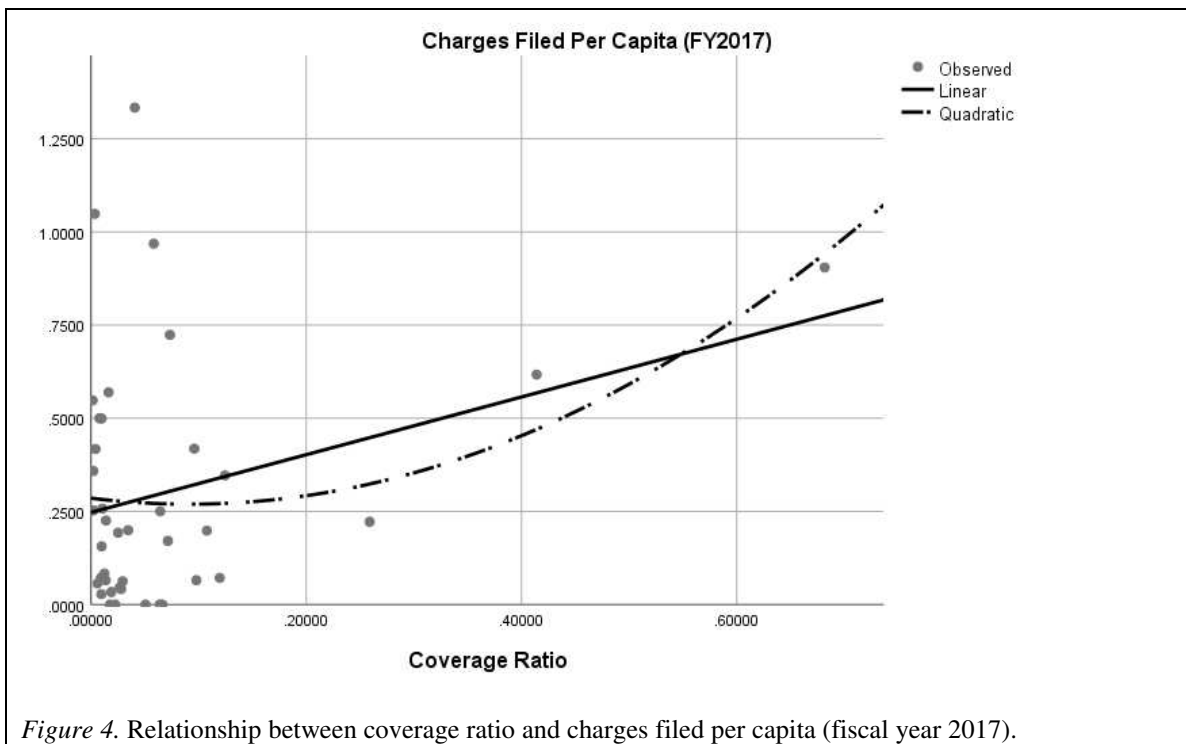


Figure 4. Relationship between coverage ratio and charges filed per capita (fiscal year 2017).

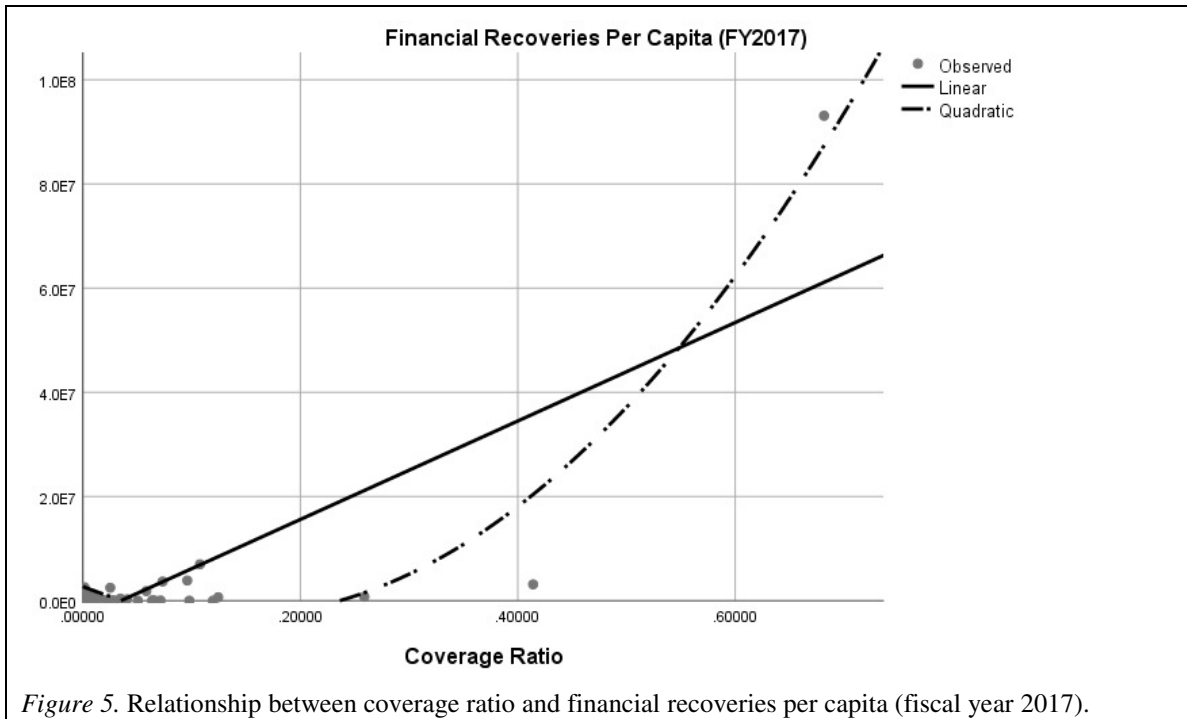


Figure 5. Relationship between coverage ratio and financial recoveries per capita (fiscal year 2017).

Regarding the regression of coverage ratio on questioned costs per capita, neither the linear nor quadratic model showed a statistically significant relationship between coverage ratio and questioned costs per capita (linear: $r = .055$, $r^2 = .003$, $p = .748$; quadratic: $r = .077$, $r^2 = .006$, $p = .901$). The data points are shown in Figure 6.

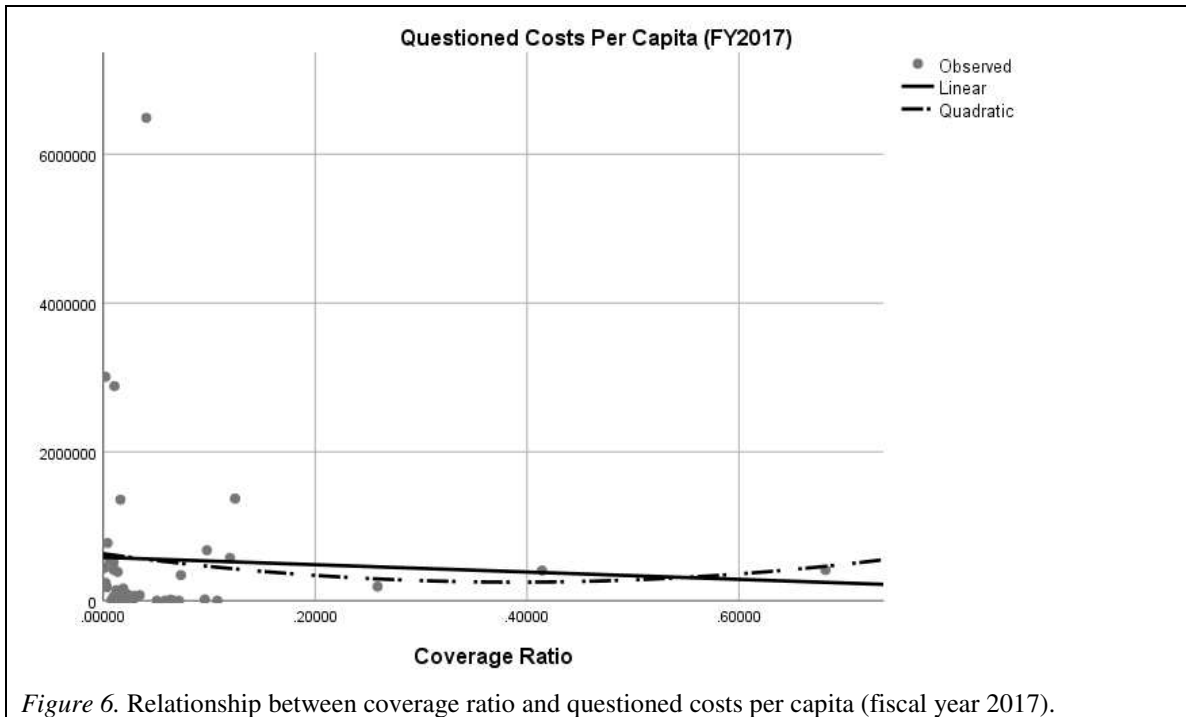


Figure 6. Relationship between coverage ratio and questioned costs per capita (fiscal year 2017).

Fiscal year 2018. The coverage ratio ranged from 0.00137 to 0.63063 ($N = 40$, $M = 0.06999$, $SD = 0.12277$). Charges filed per capita ranged from 0 to 1.4178 ($N = 40$, $M = 0.32073$, $SD = 0.34526$). Financial recoveries per capita ranged from 0 to 72,536,727 ($N = 40$, $M = 2,315,005.18$, $SD = 11,442,262.904$). Questioned costs per capita ranged from 0 to 7,861,556 ($N = 40$, $M = 617,283.60$, $SD = 1,423,353.592$).

Regarding the regression of coverage ratio on charges filed per capita, neither the linear nor quadratic model showed a statistically significant relationship between coverage ratio and charges filed per capita (linear: $r = .235$, $r^2 = .055$, $p = .144$; quadratic: $r = .292$, $r^2 = .085$, $p = .194$). The data points are shown in Figure 7.

Regarding the regression of coverage ratio on financial recoveries per capita, both the linear and quadratic model showed a statistically significant relationship between coverage ratio and financial recoveries per capita (linear: $r = .760$, $r^2 = .578$, $p < .001$; quadratic: $r = .927$, $r^2 = .859$, $p < .001$). However, at coverage ratios between 0.03541

and 0.25550 (which represent 35% of the range), the quadratic model results in negative financial recoveries per capita, which is impossible. The linear model also results in negative financial recoveries per capita at coverage ratios less than 0.03732 (which represent 4% of the range). The linear model is depicted by the following equation: (Financial Recoveries Per Capita) = -2,644,265.446 + [70,857,857.968 * (Coverage Ratio)]. The quadratic model is depicted by the following equation: (Financial Recoveries Per Capita) = 2,529,154.591 + [-81,331,902.185 * (Coverage Ratio)] + [279,577,158.747 * (Coverage Ratio)²]. The data points are shown in Figure 8.

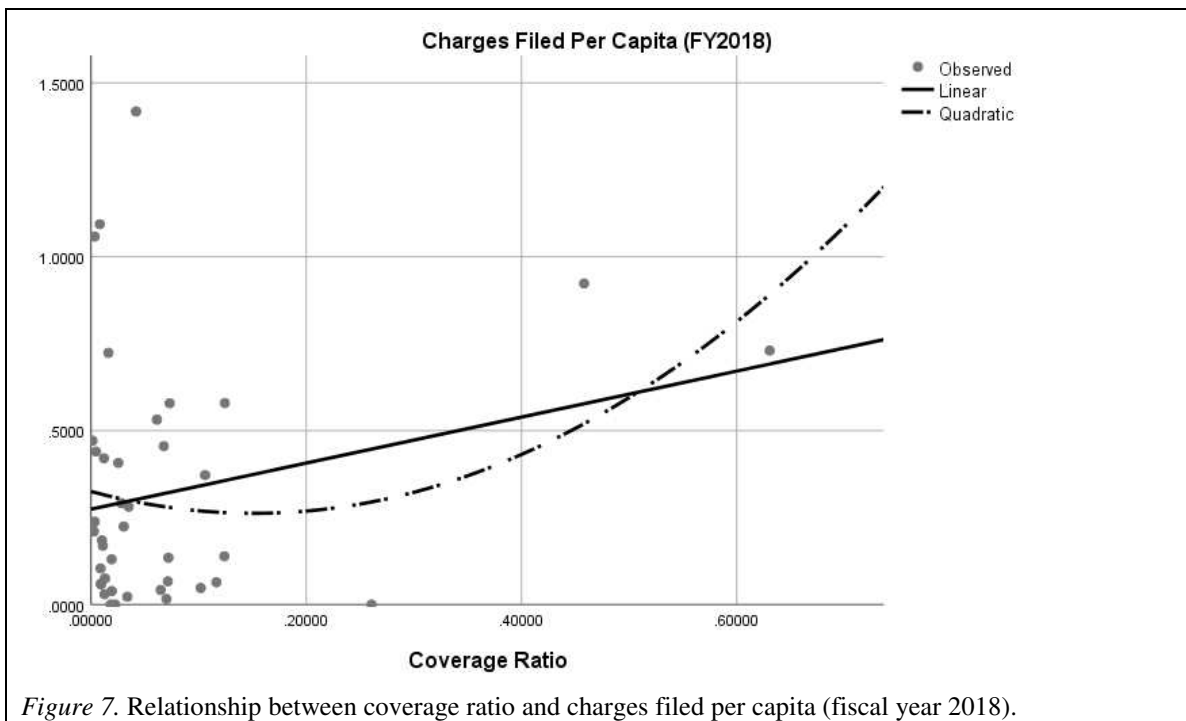


Figure 7. Relationship between coverage ratio and charges filed per capita (fiscal year 2018).

Regarding the regression of coverage ratio on questioned costs per capita, both the linear and quadratic model showed a statistically significant relationship between coverage ratio and questioned costs per capita (linear: $r = .378$, $r^2 = .143$, $p = .016$; quadratic: $r = .400$, $r^2 = .160$, $p = .040$). The linear model is depicted by the following equation: (Questioned Costs Per Capita) = 310,670.532 + [4,380,875.112 * (Coverage

Ratio)]. The quadratic model is depicted by the following equation: (Questioned Costs Per Capita) = 151,578.230 + [9,060,993.705 * (Coverage Ratio)] + [-8,597,518.370 * (Coverage Ratio)²]. The data points are shown in Figure 9.

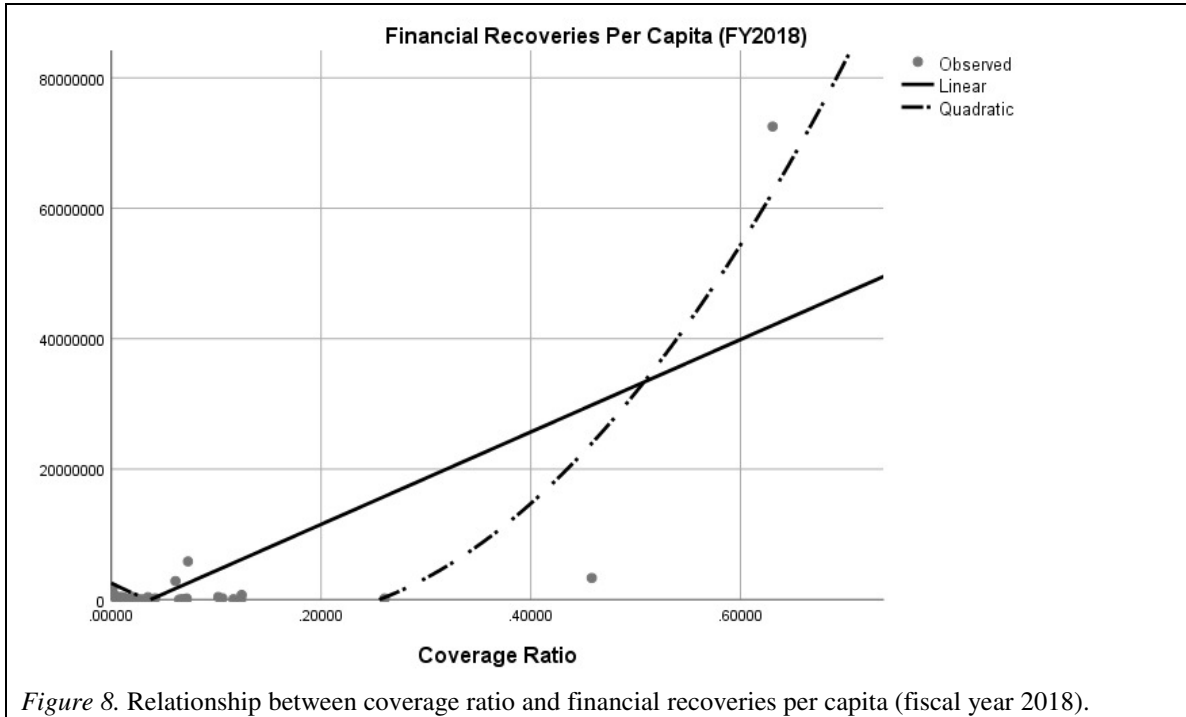


Figure 8. Relationship between coverage ratio and financial recoveries per capita (fiscal year 2018).

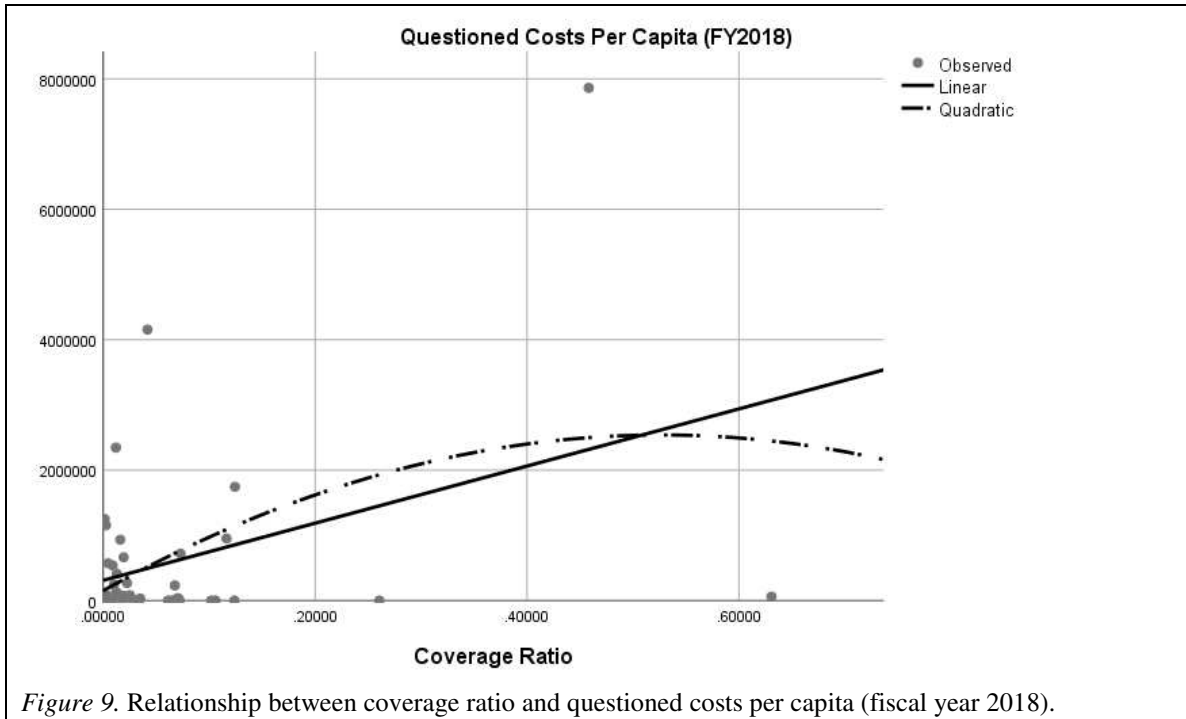
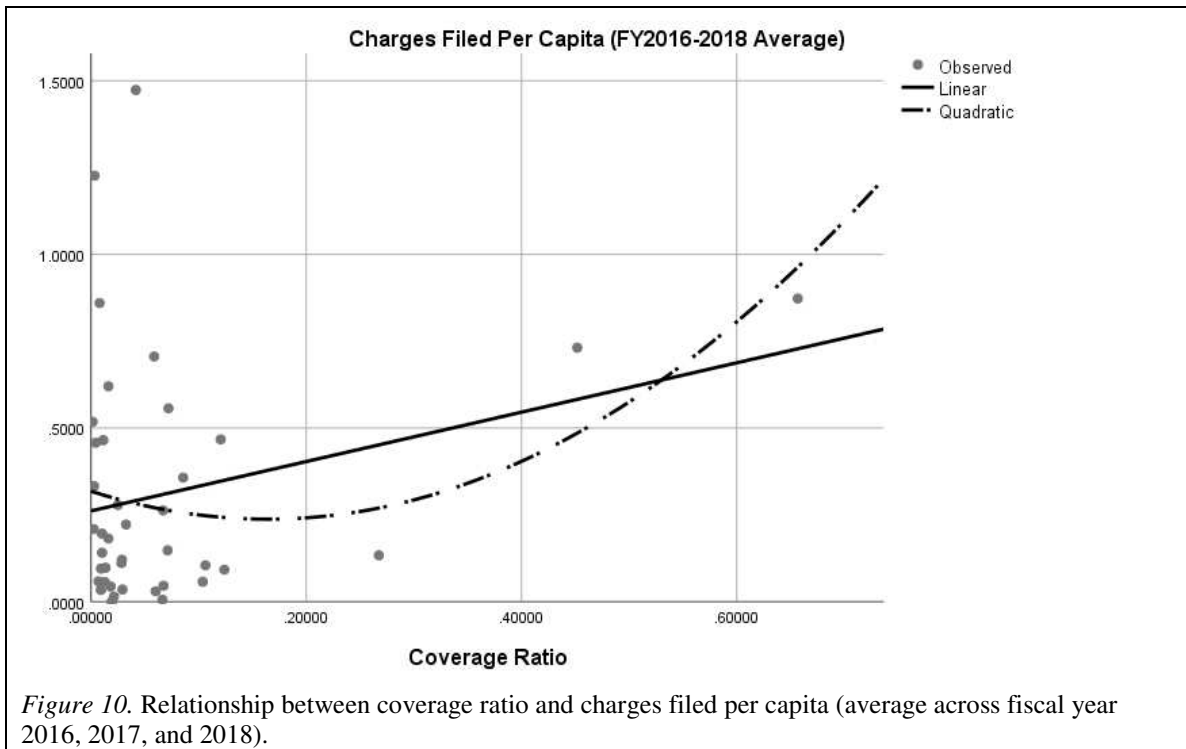


Figure 9. Relationship between coverage ratio and questioned costs per capita (fiscal year 2018).

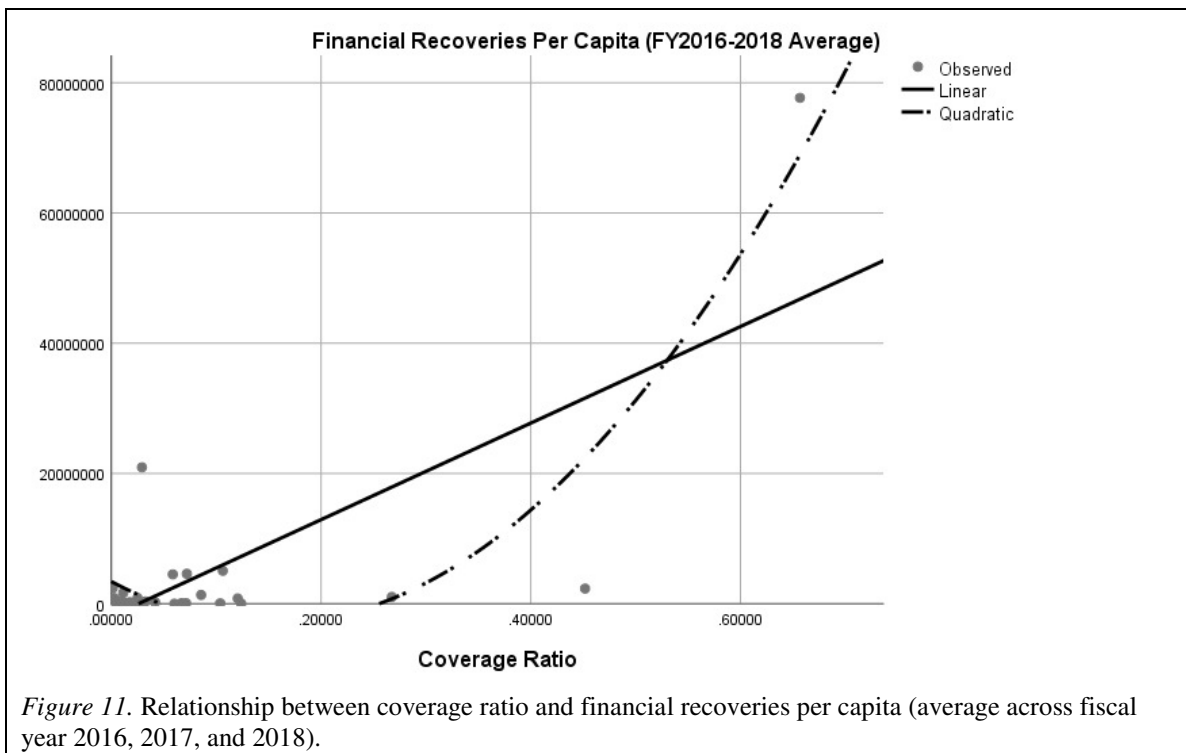
Average across fiscal years 2016, 2017, and 2018. The coverage ratio ranged from 0.00140 to 0.65675 ($N = 40$, $M = 0.06898$, $SD = 0.12559$). Charges filed per capita ranged from 0 to 1.4732 ($N = 40$, $M = 0.310508$, $SD = 0.34532$). Financial recoveries per capita ranged from 0 to 77,684,012 ($N = 40$, $M = 3,190,956.50$, $SD = 12,560,703.704$). Questioned costs per capita ranged from 0 to 7,131,474 ($N = 40$, $M = 649,277.45$, $SD = 1,296,551.497$).

Regarding the regression of coverage ratio on charges filed per capita, neither the linear nor quadratic model showed a statistically significant relationship between coverage ratio and charges filed per capita (linear: $r = .259$, $r^2 = .067$, $p = .107$; quadratic: $r = .326$, $r^2 = .106$, $p = .125$). The data points are shown in Figure 10.



Regarding the regression of coverage ratio on financial recoveries per capita, both the linear and quadratic model showed a statistically significant relationship between coverage ratio and financial recoveries per capita (linear: $r = .741$, $r^2 = .549$, $p < .001$;

quadratic: $r = .903$, $r^2 = .816$, $p < .001$). However, at coverage ratios between 0.04723 and 0.25535 (which represent 32% of the range), the quadratic model results in negative financial recoveries per capita, which is impossible. The linear model also results in negative financial recoveries per capita at coverage ratios less than 0.02594 (which represent 4% of the range). The linear model is depicted by the following equation: (Financial Recoveries Per Capita) = $-1,923,371.532 + [74,139,499.610 * (\text{Coverage Ratio})]$. The quadratic model is depicted by the following equation: (Financial Recoveries Per Capita) = $3,398,370.026 + [-85,269,322.251 * (\text{Coverage Ratio})] + [281,813,906.309 * (\text{Coverage Ratio})^2]$. The data points are shown in Figure 11.



Regarding the regression of coverage ratio on questioned costs per capita, the linear model, but not the quadratic model, showed a statistically significant relationship between coverage ratio and questioned costs per capita (linear: $r = .354$, $r^2 = .125$, $p = .025$; quadratic: $r = .381$, $r^2 = .145$, $p = .055$). The linear model is depicted by the

following equation: (Questioned Costs Per Capita) = 397,164.199 + [3,654,742.159 * (Coverage Ratio)]. The data points are shown in Figure 12.

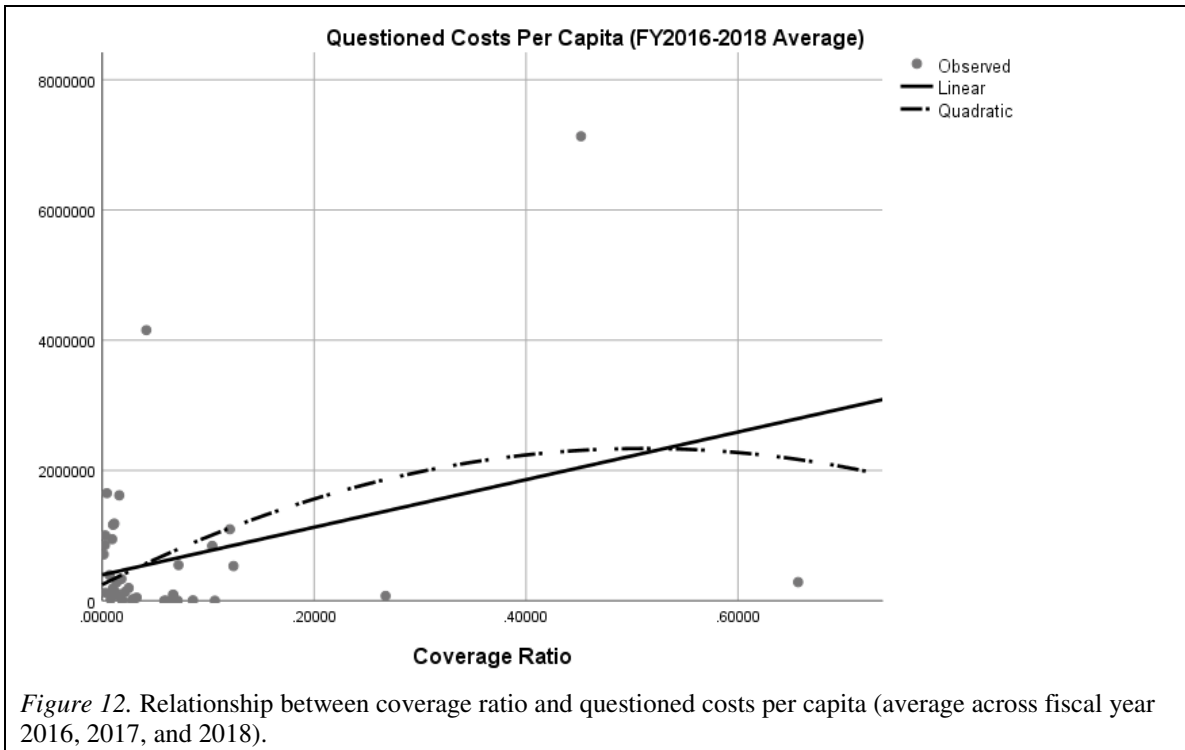


Figure 12. Relationship between coverage ratio and questioned costs per capita (average across fiscal year 2016, 2017, and 2018).

Summary of results for research question 1. In summary, no statistically significant relationship was found between coverage ratio and charges filed per capita. A positive correlation was found between coverage ratio and financial recoveries per capita using both quadratic and linear regression. However, the linear regression equation results in negative financial recoveries per capita (an impossible result) for 4-5% of the lowest end of the coverage ratio range, and the quadratic regression equation results in negative financial recoveries per capita for 20-35% of the coverage ratio range. On the other hand, whether a relationship exists between coverage ratio and questioned costs per capita varies by year: a linear and quadratic relationship was found for 2016 and 2018; no relationship was found for 2017; and a linear relationship was found for the 2016-2018 average.

Research Question 2

The second research question asked, “What is the relationship between the audit-related performance outcome of questioned costs per capita and the investigative-related performance outcomes of charges filed per capita and financial recoveries per capita?”

Data analysis was performed on four data sets: fiscal year 2016 (October 1, 2015, through September 30, 2016), fiscal year 2017 (October 1, 2016, through September 30, 2017), fiscal year 2018 (October 1, 2017, through September 30, 2018), and the average across fiscal years 2016, 2017, and 2018.

Fiscal year 2016. Questioned costs per capita ranged from 0 to 12,694,699 ($N = 40$, $M = 773,711.28$, $SD = 2,117,791.235$). Charges filed per capita ranged from 0 to 1.6648 ($N = 40$, $M = 0.30851$, $SD = 0.39611$). Financial recoveries per capita ranged from 0 to 66,640,403 ($N = 40$, $M = 4,198,488.93$, $SD = 14,595,851.485$).

Regarding the regression of questioned costs per capita on charges filed per capita, neither the linear nor quadratic model showed a statistically significant relationship between questioned costs per capita and charges filed per capita (linear: $r = .230$, $r^2 = .053$, $p = .152$; quadratic: $r = .307$, $r^2 = .094$, $p = .162$). The data points are shown in Figure 13.

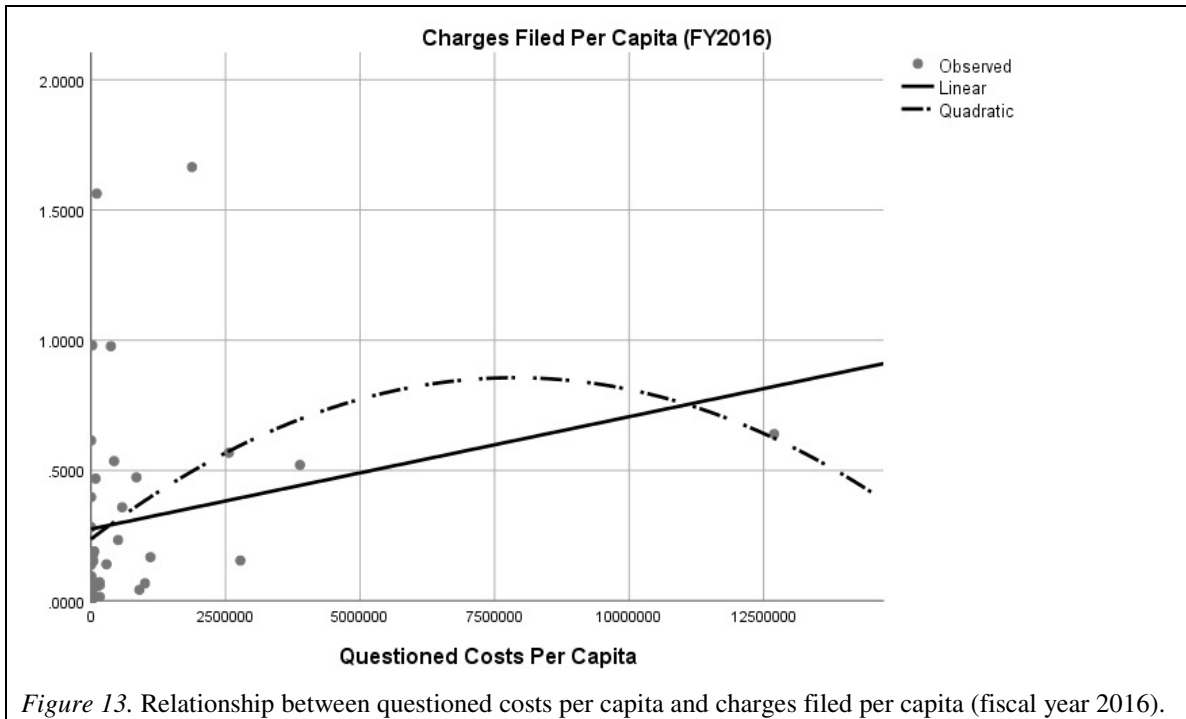
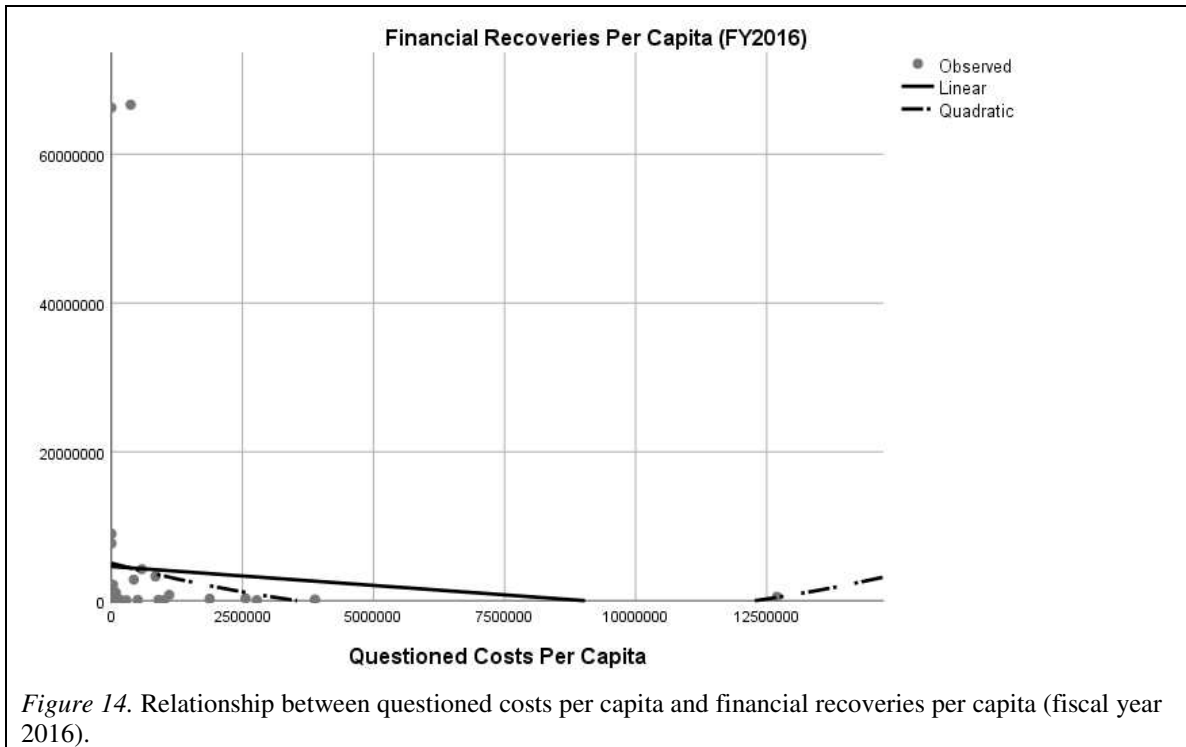


Figure 13. Relationship between questioned costs per capita and charges filed per capita (fiscal year 2016).

Regarding the regression of questioned costs per capita on financial recoveries per capita, neither the linear nor quadratic model showed a statistically significant relationship between questioned costs per capita and financial recoveries per capita (linear: $r = .071$, $r^2 = .005$, $p = .651$; quadratic: $r = .095$, $r^2 = .009$, $p = .839$). The data points are shown in Figure 14.



Fiscal year 2017. Questioned costs per capita ranged from 0 to 6,487,719 ($N = 40$, $M = 548,282.95$, $SD = 1,179,677.798$). Charges filed per capita ranged from 0 to 1.3333 ($N = 40$, $M = 0.30006$, $SD = 0.32652$). Financial recoveries per capita ranged from 0 to 93,090,413 ($N = 40$, $M = 3,127,711.50$, $SD = 14,661,368.117$).

Regarding the regression of questioned costs per capita on charges filed per capita, both the linear and quadratic model showed a statistically significant relationship between questioned costs per capita and charges filed per capita (linear: $r = .490$, $r^2 = .240$, $p = .001$; quadratic: $r = .510$, $r^2 = .260$, $p = .004$). The linear model is depicted by the following equation: $(\text{Charges Filed Per Capita}) = 0.226 + [(1.357 * 10^{-7}) * (\text{Questioned Costs Per Capita})]$. The quadratic model is depicted by the following equation: $(\text{Charges Filed Per Capita}) = 0.251 + [(3.001 * 10^{-8}) * (\text{Questioned Costs Per Capita})] + [(1.947 * 10^{-14}) * (\text{Questioned Costs Per Capita})^2]$. The data points are shown in Figure 15.

Regarding the regression of questioned costs per capita on financial recoveries per capita, neither the linear nor quadratic model showed a statistically significant relationship between questioned costs per capita and financial recoveries per capita (linear: $r = .032$, $r^2 = .001$, $p = .848$; quadratic: $r = .055$, $r^2 = .003$, $p = .948$). The data points are shown in Figure 16.

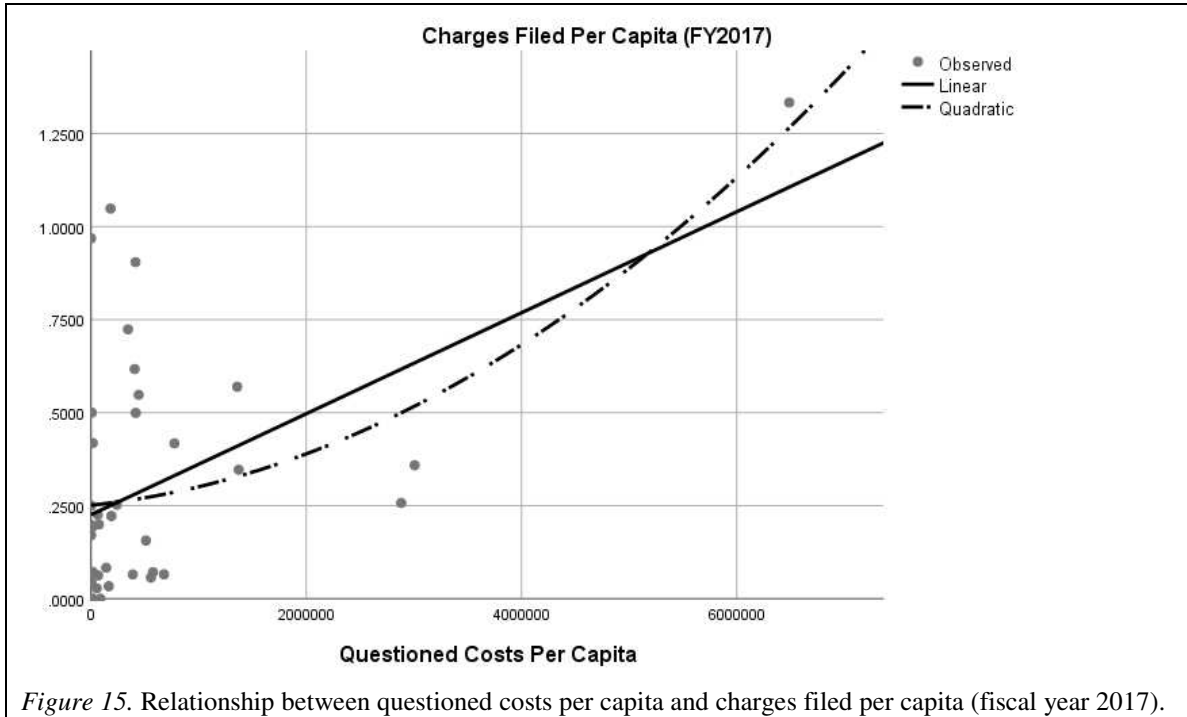
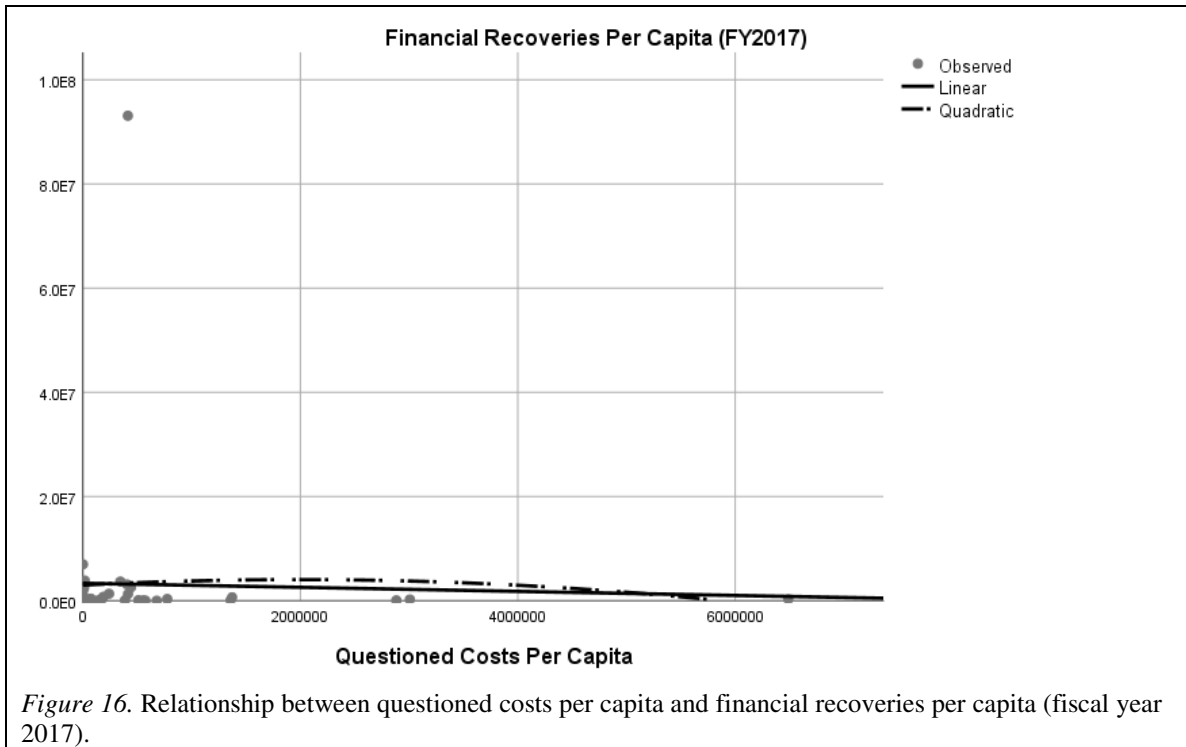


Figure 15. Relationship between questioned costs per capita and charges filed per capita (fiscal year 2017).



Fiscal year 2018. Questioned costs per capita ranged from 0 to 7,861,556 ($N = 40$, $M = 617,283.60$, $SD = 1,423,353.592$). Charges filed per capita ranged from 0 to 1.4178 ($N = 40$, $M = 0.32073$, $SD = 0.34526$). Financial recoveries per capita ranged from 0 to 72,536,727 ($N = 40$, $M = 2,315,005.18$, $SD = 11,442,262.904$).

Regarding the regression of questioned costs per capita on charges filed per capita, both the linear and quadratic model showed a statistically significant relationship between questioned costs per capita and charges filed per capita (linear: $r = .520$, $r^2 = .270$, $p = .001$; quadratic: $r = .550$, $r^2 = .303$, $p = .001$). The linear model is depicted by the following equation: $(\text{Charges Filed Per Capita}) = 0.243 + [(1.261 * 10^{-7}) * (\text{Questioned Costs Per Capita})]$. The quadratic model is depicted by the following equation: $(\text{Charges Filed Per Capita}) = 0.212 + [(2.454 * 10^{-7}) * (\text{Questioned Costs Per Capita})] + [(-1.800 * 10^{-14}) * (\text{Questioned Costs Per Capita})^2]$. The data points are shown in Figure 17.

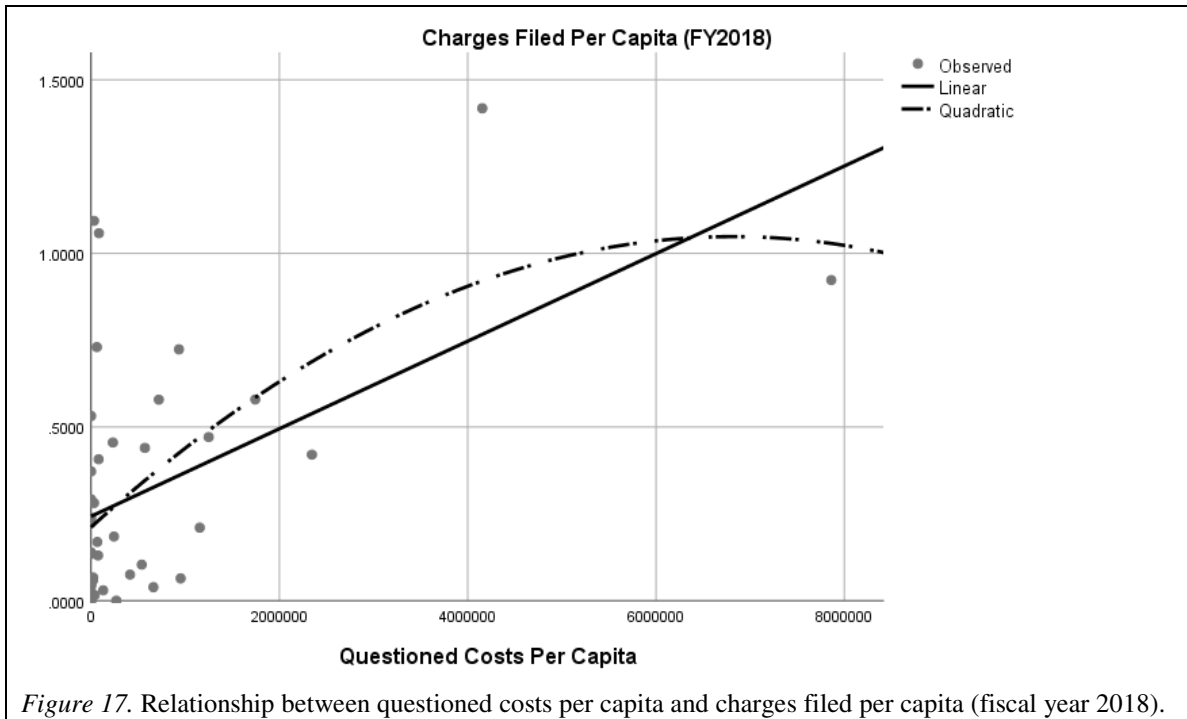
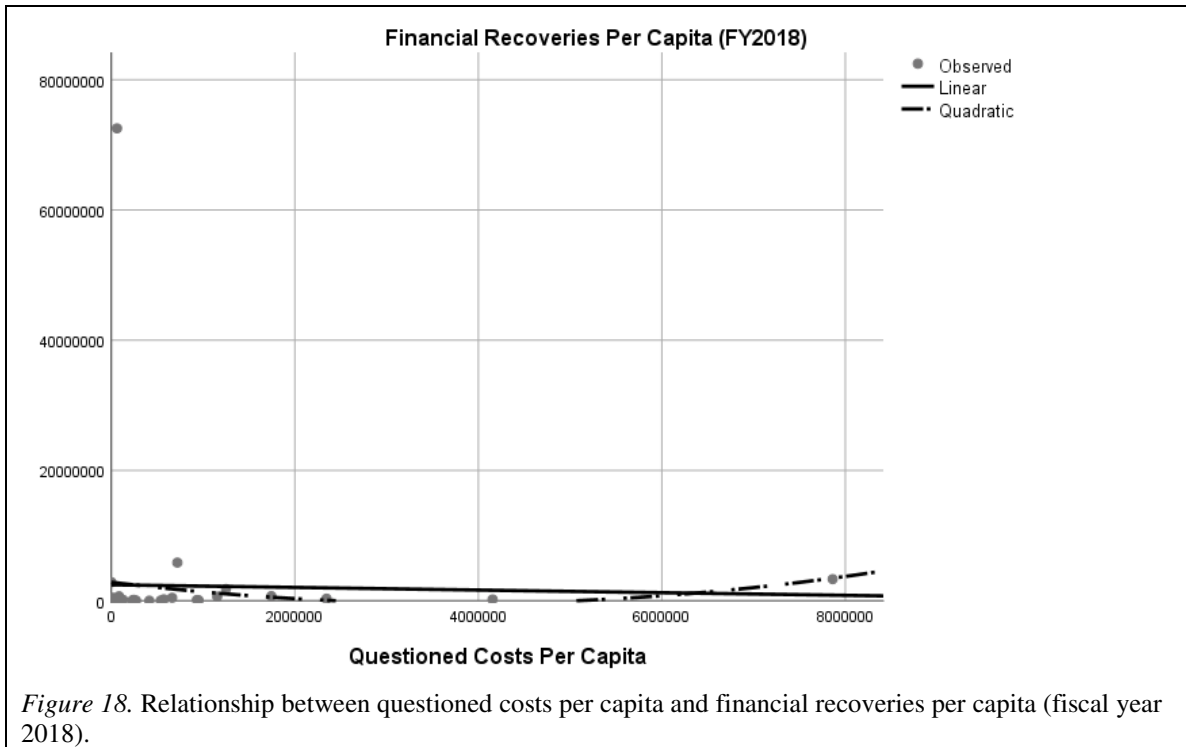


Figure 17. Relationship between questioned costs per capita and charges filed per capita (fiscal year 2018).

Regarding the regression of questioned costs per capita on financial recoveries per capita, neither the linear nor quadratic model showed a statistically significant relationship between questioned costs per capita and financial recoveries per capita (linear: $r = .032$, $r^2 = .001$, $p = .878$; quadratic: $r = .071$, $r^2 = .005$, $p = .904$). The data points are shown in Figure 18.



Average across fiscal years 2016, 2017, and 2018. Questioned costs per capita ranged from 0 to 7,131,474 ($N = 40$, $M = 649,277.45$, $SD = 1,296,551.497$). Charges filed per capita ranged from 0 to 1.4732 ($N = 40$, $M = 0.310508$, $SD = 0.34532$). Financial recoveries per capita ranged from 0 to 77,684,012 ($N = 40$, $M = 3,190,956.50$, $SD = 12,560,703.704$).

Regarding the regression of questioned costs per capita on charges filed per capita, both the linear and quadratic model showed a statistically significant relationship between questioned costs per capita and charges filed per capita (linear: $r = .477$, $r^2 = .228$, $p = .002$; quadratic: $r = .521$, $r^2 = .271$, $p = .003$). The linear model is depicted by the following equation: (Charges Filed Per Capita) = $0.228 + [(1.271 * 10^{-7}) * (\text{Questioned Costs Per Capita})]$. The quadratic model is depicted by the following equation: (Charges Filed Per Capita) = $0.181 + [(2.793 * 10^{-7}) * (\text{Questioned Costs Per Capita})] + [(-2.505 * 10^{-14}) * (\text{Questioned Costs Per Capita})^2]$. The data points are shown

in Figure 19.

Regarding the regression of questioned costs per capita on financial recoveries per capita, neither the linear nor quadratic model showed a statistically significant relationship between questioned costs per capita and financial recoveries per capita (linear: $r = .055$, $r^2 = .003$, $p = .748$; quadratic: $r = .077$, $r^2 = .006$, $p = .899$). The data points are shown in Figure 20.

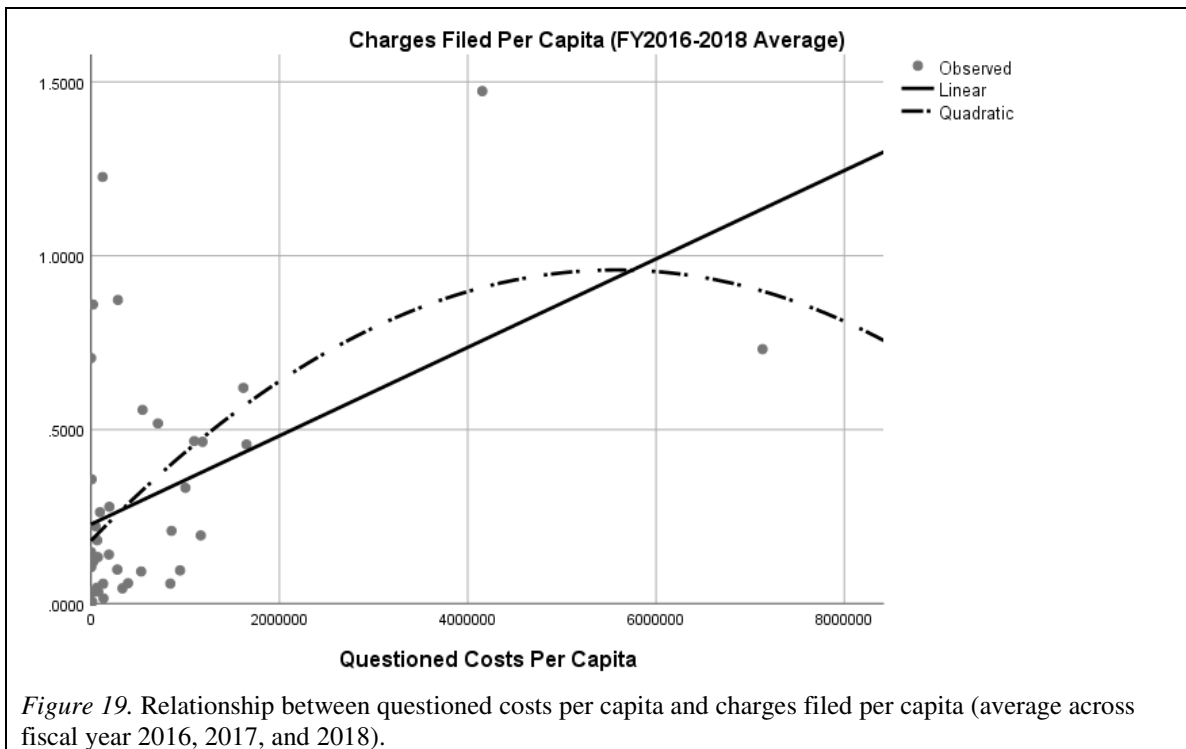
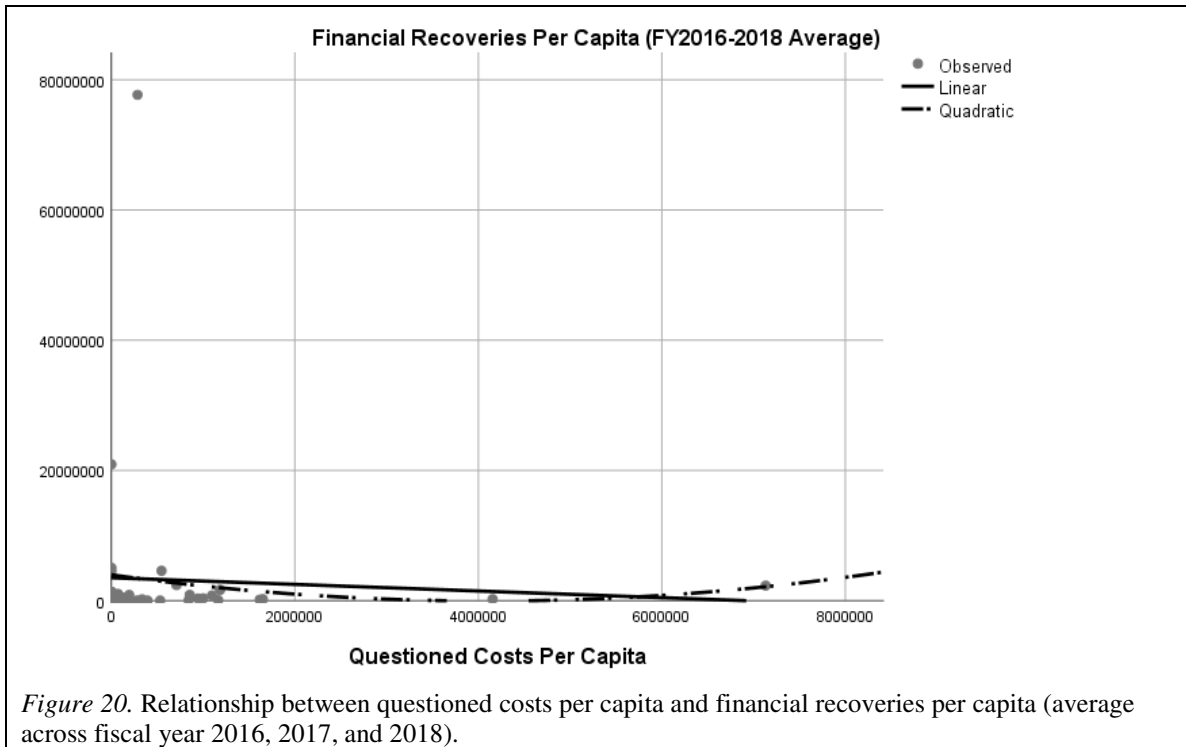


Figure 19. Relationship between questioned costs per capita and charges filed per capita (average across fiscal year 2016, 2017, and 2018).



Summary of results for research question 2. In summary, no statistically significant relationship was found between questioned costs per capita and financial recoveries per capita. On the other hand, for 2017, 2018, and the 2016-2018 average, a linear and quadratic relationship was found between questioned costs per capita and charges filed per capita. No such relationship was found for 2016, however.

Research Question 3

The third research question asked, “What is the optimal coverage ratio beyond which the per capita performance outcomes of charges filed per capita, financial recoveries per capita, and questioned costs per capita begin to decrease?” Data analysis was performed on four data sets: fiscal year 2016 (October 1, 2015, through September 30, 2016), fiscal year 2017 (October 1, 2016, through September 30, 2017), fiscal year 2018 (October 1, 2017, through September 30, 2018), and the average across fiscal years 2016, 2017, and 2018.

Fiscal year 2016. The coverage ratio ranged from 0.00141 to 0.65796 ($N = 40$, $M = 0.06941$, $SD = 0.12918$). Charges filed per capita ranged from 0 to 1.6648 ($N = 40$, $M = 0.30851$, $SD = 0.39611$). Financial recoveries per capita ranged from 0 to 66,640,403 ($N = 40$, $M = 4,198,488.93$, $SD = 14,595,851.485$). Questioned costs per capita ranged from 0 to 12,694,699 ($N = 40$, $M = 773,711.28$, $SD = 2,117,791.235$).

Tables 1 and 2 depict, for each OIG, the technical efficiency score (with 1.000 representing maximum efficiency), the actual coverage ratio (the input), the efficient coverage ratio given the actual outputs (charges filed per capita, financial recoveries per capita, and questioned costs per capita), the actual coverage ratio as a percentage of the efficient coverage ratio, and the actual outputs. A technical efficiency score of 1.000 means that the OIG had the highest outputs-to-inputs ratio (in other words, that entity produced the most output for each unit of input). Technical efficiency scores of less than 1.000 represent the degree of efficiency relative to the most efficient OIG. For example, in Table 1, the HHS, USDA, VA, and EPA OIGs have efficiency scores of 1.000, meaning they were the most efficient OIGs; DOD OIG has an efficiency score of .577, meaning it has 57.7% the efficiency of the HHS, UDA, VA, and EPA OIGs. The coverage ratio is considered the input. The “actual” coverage ratio represents the coverage ratio that the OIG actually had. The “efficient” coverage ratio represents the coverage ratio that the OIG needs to have to be most efficient (to have an efficiency score of 1.000) in light of the outputs the OIG produced. “Actual as a % of efficient” represents the actual coverage ratio divided by the efficient coverage ratio. For example, DOD OIG has 173% as its “actual as a % of efficient,” meaning its actual coverage ratio is 1.73 times the coverage ratio it needs to have to be considered optimally efficient. The

three columns underneath “actual performance” represent the outputs (the performance outcomes) – charges filed per capita, financial recoveries per capita, and questioned costs per capita, as defined earlier in this paper.

The HHS, USDA, VA, and EPA OIGs had efficiency scores of 1.000, meaning they were the most efficient OIGs. HHS OIG had a coverage ratio of 0.00141 (corresponding to 0.53587 charges filed per capita; 2,831,746 financial recoveries per capita; and 427,794 questioned costs per capita); USDA OIG had a coverage ratio of 0.00296 (corresponding to 1.56301 charges filed per capita; 321,667 financial recoveries per capita; and 106,353 questioned costs per capita); VA OIG had a coverage ratio of 0.00423 (corresponding to 0.52125 charges filed per capita; 152,550 financial recoveries per capita; and 3,882,720 questioned costs per capita); and EPA OIG had a coverage ratio of 0.02738 (corresponding to 0.04000 charges filed per capita; 66,241,920 financial recoveries per capita; and 161 questioned costs per capita).

Research question one identified a positive correlation between coverage ratio and financial recoveries per capita for fiscal year 2016 using linear and quadratic regression. Linear regression analysis produced the following equation: (Financial Recoveries Per Capita) = 279,040.194 + [56,466,849.606 * (Coverage Ratio)]. Using this regression equation, HHS OIG’s coverage ratio of 0.00141 was expected to result in 358,658,451.944 financial recoveries per capita; USDA OIG’s coverage ratio of 0.00296 was expected to result in 446,182,068.834 financial recoveries per capita; VA OIG’s coverage ratio of 0.00423 was expected to result in 517,894,967.833 financial recoveries per capita; and EPA OIG’s coverage ratio of 0.02738 was expected to result in 1,825,102,536.212 financial recoveries per capita. Quadratic regression analysis

produced the following equation: (Financial Recoveries Per Capita) = 4,793,762.248 + [-82,192,664.677 * (Coverage Ratio)] + [242,294,481.135 * (Coverage Ratio)²]. Using this regression equation, HHS OIG's coverage ratio of 0.00141 was expected to result in 4,678,352.296 financial recoveries per capita; USDA OIG's coverage ratio of 0.00296 was expected to result in 4,552,594.848 financial recoveries per capita; VA OIG's coverage ratio of 0.00423 was expected to result in 4,450,422.627 financial recoveries per capita; and EPA OIG's coverage ratio of 0.02738 was expected to result in 2,724,966.636 financial recoveries per capita.

Table 1:

Data Envelopment Analysis Results for Fiscal Year 2016, Part 1 of 2

OIG	Technical Efficiency	Coverage Ratio			Actual Performance		
		Actual	Efficient	Actual as % of Efficient	Charges Filed Per Capita	Financial Recoveries Per Capita	Questioned Costs Per Capita
HHS	1.000	0.00141	0.00141	100%	0.53587	2,831,746	427,794
USDA	1.000	0.00296	0.00296	100%	1.56301	321,667	106,353
VA	1.000	0.00423	0.00423	100%	0.52125	152,550	3,882,720
EPA	1.000	0.02738	0.02738	100%	0.04000	66,241,920	161
DOD	0.577	0.00251	0.00145	173%	0.16722	773,579	1,104,117
DOE	0.320	0.00944	0.00303	312%	0.15412	60,089	2,775,086
Education	0.264	0.00312	0.00083	378%	0.39754	581,244	2,075
DOL	0.247	0.00778	0.00192	404%	0.98039	660,523	24,370
USPS	0.201	0.01597	0.00321	498%	0.56776	302,925	2,560,792
HUD	0.160	0.01252	0.00200	626%	0.47377	3,268,308	842,824
SSA	0.109	0.04249	0.00464	915%	1.66475	246,690	1,875,720
FDIC	0.071	0.05647	0.00399	1415%	0.61475	8,998,855	451
DHS	0.050	0.00992	0.00050	1988%	0.14000	51,624	286,178
FHFA	0.042	0.65796	0.02796	2353%	0.97710	66,640,403	368,163
DOT	0.035	0.02439	0.00085	2859%	0.23291	107,850	502,417
OPM	0.030	0.06952	0.00207	3360%	0.35862	4,228,756	578,511
FRS	0.029	0.10952	0.00321	3410%	0.06923	7,700,988	0
RRB	0.028	0.48644	0.01385	3512%	0.64000	528,910	12,694,699
NSF	0.026	0.00845	0.00022	3888%	0.01493	133,235	160,409
DOJ	0.024	0.01633	0.00040	4106%	0.18950	17,245	58,325

Table 2:

Data Envelopment Analysis Results for Fiscal Year 2016, Part 2 of 2

OIG	Technical Efficiency	Coverage Ratio			Actual Performance		
		Actual	Efficient	Actual as % of Efficient	Charges Filed Per Capita	Financial Recoveries Per Capita	Questioned Costs Per Capita
DOI	0.023	0.01391	0.00031	4429%	0.15209	28,146	40,846
NASA	0.018	0.00992	0.00018	5438%	0.09424	45,866	4,124
State	0.016	0.00643	0.00010	6348%	0.01572	14,617	85,561
DOC	0.015	0.01641	0.00025	6668%	0.05988	67,051	159,916
TVA	0.015	0.01307	0.00020	6566%	0.05556	44,856	113,981
GSA	0.013	0.02869	0.00038	7566%	0.18456	241,848	39,246
USAID	0.010	0.09855	0.00101	9778%	0.04167	121,282	898,141
GPO	0.009	0.12813	0.00110	11690%	0.06667	50,000	1,002,111
SBA	0.009	0.11279	0.00103	10932%	0.46875	1,090,199	83,720
Treasury	0.008	0.06543	0.00054	12016%	0.28235	121,831	0
CNCS	0.006	0.01927	0.00011	16855%	0.04762	38,668	31,000
SEC	0.005	0.02638	0.00013	20404%	0.06818	909	4,573
PC	0.004	0.06707	0.00026	25374%	0.07143	32,160	157,258
TIGTA	0.004	0.07023	0.00026	26754%	0.13815	32,339	475
EXIM	0.003	0.28336	0.00096	29555%	0.17593	2,132,039	31,542
Amtrak	0.002	0.06906	0.00017	40191%	0.07292	14,484	44,792
NARA	0.001	0.06518	0.00008	82506%	0.04167	620	0
Smithsonian	0.000	0.02868	<0.00001	607648%	0.00000	11,413	0
NRC	0.000	0.06318	<0.00001	7179464%	0.00000	2,122	0
LOC	0.000	0.02191	0.00000	-	0.00000	0	0

Fiscal year 2017. The coverage ratio ranged from 0.00141 to 0.68170 ($N = 40$, $M = 0.06807$, $SD = 0.12562$). Charges filed per capita ranged from 0 to 1.3333 ($N = 40$, $M = 0.30006$, $SD = 0.32652$). Financial recoveries per capita ranged from 0 to 93,090,413 ($N = 40$, $M = 3,127,711.50$, $SD = 14,661,368.117$). Questioned costs per capita ranged from 0 to 6,487,719 ($N = 40$, $M = 548,282.95$, $SD = 1,179,677.798$).

Tables 3 and 4 depict, for each OIG, the technical efficiency score (with 1.000 representing maximum efficiency), the actual coverage ratio, the efficient coverage ratio given the actual outputs (charges filed per capita, financial recoveries per capita, and

questioned costs per capita), the actual coverage ratio as a percentage of the efficient coverage ratio, and the actual outputs. The HHS and Education OIGs had efficiency scores of 1.000, meaning they were the most efficient OIGs. HHS OIG had a coverage ratio of 0.00141 (corresponding to 0.54789 charges filed per capita; 2,568,408 financial recoveries per capita; and 443,042 questioned costs per capita); and Education OIG had a coverage ratio of 0.00207 (corresponding to 0.35865 charges filed per capita; 244,236 financial recoveries per capita; and 3,007,093 questioned costs per capita).

Research question one identified a positive correlation between coverage ratio and financial recoveries per capita for fiscal year 2017 using linear and quadratic regression. Linear regression analysis produced the following equation: (Financial Recoveries Per Capita) = -3,304,453.391 + [94,496,858.138 * (Coverage Ratio)]. Using this regression equation, HHS OIG's coverage ratio of 0.00141 was expected to result in -3,171,212.821 financial recoveries per capita (an impossible result), and Education OIG's coverage ratio of 0.00207 was expected to result in -3,108,844.895 financial recoveries per capita (also an impossible result). Quadratic regression analysis produced the following equation: (Financial Recoveries Per Capita) = 2,708,253.522 + [-83,400,111.073 * (Coverage Ratio)] + [304,541,057.751 * (Coverage Ratio)²]. Using this regression equation, HHS OIG's coverage ratio of 0.00141 was expected to result in 2,591,264.823 financial recoveries per capita, and Education OIG's coverage ratio of 0.00207 was expected to result in 2,536,920.22 financial recoveries per capita.

Table 3:

Data Envelopment Analysis Results for Fiscal Year 2017, Part 1 of 2

OIG	Technical Efficiency	Coverage Ratio			Actual Performance		
		Actual	Efficient	Actual as % of Efficient	Charges Filed Per Capita	Financial Recoveries Per Capita	Questioned Costs Per Capita
HHS	1.000	0.00141	0.00141	100%	0.54789	2,568,408	443,042
Education	1.000	0.00207	0.00207	100%	0.35865	244,236	3,007,093
USDA	0.773	0.00348	0.00269	129%	1.04842	508,695	180,570
DOD	0.332	0.00222	0.00074	301%	0.25270	1,333,636	239,942
VA	0.307	0.00409	0.00126	325%	0.41745	317,584	774,899
DHS	0.188	0.01054	0.00199	531%	0.25730	66,996	2,882,508
DOL	0.164	0.00784	0.00128	611%	0.50000	298,074	7,018
SSA	0.141	0.04060	0.00572	710%	1.33333	271,811	6,487,719
HUD	0.131	0.00982	0.00129	764%	0.49916	1,278,511	415,067
USPS	0.113	0.01626	0.00184	882%	0.56953	78,048	1,358,061
FHFA	0.075	0.68170	0.05096	1338%	0.90441	93,090,413	413,235
State	0.066	0.00590	0.00039	1517%	0.05660	59,874	555,612
NASA	0.058	0.00979	0.00056	1736%	0.15625	94,006	510,064
DOT	0.054	0.02513	0.00136	1849%	0.19268	2,482,402	11,324
FDIC	0.043	0.05825	0.00248	2344%	0.96825	1,835,454	1,005
DOJ	0.042	0.01382	0.00058	2388%	0.22558	64,559	62,302
FRS	0.036	0.10761	0.00382	2816%	0.19841	6,979,515	0
DOE	0.032	0.00929	0.00029	3150%	0.07168	538,487	15,542
OPM	0.028	0.07329	0.00202	3631%	0.72368	3,687,266	343,770
DOI	0.023	0.01359	0.00031	4397%	0.06513	86,418	387,266

Table 4:

Data Envelopment Analysis Results for Fiscal Year 2017, Part 2 of 2

OIG	Technical Efficiency	Coverage Ratio			Actual Performance		
		Actual	Efficient	Actual as % of Efficient	Charges Filed Per Capita	Financial Recoveries Per Capita	Questioned Costs Per Capita
Treasury	0.022	0.09593	0.00212	4522%	0.41818	3,875,564	16,495
TVA	0.020	0.01236	0.00024	5044%	0.08333	58,823	140,769
GSA	0.015	0.03443	0.00051	6730%	0.19936	390,581	72,866
SBA	0.011	0.12441	0.00135	9200%	0.34653	658,082	1,372,167
Amtrak	0.010	0.06421	0.00064	10009%	0.25000	26,675	0
NSF	0.009	0.00961	0.00008	11413%	0.02778	80,000	53,016
DOC	0.008	0.01882	0.00014	13051%	0.03352	84,690	164,254
SEC	0.006	0.02933	0.00017	17579%	0.06250	223	65,710
TIGTA	0.006	0.07138	0.00044	16284%	0.17082	39,803	0
USAID	0.005	0.09784	0.00047	20941%	0.06538	19,048	677,947
EPA	0.004	0.02666	0.00012	22747%	0.04566	27,548	772
RRB	0.004	0.41410	0.00171	24162%	0.61702	3,130,642	405,399
Smithsonian	0.004	0.02791	0.00011	26103%	0.04167	247	0
CNCS	0.003	0.02245	0.00007	30232%	0.00000	39,158	87,522
GPO	0.003	0.11959	0.00040	29690%	0.07143	0	575,397
EXIM	0.002	0.25887	0.00057	45085%	0.22222	750,698	188,889
PC	0.000	0.06374	0.00003	234583%	0.00000	41,325	14,076
NARA	0.000	0.05055	<0.00001	9538560%	0.00000	960	0
LOC	0.000	0.01762	0.00000	-	0.00000	0	0
NRC	0.000	0.06619	0.00000	-	0.00000	0	0

Fiscal year 2018. The coverage ratio ranged from 0.00137 to 0.63063 ($N = 40$, $M = 0.06999$, $SD = 0.12277$). Charges filed per capita ranged from 0 to 1.4178 ($N = 40$, $M = 0.32073$, $SD = 0.34526$). Financial recoveries per capita ranged from 0 to 72,536,727 ($N = 40$, $M = 2,315,005.18$, $SD = 11,442,262.904$). Questioned costs per capita ranged from 0 to 7,861,556 ($N = 40$, $M = 617,283.60$, $SD = 1,423,353.592$).

Tables 5 and 6 depict, for each OIG, the technical efficiency score (with 1.000 representing maximum efficiency), the actual coverage ratio, the efficient coverage ratio given the actual outputs (charges filed per capita, financial recoveries per capita, and

questioned costs per capita), the actual coverage ratio as a percentage of the efficient coverage ratio, and the actual outputs. Only HHS OIG had an efficiency score of 1.000, meaning HHS OIG was the most efficient OIG. HHS OIG had a coverage ratio of 0.00137 (corresponding to 0.47102 charges filed per capita; 1,794,081 financial recoveries per capita; and 1,248,940 questioned costs per capita).

Research question one identified a positive correlation between coverage ratio and financial recoveries per capita for fiscal year 2018 using linear and quadratic regression. Linear regression analysis produced the following equation: (Financial Recoveries Per Capita) = -2,644,265.446 + [70,857,857.968 * (Coverage Ratio)]. Using this regression equation, HHS OIG's coverage ratio of 0.00137 was expected to result in -2,547,190.181 financial recoveries per capita (an impossible result). Quadratic regression analysis produced the following equation: (Financial Recoveries Per Capita) = 2,529,154.591 + [-81,331,902.185 * (Coverage Ratio)] + [279,577,158.747 * (Coverage Ratio)²]. Using this regression equation, HHS OIG's coverage ratio of 0.00137 was expected to result in 2,418,254.623 financial recoveries per capita.

Table 5:

Data Envelopment Analysis Results for Fiscal Year 2018, Part 1 of 2

OIG	Technical Efficiency	Coverage Ratio			Actual Performance		
		<i>Actual</i>	<i>Efficient</i>	<i>Actual as % of Efficient</i>	<i>Charges Filed Per Capita</i>	<i>Financial Recoveries Per Capita</i>	<i>Questioned Costs Per Capita</i>
HHS	1.000	0.00137	0.00137	100%	0.47102	1,794,081	1,248,940
USDA	0.918	0.00336	0.00308	109%	1.05809	675,477	83,015
DOD	0.491	0.00258	0.00127	204%	0.21026	626,139	1,154,092
DOL	0.393	0.00810	0.00319	254%	1.09357	209,370	31,287
VA	0.281	0.00456	0.00128	356%	0.43977	213,333	571,462
HUD	0.215	0.01199	0.00258	465%	0.42059	321,475	2,345,383
Education	0.211	0.00329	0.00069	474%	0.23810	269,115	422
USPS	0.131	0.01608	0.00211	762%	0.72365	111,324	933,383
SSA	0.109	0.04181	0.00457	915%	1.41779	190,961	4,154,962
FHFA	0.088	0.63063	0.05552	1136%	0.73016	72,536,727	61,111
State	0.067	0.00882	0.00059	1490%	0.10377	19,504	538,306
OPM	0.061	0.07305	0.00448	1632%	0.57895	5,846,637	719,496
DHS	0.053	0.01013	0.00054	1882%	0.18472	143,905	243,241
DOT	0.047	0.02530	0.00119	2130%	0.40732	49,586	80,324
NASA	0.045	0.01093	0.00049	2219%	0.16901	55,273	65,666
DOC	0.038	0.01926	0.00073	2645%	0.03889	452,324	662,299
DOE	0.037	0.00901	0.00033	2728%	0.05926	431,226	14,347
DOI	0.035	0.01288	0.00046	2830%	0.07510	3,871	413,856
FDIC	0.035	0.06117	0.00217	2824%	0.53175	2,830,157	0
Smithsonian	0.030	0.02810	0.00085	3305%	0.29167	456	0

Table 6:

Data Envelopment Analysis Results for Fiscal Year 2018, Part 2 of 2

OIG	Technical Efficiency	Coverage Ratio			Actual Performance		
		Actual	Efficient	Actual as % of Efficient	Charges Filed Per Capita	Financial Recoveries Per Capita	Questioned Costs Per Capita
GSA	0.023	0.03492	0.00082	4260%	0.28115	354,820	31,052
SEC	0.022	0.03033	0.00065	4635%	0.22449	2,247	0
Amtrak	0.020	0.06756	0.00133	5088%	0.45545	60,269	231,683
DOJ	0.020	0.01910	0.00038	5031%	0.13023	189,580	73,961
RRB	0.019	0.45815	0.00864	5300%	0.92308	3,311,538	7,861,556
NSF	0.018	0.00932	0.00017	5512%	0.05797	79,425	19,093
SBA	0.015	0.12428	0.00192	6482%	0.57944	703,196	1,743,741
CNCS	0.013	0.02245	0.00029	7623%	0.00000	25,449	267,829
TVA	0.011	0.01245	0.00014	8808%	0.02970	114,750	128,554
Treasury	0.010	0.10596	0.00109	9764%	0.37222	192,222	726
USAID	0.009	0.11639	0.00105	11130%	0.06410	60,009	951,063
TIGTA	0.005	0.07187	0.00039	18307%	0.13466	156,056	16
FRS	0.003	0.10188	0.00030	34183%	0.04762	389,369	0
GPO	0.003	0.12386	0.00040	30592%	0.13887	1,454	0
PC	0.003	0.07133	0.00019	36698%	0.06667	688	22,357
EPA	0.002	0.03365	0.00007	51551%	0.02239	6,159	649
NARA	0.002	0.06469	0.00012	53254%	0.04167	1,857	0
NRC	0.001	0.07009	0.00005	151438%	0.01587	0	37,472
EXIM	0.000	0.26062	0.00013	200075%	0.00000	170,178	0
LOC	0.000	0.01824	0.00000	-	0.00000	0	0

Average across fiscal years 2016, 2017, and 2018. The coverage ratio ranged from 0.00140 to 0.65675 ($N = 40$, $M = 0.06898$, $SD = 0.12559$). Charges filed per capita ranged from 0 to 1.4732 ($N = 40$, $M = 0.310508$, $SD = 0.34532$). Financial recoveries per capita ranged from 0 to 77,684,012 ($N = 40$, $M = 3,190,956.50$, $SD = 12,560,703.704$). Questioned costs per capita ranged from 0 to 7,131,474 ($N = 40$, $M = 649,277.45$, $SD = 1,296,551.497$).

Tables 7 and 8 depict, for each OIG, the technical efficiency score (with 1.000 representing maximum efficiency), the actual coverage ratio, the efficient coverage ratio

given the actual outputs (charges filed per capita, financial recoveries per capita, and questioned costs per capita), the actual coverage ratio as a percentage of the efficient coverage ratio, and the actual outputs. The HHS and USDA OIGs had efficiency scores of 1.000, meaning they were the most efficient OIGs. HHS OIG had a coverage ratio of 0.00140 (corresponding to 0.51800 charges filed per capita; 2,393,340 financial recoveries per capita; and 710,087 questioned costs per capita), and USDA OIG had a coverage ratio of 0.00325 (corresponding to 1.22636 charges filed per capita; 500,669 financial recoveries per capita; and 122,919 questioned costs per capita).

Research question one identified a positive correlation between coverage ratio and financial recoveries per capita for the 2016-2018 fiscal year average using linear and quadratic regression. Linear regression analysis produced the following equation: (Financial Recoveries Per Capita) = -1,923,371.532 + [74,139,499.610 * (Coverage Ratio)]. Using this regression equation, HHS OIG's coverage ratio of 0.00140 was expected to result in -1,682,418.158 financial recoveries per capita (an impossible result), and USDA OIG's coverage ratio of 0.00325 was expected to result in -1,682,418.158 financial recoveries per capita (also an impossible result). Quadratic regression analysis produced the following equation: (Financial Recoveries Per Capita) = 3,398,370.026 + [-85,269,322.251 * (Coverage Ratio)] + [281,813,906.309 * (Coverage Ratio)²]. Using this regression equation, HHS OIG's coverage ratio of 0.00140 was expected to result in 3,279.545.33 financial recoveries per capita, and USDA OIG's coverage ratio of 0.00325 was expected to result in 3,124,221.388 financial recoveries per capita.

Table 7:

*Data Envelopment Analysis Results for the Average of Fiscal Years 2016-2018,**Part 1 of 2*

OIG	Technical Efficiency	Coverage Ratio			Actual Performance		
		<i>Actual</i>	<i>Efficient</i>	<i>Actual as % of Efficient</i>	<i>Charges Filed Per Capita</i>	<i>Financial Recoveries Per Capita</i>	<i>Questioned Costs Per Capita</i>
HHS	1.000	0.00140	0.00140	100%	0.51800	2,393,340	710,087
USDA	1.000	0.00325	0.00325	100%	1.22636	500,669	122,919
VA	0.754	0.00430	0.00324	133%	0.45750	228,404	1,650,954
Education	0.726	0.00271	0.00197	138%	0.33287	367,799	1,001,805
DOD	0.689	0.00244	0.00168	145%	0.20906	894,576	854,122
EPA	0.418	0.02918	0.01221	239%	0.03511	20,943,983	533
DOL	0.288	0.00790	0.00228	347%	0.85975	393,230	20,941
DHS	0.224	0.01020	0.00229	446%	0.19579	88,721	1,164,994
HUD	0.206	0.01132	0.00233	486%	0.46513	1,652,749	1,183,910
DOE	0.201	0.00924	0.00186	498%	0.09541	342,311	944,999
USPS	0.197	0.01610	0.00318	507%	0.62031	164,099	1,617,412
SSA	0.196	0.04163	0.00816	510%	1.47321	236,361	4,154,924
State	0.113	0.00685	0.00077	886%	0.05870	31,332	393,159
FHFA	0.069	0.65675	0.04529	1450%	0.87277	77,684,012	285,316
FDIC	0.045	0.05859	0.00263	2230%	0.70588	4,507,292	486
DOI	0.041	0.01345	0.00055	2456%	0.09781	39,816	278,667
NASA	0.037	0.01022	0.00038	2692%	0.14094	64,736	189,105
OPM	0.037	0.07195	0.00268	2687%	0.55679	4,593,147	546,772
DOC	0.036	0.01812	0.00065	2766%	0.04373	204,896	333,310
RRB	0.031	0.45181	0.01401	3224%	0.73154	2,320,709	7,131,474

Table 8:

*Data Envelopment Analysis Results for the Average of Fiscal Years 2016-2018,**Part 2 of 2*

OIG	Technical Efficiency	Coverage Ratio			Actual Performance		
		Actual	Efficient	Actual as % of Efficient	Charges Filed Per Capita	Financial Recoveries Per Capita	Questioned Costs Per Capita
DOJ	0.030	0.01614	0.00048	3338%	0.18182	90,010	64,823
DOT	0.030	0.02494	0.00075	3347%	0.27819	889,478	194,264
FRS	0.028	0.10627	0.00294	3608%	0.10471	5,051,329	0
TVA	0.020	0.01262	0.00025	5027%	0.05678	71,884	127,751
GSA	0.018	0.03249	0.00059	5491%	0.22234	330,369	47,805
SBA	0.018	0.12044	0.00215	5592%	0.46711	810,419	1,096,073
NSF	0.016	0.00911	0.00015	6074%	0.03365	96,957	76,356
USAID	0.016	0.10378	0.00165	6272%	0.05740	65,658	842,015
CNCS	0.012	0.02135	0.00026	8248%	0.01493	34,298	131,702
SEC	0.011	0.02866	0.00032	8960%	0.12057	1,140	23,797
Treasury	0.011	0.08559	0.00096	8923%	0.35728	1,349,086	5,538
Amtrak	0.010	0.06689	0.00070	9575%	0.26280	34,261	94,539
Smithsonian	0.010	0.02823	0.00029	9590%	0.11111	4,039	0
GPO	0.008	0.12386	0.00105	11850%	0.09216	17,763	531,945
TIGTA	0.006	0.07116	0.00039	18149%	0.14793	76,303	162
EXIM	0.002	0.26743	0.00060	44240%	0.13346	1,036,852	72,754
PC	0.002	0.06728	0.00012	54324%	0.04598	24,363	63,013
NARA	0.001	0.06009	0.00008	75982%	0.02985	1,160	0
NRC	0.000	0.06638	0.00002	266593%	0.00537	709	12,672
LOC	0.000	0.01918	0.00000	-	0.00000	0	0

Chapter 5: Discussion

Each year, the federal government spends vast sums of money. In fiscal year 2017, this amount was approximately \$4 trillion (Congressional Budget Office, n.d.). Of this amount, over \$3.1 trillion was spent on contracts, grants, loans, and other forms of financial assistance. Seventy-three federal OIGs are charged with the responsibility of auditing and investigating activities associated with the trillions of dollars the federal government spends each year. Forty-two of the OIGs have law enforcement authority

(Ginsberg, 2014), and forty of these OIGs are attached to and have oversight responsibilities for parent agencies (the remaining two OIGs are temporary OIGs for special government funding programs – the Troubled Assets Relief Program and Afghanistan Reconstruction funds).

Publicly available data on the OIGs’ staffing and performance levels, coupled with a significant lack of literature on criminal justice staffing and on OIGs as a whole, presented an important research opportunity: determining whether correlations exist between performance outcomes and staffing levels, which are critical factors in law enforcement organizations across the United States (Wilson and Heinonen, 2011) and are top considerations of law enforcement leaders (Mendel, Fyfe, and Den Heyer, 2017). These correlations – or the lack thereof – are needed to inform the criminal justice field of the ideal staffing ratios, particularly with respect to OIGs, many of which are small in size, lack resources for mission-related work, and lack the time and resources to conduct such research. Additionally, the existence and direction of any correlation between OIG investigative- and audit-related performance outcomes are needed to inform the field on the potential relationship between the investigative and audit functions of OIGs.

Specifically, this study compared the number of personnel each OIG has, expressed in proportion to the budget dollars (in millions) of the OIG’s parent agency (the “coverage ratio”), with the number of per capita enforcement-related actions (investigative-related criminal charges filed and financial recoveries, as well as audit-related questioned costs) attributable to the OIG’s work. As audits and investigations are the two primary but distinct functions of OIGs, this study also examined the nature of the relationship between the investigative- and audit-related performance outcomes.

The emphasis of this study was “per capita”; this means that each OIG’s performance was analyzed relative to the number of personnel it had. This enabled the identification of any tipping points in the coverage ratio that mark the beginning of decreasing performance results. That is, there may be an optimal threshold of personnel with respect to per capita performance outcomes. For example, due to division of labor, the existence of specialized units with a niche expertise, and sufficient numbers of personnel to allow for the shifting of resources, an organization with a large number of personnel may have better per capita performance than an organization with a small number of personnel. However, there may come a tipping point where adding more personnel lowers the agency’s overall per capita performance due to the relative bureaucracy and inflexibility that can be associated with large organizations

Regression and data envelopment analysis was used to determine the nature of the relationship between the coverage ratio and the performance outcomes; the nature of the relationship between the audit-related performance outcome of questioned costs per capita and the investigative-related performance outcomes of charges filed per capita and financial recoveries per capita; and the optimal coverage ratio beyond which performance outcomes begin to decrease. Data envelopment analysis is a technique that calculates the relative efficiency of organizations by comparing their inputs and outputs, and prior research supports the use of this technique in assessing police performance (Alda, 2014).

Research Question 1

The first research question asked, “What is the relationship between the coverage ratio and the per capita performance outcomes of charges filed per capita, financial recoveries per capita, and questioned costs per capita?” The relationship

between the coverage ratio and each of the three performance outcomes was tested separately using linear and quadratic regression. These tests were performed on four sets of data: fiscal year 2016, fiscal year 2017, fiscal year 2018, and the average of the three.

Conclusions regarding the relationship between coverage ratio and charges filed per capita. For all fiscal years and for the average of the three, no statistically significant relationship was found between the coverage ratio and charges filed per capita (p ranged from .062 to .162 for the linear model and from .099 to .194 for the quadratic model). As such, the null hypothesis that there is no relationship is accepted. Therefore, this study concludes that there is no statistically significant relationship between coverage ratio and charges filed per capita.

Conclusions regarding the relationship between coverage ratio and financial recoveries per capita. For all fiscal years and for the average of the three, both the linear and quadratic models indicated a statistically significant relationship between the coverage ratio and financial recoveries per capita. Therefore, the null hypothesis that there is no relationship is rejected. The probability values of both the linear and quadratic models are nearly equal ($p < .001$). The quadratic regression equation fits the data more closely than the linear equation (the quadratic r^2 was greater than the linear r^2 for all four data sets: .389 compared to .250 for 2016; .929 compared to .655 for 2017; .859 compared to .578 for 2018; and .816 compared to .549 for the average). However, the quadratic regression equation for all data sets predicts negative financial recoveries per capita for 20-35% of the coverage ratios between the lowest and highest points, which is an impossible result. The linear model also sometimes predicts negative financial recoveries per capita – for 4-5% of the lowest end of the coverage ratio range. This

suggests that the linear and quadratic regression equation's accuracy is questionable and its usefulness is limited. However, it should be noted that under both the linear and quadratic model, there is a positive correlation between coverage ratio and financial recoveries per capita (with r ranging from .500 to .741 under the linear model and from .624 to .903 under the quadratic model). This indicates that as the coverage ratio increases, so too does the financial recoveries per capita, with no tipping point beyond which financial recoveries per capita begin to decrease. Based on this data, it appears that there is a positive correlation between coverage ratio and financial recoveries per capita; however, for the reasons described in the discussion of research question three below, this positive correlation is questionable.

Conclusions regarding the relationship between coverage ratio and questioned costs per capita. For fiscal years 2016 and 2018, both the linear and quadratic models indicated a statistically significant relationship between the coverage ratio and questioned costs per capita. The quadratic model has a higher probability value (quadratic p is .013 compared to linear .004 for 2016; quadratic p is .040 compared to linear .016 for 2018) but a slightly better-fitting equation (quadratic r^2 is .208 compared to linear .199 for 2016; quadratic r^2 is .160 compared to linear .143 for 2018). Under the linear model, there is a moderate positive correlation between the coverage ratio and questioned costs per capita (r is .446 for 2016 and .378 for 2018). Under the quadratic model, questioned costs per capita in 2016 reaches a maximum level of 4,420,615 when the coverage ratio is 0.69530; in 2018, questioned costs per capita reaches a maximum level of 2,538,942 when the coverage ratio is 0.52695. After these tipping points are reached, questioned costs per capita begin to decrease. This indicates that at

least for 2016 and 2018, there is an optimal coverage ratio, albeit that coverage ratio is substantially different between 2016 and 2018 (the 2018 optimal coverage ratio is approximately 32% higher than the 2016 optimal coverage ratio).

However, in 2017, both the quadratic and linear models indicate that there is no statistically significant relationship between the coverage ratio and questioned costs per capita (linear $p = .748$; quadratic $p = .901$). It is possible that 2017 represents an anomaly; however, with only three years of data examined, this cannot be concluded. Additionally, for the 2016-2018 average, a statistically significant relationship only exists in the linear model (linear $p = .025$; quadratic $p = .055$). The linear model indicates a moderate positive correlation between coverage ratio and questioned costs per capita ($r = .354$), with no tipping point beyond which questioned costs per capita begin to decrease. The probability value for the quadratic model is only slightly above .05 ($p = .055$) and may have been affected by the 2017 data; however, with only three years of data analyzed, 2017 cannot be ruled as an anomaly. Because no statistically significant relationship was found for 2017, the results do not replicate year-to-year. Therefore, the null hypothesis that there is no relationship between coverage ratio and questioned costs per capita is accepted. Therefore, this study concludes that there is no statistically significant relationship between coverage ratio and questioned costs per capita.

Implications and context of findings. Regardless of how law enforcement organizational performance is measured, one input factor that is continually referenced in the literature is the number of personnel. Mendel et al. (2017) conducted a meta-analysis of studies into the effect of personnel levels on performance outcomes and concluded that there is no simple cause-and-effect relationship. Zhao et al. (2011), on the other hand,

found that federal grants, which include funds for additional personnel, were positively correlated with the number of arrests.

The present study examined the correlation of staffing levels – expressed as the coverage ratio – with performance outcomes, specifically for federal OIGs. Three performance outcomes were examined: charges filed per capita, financial recoveries per capita, and questioned costs per capita. A statistically significant relationship was only found to exist between the coverage ratio and financial recoveries per capita. That relationship is one of positive correlation, depicted by a linear model with no optimal (tipping) point.

The results of this study provide support for the notion that staffing levels, represented proportionally to the constituents they serve, may indeed have a positive effect on at least one police performance measure. In the federal Inspector General community specifically, increased per capita staffing levels may have a positive effect on financial recoveries. However, it must be noted that this study examined correlations only, and therefore, no cause-and-effect relationship can be established.

It must also be noted that despite finding a statistically significant correlation, this study did not find evidence of an optimal per capita staffing level (coverage ratio) using linear or quadratic regression. Using regression, the study found no upper limit to the staffing level beyond which performance starts to decrease. There may indeed exist such a limit – as in the case of having a high enough staffing level whereby personnel begin to interfere in each other's work – but that limit was not found using regression in the present study. Therefore, the current study does not lend support for using regression to determine optimal staffing levels on a per capita basis.

Research Question 2

The second research question asked, “What is the relationship between the audit-related performance outcome of questioned costs per capita and the investigative-related performance outcomes of charges filed per capita and financial recoveries per capita?” The relationship between questioned costs per capita and each of the two investigative-related performance outcomes was tested separately using linear and quadratic regression. These tests were performed on four sets of data: fiscal year 2016, fiscal year 2017, fiscal year 2018, and the average of the three.

Conclusions regarding the relationship between questioned costs per capita and charges filed per capita. For fiscal years 2017 and 2018, both the linear and quadratic models indicated a statistically significant relationship between questioned costs per capita and charges filed per capita. The quadratic model has a higher probability value for 2017 (quadratic p is .004 compared to linear .001 for 2017; quadratic and linear p is .001 in 2018) but a slightly better-fitting equation for both 2017 and 2018 (quadratic r^2 is .260 compared to linear .240 for 2017; quadratic r^2 is .303 compared to linear .270 for 2018). Under the linear model, there is a moderate positive correlation between questioned costs per capita and charges filed per capita (r is .490 for 2017 and .520 for 2018). Under the quadratic model for 2017, there is no upper limit to charges filed per capita, indicating that at least for 2017, there is no optimal questioned costs per capita beyond which charges filed per capita begin to decrease. However, under the quadratic model for 2018, charges filed per capita reach a maximum level of 1.04841 when questioned costs per capita is 6,816,667. After this tipping point is reached, charges filed per capita begin to decrease. This indicates that at least for and 2018, there

is an optimal questioned costs per capita.

On the other hand, for 2016 and the 2016-2018 average, both the quadratic and linear models indicate that there is no statistically significant relationship between the coverage ratio and questioned costs per capita (2016: linear $p = .152$; quadratic $p = .162$; 2016-2018 average: linear $p = .748$; quadratic $p = .899$). It is possible that 2016 – and, as a result, the 2016-2018 average – represents an anomaly; however, with only three years of data examined, this cannot be concluded. Because no statistically significant relationship was found for 2016 or the 2016-2018 average, the results do not replicate year-to-year. Therefore, the null hypothesis that there is no relationship between questioned costs per capita and charges filed per capita is accepted. Therefore, this study concludes that there is no statistically significant relationship between questioned costs per capita and charges filed per capita.

Conclusions regarding the relationship between questioned costs per capita and financial recoveries per capita. For all fiscal years and for the average of the three, no statistically significant relationship was found between questioned costs per capita and financial recoveries per capita (p ranged from .651 to .878 for the linear model and from .839 to .948 for the quadratic model). As such, the null hypothesis that there is no relationship is accepted. Therefore, this study concludes that there is no statistically significant relationship between questioned costs per capita and financial recoveries per capita.

Implications and context of findings. Organizational management decisions on resource allocation have been shown to affect police performance. For example, murder clearance rates are positively affected by adequate levels of supervision (Keel et al.,

2009), and management directives on how officers should spend their time are positively correlated with officer productivity (Famega et al., 2005). Additionally, the literature has shown that the quality of investigations is correlated with organizational management decisions (Kisil, 2014).

The present study examined indirectly the effect of management resource allocation decisions on performance outcomes. Specifically, this study examined the correlation between the two primary but distinct functions of an OIG – audits and investigations, to which OIG executives must allocate resources from the same overall OIG budget. This examination was done by analyzing the correlation between the two investigative-related performance outcomes (charges filed per capita and financial recoveries per capita) and the one audit-related performance outcome (questioned costs per capita); a negative correlation would potentially indicate that as attention or resources are allocated to one function instead of another, that function's performance increases at the expense of the other's, while a positive correlation would potentially indicate a symbiotic relationship between the two functions, whereby one's performance aids in the other's.

No statistically significant relationship was found between questioned costs per capita and either charges filed per capita or financial recoveries per capita. This indicates that there is neither a detrimental nor a symbiotic relationship between the performance outcomes of the two primary OIG functions (auditing and investigating). This study further suggests that although organizational management decisions may indeed affect performance outcomes as referenced in the literature, correlating the performance outcomes of the two primary OIG functions neither supports nor refutes the notion.

Research Question 3

The third research question asked, “What is the optimal coverage ratio beyond which the per capita performance outcomes of charges filed per capita, financial recoveries per capita, and questioned costs per capita begin to decrease?” Data envelopment analysis was performed to determine the technical efficiency scores of all OIGs in the study sample. The coverage ratios of the OIGs with the highest efficiency scores were deemed to be the optimal ratios because those ratios produced the highest performance outcomes (charges filed per capita, financial recoveries per capita, and questioned costs per capita). The analysis was performed on four sets of data: fiscal year 2016, fiscal year 2017, fiscal year 2018, and the average of the three.

Conclusions. Across all four data sets, the efficiency scores ranged from 1.000, indicating maximum efficiency, to 0.000. All efficiency scores below 1.000 represent how efficiently an OIG is operating (given the inputs and outputs) relative to the most efficient OIGs. Although data envelopment analysis always awards a score of 1.000 to the most efficient operating units, there is no minimum score. Therefore, the fact that some OIGs received an efficiency score of zero indicate that they are operating at an efficiency level of nearly zero percent of the level of the most efficient OIGs. This means that OIGs as a whole had a substantially high degree of variance in their performance outcomes relative to their per capita staffing level (represented by the coverage ratio).

For 2016, the HHS, USDA, VA, and EPA OIGs were the most efficient OIGs. Their coverage ratios were, respectively, 0.00141, 0.00296, 0.00423, and 0.02738. The reason that four separate coverage ratios produced the maximum performance outcomes

is that each of the four OIGs excelled in different performance outcomes. USDA OIG had the highest charges filed per capita (1.56301 compared to EPA OIG's 0.04000, the lowest of the four); EPA OIG had the highest financial recoveries per capita (66,241,920 compared to VA OIG's 152,550, the lowest of the four); VA OIG had the highest questioned costs per capita (3,882,720 compared to EPA OIG's 161, the lowest of the four); and HHS OIG had the second-highest outcomes in all three performance outcomes (0.53587 charges filed per capita; 2,831,746 financial recoveries per capita; and 427,794 questioned costs per capita). The linear regression equation (from research question one) depicting the relationship between coverage ratio and financial recoveries per capita produced expected results that vary substantially from the actual results. The regression equation predicts that HHS OIG's coverage ratio of 0.00141 will result in 358,658,451.944 financial recoveries per capita (versus the 2,831,746 that HHS OIG actually produced); USDA OIG's coverage ratio of 0.00296 will result in 446,182,068.834 financial recoveries per capita (versus the 321,667 USDA OIG actually produced); VA OIG's coverage ratio of 0.00423 will result in 517,894,967.833 financial recoveries per capita (versus the 152,550 financial recoveries per capita VA OIG actually produced); and EPA OIG's coverage ratio of 0.02738 will result in 1,825,102,536.212 financial recoveries per capita (versus the 66,241,920 financial recoveries per capita EPA OIG actually produced). This calls into question the accuracy of the linear regression equation for 2016 and suggests that the equation has limited usefulness. The quadratic regression equation (from research question one) depicting the relationship between coverage ratio and financial recoveries per capita also produced expected results that vary substantially from the actual results. The regression equation predicts that HHS OIG's

coverage ratio of 0.00141 will result in 4,678,352.296 financial recoveries per capita (versus the 2,831,746 that HHS OIG actually produced); USDA OIG's coverage ratio of 0.00296 will result in 4,552,594.848 financial recoveries per capita (versus the 321,667 USDA OIG actually produced); VA OIG's coverage ratio of 0.00423 will result in 4,450,422.627 financial recoveries per capita (versus the 152,550 financial recoveries per capita VA OIG actually produced); and EPA OIG's coverage ratio of 2,724,966.636 will result in 1,825,102,536.212 financial recoveries per capita (versus the 66,241,920 financial recoveries per capita EPA OIG actually produced). This calls into question the accuracy of the quadratic regression equation for 2016 and suggests that the equation has limited usefulness.

For 2017, the HHS and Education OIGs were the most efficient OIGs. Their coverage ratios were, respectively, 0.00141 and 0.00207. Compared to Education OIG, HHS OIG had higher charges filed per capita (0.54789 compared to Education OIG's 0.35865) and financial recoveries per capita (2,568,408 compared to Education OIG's 244,236). However, Education OIG had more questioned costs per capita (3,007,093) than HHS OIG (443,042). The linear regression equation (from research question one) depicting the relationship between coverage ratio and financial recoveries per capita produced expected results that vary substantially from the actual results. The regression equation predicts that HHS OIG's coverage ratio of 0.00141 will result in -3,171,212.821 financial recoveries per capita (versus the 2,831,746 that HHS OIG actually produced), and Education OIG's coverage ratio of 0.00207 will result in -3,108,844.895 financial recoveries per capita (versus the 321,667 USDA OIG actually produced). Additionally, these negative financial recoveries per capita are impossible results. This calls into

question the accuracy of the linear regression equation for 2017 and suggests that the equation has limited usefulness. The quadratic regression equation (from research question one) depicting the relationship between coverage ratio and financial recoveries per capita also produced expected results that vary substantially from the actual results. The regression equation predicts that HHS OIG's coverage ratio of 0.00141 will result in 2,591,264.823 financial recoveries per capita (versus the 2,831,746 that HHS OIG actually produced), and Education OIG's coverage ratio of 0.00207 will result 2,536,920.22 financial recoveries per capita (versus the 321,667 USDA OIG actually produced). This calls into question the accuracy of the quadratic regression equation for 2017 and suggests that the equation has limited usefulness.

For 2018, HHS was the single most efficient OIG. Its coverage ratio was 0.00137. Its performance outcomes were 0.47102 charges filed per capita; 1,794,081 financial recoveries per capita; and 1,248,940 questioned costs per capita. The linear regression equation (from research question one) depicting the relationship between coverage ratio and financial recoveries per capita produced expected results that vary substantially from the actual results. The regression equation predicts that HHS OIG's coverage ratio of 0.00137 will result in -2,547,190.181 financial recoveries per capita (versus the 1,794,081 that HHS OIG actually produced). Additionally, this negative financial recoveries per capita is an impossible result. This calls into question the accuracy of the linear regression equation for 2018 and suggests that the equation has limited usefulness. The quadratic regression equation (from research question one) depicting the relationship between coverage ratio and financial recoveries per capita also produced expected results that vary substantially from the actual results. The regression

equation predicts that HHS OIG's coverage ratio of 0.00137 will result in 2,418,254.623 financial recoveries per capita (versus the 1,794,081 that HHS OIG actually produced). This calls into question the accuracy of the quadratic regression equation for 2018 and suggests that the equation has limited usefulness.

For the 2016-2018 average, the HHS and USDA OIGs were the most efficient OIGs. Their coverage ratios were, respectively, 0.00140 and 0.00325. Compared to USDA OIG, HHS OIG had higher financial recoveries per capita (2,393,340 compared to USDA OIG's 500,669) and questioned costs per capita (710,087 compared to USDA OIG's 122,919). However, USDA OIG had more charges filed per capita (1.22636) than HHS OIG (0.51800). The linear regression equation (from research question one) depicting the relationship between coverage ratio and financial recoveries per capita produced expected results that vary substantially from the actual results. The regression equation predicts that HHS OIG's coverage ratio of 0.00140 will result in -1,682,418.158 financial recoveries per capita (versus the 2,393,340 that HHS OIG actually produced), and USDA OIG's coverage ratio of 0.00325 will result in -1,682,418.15 financial recoveries per capita (versus the 500,669 USDA OIG actually produced). Additionally, these negative financial recoveries per capita are impossible results. This calls into question the accuracy of the linear regression equation for the 2016-2018 average and suggests that the equation has limited usefulness. The quadratic regression equation (from research question one) depicting the relationship between coverage ratio and financial recoveries per capita also produced expected results that vary substantially from the actual results. The regression equation predicts that HHS OIG's coverage ratio of 0.00140 will result in 3,279.545.33 financial recoveries per capita (versus the 2,393,340

that HHS OIG actually produced), and USDA OIG's coverage ratio of 0.00325 will result in 3,124,221.388 financial recoveries per capita (versus the 500,669 USDA OIG actually produced). This calls into question the accuracy of the quadratic regression equation for the 2016-2018 average and suggests that the equation has limited usefulness.

Across all data sets, the coverage ratios for all OIGs in the sample ranged from 0.00137 to 0.68170. The highest performing OIGs had coverage ratios between 0.00137 and 0.02738, inclusive. This indicates that the optimal staffing level for federal OIGs is a range from 0.00137 to 0.02738 full-time equivalents for every million dollars of their parent agency's budget. OIGs having staffing levels within this range were 1.089 to 1,000 times more efficient than OIGs with staffing levels outside the range. This range can be considered optimal because OIGs with staffing levels outside this range had lower performance outcomes than OIGs with staffing levels inside the range. It must be noted that some OIGs had staffing levels within the optimal range for a particular data set but received efficiency scores of less than 1.000; this is because their performance outcomes, relative to their coverage ratio, were lower than the most efficient OIGs. However, these occurrences were limited primarily to the 2016 data set, when there were 18 such instances (there were two instances for the 2016-2018 average data set and no instances for the 2017 and 2018 data sets). Employing the regression equations for the 2016-2018 average (identified in research question one) that predicts financial recoveries per capita based on the coverage ratio, the optimally efficient coverage ratio of 0.00137 to 0.02738 is expected to result in -1,821,800.418 to 106,567.967 financial recoveries per capita (increasing as the coverage ratio increases) under the linear model, and 3,282,079.991 to 1,274,961.836 (decreasing as the coverage ratio increases) under the quadratic model.

Negative financial recoveries per capita are an impossible result, and the predicted results differ substantially from the actual results; therefore, the regression equation's accuracy is questionable and its usefulness is limited. This also calls into the question the notion that coverage ratio and financial recoveries per capita are positively correlated across the full range of coverage ratios, as increasing coverage ratio has been shown to not necessarily result in an increase to financial recoveries per capita. Although the linear and quadratic models have not been shown to accurately depict the nature of the relationship between coverage ratio and financial recoveries per capita, the data indicates a potential correlation between the two that may be accurately depicted by some other type of non-linear and non-quadratic equation – a topic for future research studies to address.

It is also noteworthy that in each of the four data sets, HHS OIG – which was a maximum-efficiency OIG – had the lowest coverage ratio of all OIGs. For 2016, two other maximum-efficiency OIGs – USDA and VA – had the third- and fifth-lowest coverage ratios, respectively (EPA OIG, the fourth maximum-efficiency OIG, had the twenty-second lowest coverage ratio). For 2017, the two maximum-efficiency OIGs (HHS and Education) had the first- and second-lowest coverage ratio, respectively. For 2018, HHS OIG (the sole maximum-efficiency OIG) had the lowest coverage ratio. For the 2016-2018 average, the HHS and USDA OIGs (the two maximum-efficiency OIGs) had the first- and fourth-lowest coverage ratios, respectively.

Implications and context of findings. This suggests that despite the existence of an apparent optimal staffing level, other factors that were not part of this study are correlated with performance outcomes. It must also be noted that based on the findings

of research question one, a potential relationship exists between coverage ratio and financial recoveries per capita, but not between coverage ratio and the other two performance outcomes used as outputs for the data envelopment analysis (charges filed per capita and questioned costs per capita). Additionally, the regression analysis does not lend support to the idea that coverage ratio can lead to increases in financial recoveries per capita in a predictable way. As such, the results of the data envelopment analysis may have limited applicability. Therefore, the optimal federal OIG staffing level range of 0.00137 to 0.02738 full-time equivalents for every million dollars of the OIG parent agency's budget must be treated with caution. The most efficient OIGs are operating with the lowest staffing levels; therefore, the optimal range should be viewed as the range within which maximum performance is able to be achieved – this is distinct from viewing the optimal range as the target range that federal OIGs should strive to achieve.

Although data envelopment analysis has been used in the law enforcement context in the past, there is not an extensive number of these studies. The present study contributes to the literature by employing data envelopment analysis in not just the law enforcement context, but the federal OIG context, for which there is a significant lack of literature. Additionally, the use of charges filed per capita, financial recoveries per capita, and questioned costs per capita as performance outcomes makes positive use of the notion that OIGs have been measuring their effectiveness through such performance metrics (Johnston, 2010a; Newcomer, 1998).

As far as practice recommendations, it may be beneficial for organizations to maximize the potential of current employees as opposed to trying to increase the per capita staffing level; this is because maximum overall efficiency was achieved with

0.00137 to 0.02738 full-time equivalents per million dollars of the OIG parent agency's budget, and this staffing level is at the low end of the range for all OIGs (OIGs with per capita staffing levels higher than the optimally efficient range did not have higher efficiency). Additionally, the performance outcomes, or lack thereof, of one operating unit (investigations or audits) should not concern the other unit, as no relationship was found.

To reiterate, this study examined all 40 OIGs having law enforcement authority and oversight responsibility for a parent agency. Although all of these OIGs fall under the same governing body and have the mission of investigating and auditing matters related to fraud, waste, abuse, and misconduct, each OIG may possess individual characteristics affecting their performance outcomes and efficiency scores. For example, HHS OIG has the responsibility of investigating matters involving the federally-funded Medicare and Medicaid programs. Combined, these programs involved nearly \$1.3 trillion in healthcare expenditures in 2017 alone (U.S. Centers for Medicare and Medicaid Services, 2019b). HHS OIG investigates medical providers and individual patients for defrauding the programs through, for example, billing the government for medical services that were not actually performed. These types of fraud cases arguably are relatively straight-forward, with evidence focusing on the services that were billed and the fact that such services were not actually provided to the patient. The amount of money involved in these programs, the number of people who are eligible for these programs – which is in the hundreds of millions (U.S. Centers for Medicare and Medicaid Services, 2019a), the relatively straight-forward nature of the fraud cases, and the fact that HHS OIG investigates matters related to these programs may be reasons for HHS

OIG's high degree of performance outcomes, and consequently, its high efficiency score.

Some other OIGs have purview over other government programs. For example, HUD OIG investigates fraud involving federally-subsidized housing, and SSA OIG investigates fraud involving the Social Security program. Both of these programs involve the general public, similar to Medicare and Medicaid. Across the four data sets, HUD OIG had the sixth to tenth highest efficiency score, and SSA OIG had the eighth to twelfth highest. There are other programs that do not involve the general public but do involve more than the immediate agency administering the program. For example, DOL OIG has oversight of the federal workers' compensation program, which implicates all federal employees (not just DOL's). Across the four data sets, DOL OIG had the fourth to eighth highest efficiency score. As with HHS OIG, the existence, nature, and extent of the program may have impacted DOL OIG's performance outcomes and consequently, its efficiency score.

Also potentially impacting an OIG's performance outcomes and efficiency score is how focused that OIG is on achieving those outcomes. For example, SBA OIG has oversight of several programs that make small businesses eligible for non-competitive government contracts with all agencies. However, across the four data sets, its efficiency score was ranked 24 to 29 out of 40. This potentially suggests that from an organizational and leadership standpoint, some OIGs may use greater efforts in emphasizing to their employees the importance of achieving performance outcomes. Some OIGs may even make the achievement of such outcomes part of each individual employee's performance appraisal. These OIGs may have higher performance outcomes and consequently, higher efficiency scores, than OIGs that make lesser efforts in

emphasizing to their employees the importance of the performance outcomes.

Therefore, the results of this research question as well as the other two research questions may be different if the 40 OIGs examined in this study were subcategorized based on their agency-specific factors (such as program oversight responsibility and whether the performance outcomes are part of each employee's performance appraisal) and the regression and data envelopment analyses were performed for each subcategory separately, as opposed to all OIGs collectively. To illustrate, consider a possible subcategory of OIGs that have (a) oversight responsibility for a nationwide program involving the general public (e.g., Medicare, Medicaid, federally-subsidized housing, and Social Security); and (b) employee performance appraisals containing metrics for financial recoveries, criminal charges, and questioned costs. If regression and data envelopment analysis were performed for these OIGs only (with separate analyses being performed for other subcategories containing the remaining OIGs), this study may (or may not) have had different results concerning the relationship between coverage ratio and each of the three performance outcomes and the accuracy of equations stemming from linear and quadratic regression. This is a topic that future research studies can address.

Furthermore, as mentioned previously, there appears to be other input factors besides coverage ratio that affect performance outcomes and consequently, the efficiency scores. By definition, coverage ratio considers the quantity, but not the quality, of personnel. The quality of personnel may be a relevant input factor, and although quality is challenging to assess, potential quality-related input factors include average performance appraisal ratings (with the caveat that some agencies may have higher

average ratings but not actually have higher quality personnel); years of experience; number, length, and type of training courses attended; and scores from supervisor and peer surveys assessing the quality of personnel. In addition to the quality of personnel, other input factors may include tangible elements such as the number and type of investigative equipment (such as vehicles and digital forensic equipment) and intangible elements such as employee morale.

A statistically significant correlation was found between charges filed per capita and the efficiency score (2016: linear $p = .021$ and $r = .363$, quadratic $p = .064$ and $r = .371$; 2017: linear $p = .020$ and $r = .367$, quadratic $p = .021$ and $r = .434$; 2018: linear $p = .006$ and $r = .424$; quadratic $p = .017$ and $r = .445$; 2016-2018 average: linear $p = .012$ and $r = .392$, quadratic $p = .033$ and $r = .410$). However, no statistically significant correlation was found between financial recoveries per capita and the efficiency score (2016: linear $p = .085$ and $r = .276$, quadratic $p = .230$ and $r = .276$; 2017: linear $p = .893$ and $r = .000$, quadratic $p = .898$ and $r = .077$; 2018: linear $p = .982$ and $r = .000$; quadratic $p = .655$ and $r = .152$; 2016-2018 average: linear $p = .944$ and $r = .000$, quadratic $p = .606$ and $r = .164$). Furthermore, no statistically significant correlation was found between questioned costs per capita and the efficiency score (2016: linear $p = .572$ and $r = .089$, quadratic $p = .072$ and $r = .363$; 2017: linear $p = .086$ and $r = .276$, quadratic $p = .023$ and $r = .429$; 2018: linear $p = .724$ and $r = .055$; quadratic $p = .204$ and $r = .286$; 2016-2018 average: linear $p = .552$ and $r = .095$, quadratic $p = .049$ and $r = .389$). This demonstrates that among the sample, OIGs with higher charges filed per capita had higher efficiency scores, but OIGs with higher financial recoveries per capita or questioned costs per capita did not have higher efficiency scores (but note that on an

individual basis, an OIG's efficiency score would be higher if its financial recoveries per capita or questioned costs per capita were higher, assuming its coverage ratio and charges filed per capita remained the same).

Limitations

Although external validity concerns were minimized due to the entire population being included in the study, there were several research limitations stemming from internal validity factors. The study was non-experimental, so no cause-and-effect relationship could be deduced. In the same vein, the study used existing data; therefore, the effect of the predictor variables on the outcome variables could not be isolated, and there may have been other unmeasured predictor variables that had an effect.

Additionally, the data was self-reported by the various OIGs and their parent agencies. This data was taken at face value, as it was infeasible in terms of time, money, and access to request supporting documentation for every staffing and performance statistic. Therefore, there is a possibility that some data was inaccurate. An example of inaccurate data – although not related to an OIG – can be found in a previous research study examining enforcement statistics reported by the Securities and Exchange Commission (SEC), which has a large role in enforcing the various federal securities-related laws (Velikonja, 2016). Each year, the SEC produces a report detailing their enforcement statistics, which are viewed as performance measures. Using a mixed methods approach by examining the publicly reported statistics and synthesizing existing research, Velikonja (2016) found that many enforcement actions were double- or triple-counted, lacked construct validity, and were inconsistent in how they were counted. The conclusion was that the SEC's enforcement-related metrics were flawed and not accurate

measures of the agency's work. However, it should be noted that data accuracy is a concern that exists with every secondary data set, including the Uniform Crime Reports and other statistics published by the Department of Justice.

Also, there may have been instances in which multiple OIGs worked together on a single investigation that resulted in charges being filed and money being recovered. Each OIG may have reported those charges and recoveries in their semiannual reports to Congress, potentially leading to multi-counting and possibly misleading results (as would be the case if a small under-resourced agency routinely worked joint investigations with a much larger and well-resourced agency).

Finally, because only federal OIG data was used, any generalizability of the findings may be limited to only federal OIGs and similar types of organizations. The findings may not be readily applicable to traditional law enforcement agencies, such as state and local police departments. The findings also may not be readily applicable to federal agencies outside of the Inspector General community, such as the Drug Enforcement Administration.

Summary and Future Research Recommendations

In summary, this study examined (1) the relationship between per capita staffing levels and the performance outcomes of charges filed per capita; financial recoveries per capita; and questioned costs per capita; (2) the relationship between the audit-related performance outcome of questioned costs per capita and the investigative-related performance outcome of charges filed per capita and financial recoveries per capita; and (3) the optimal per capita staffing levels beyond which the above-mentioned performance outcomes begin to decrease.

Regarding the first research question, no statistically significant relationship was found between per capita staffing levels and either charges filed per capita or questioned costs per capita. However, a potential correlation was found between per capita staffing levels and financial recoveries per capita. This lends support to the notion that increased staffing levels are correlated with at least one OIG performance outcome. Regarding the second research question, no statistically significant relationship was found between questioned costs per capita and either charges filed per capita or financial recoveries per capita. This indicates that the performance outcomes of the investigative and audit functions of an OIG should not be used as a conduit to examine the correlation of organizational resource allocation decisions with performance outcomes. Regarding the third research question, an optimal OIG staffing level range was identified: 0.00137 to 0.02738 full-time equivalents for every million dollars of the OIG parent agency's budget. OIGs having staffing levels within this range were 1.089 to 1,000 times more efficient than OIGs with staffing levels outside the range. However, this range should be viewed as one within which maximum performance can be achieved as opposed to a target range that OIGs should strive to achieve.

All of the findings in this study are based on data covering three federal fiscal years: 2016, 2017, and 2018. Further research covering other years should be performed to determine whether the results from the present study replicate for other time periods. One or more of the years in the present study could represent an anomaly across the greater expanse of time, skewing the conclusions about the relationships mentioned above. Additionally, because the data in this study was self-reported and taken at face value, it would be beneficial to study the extent to which the self-reported data –

particularly the performance outcomes, as published in publicly available semiannual reports to Congress – is accurate, and the extent to which multiple agencies report performance outcomes for the same case. Such a study would involve requesting, via the federal Freedom of Information Act, the supporting documentation for the published performance outcomes and assessing the accuracy of the reported statistics. Additionally, further research could examine whether input factors beyond per capita staffing levels are correlated with performance outcomes. As discussed earlier, this research can examine individual OIG characteristics and subcategorize OIGs based on commonalities such as the extent of external-facing programs that OIGs have oversight responsibility for and the degree to which OIGs emphasize to their employees the importance of achieving performance outcomes. Furthermore, other research could examine the staffing levels and performance outcomes (similar to the present study) for law enforcement agencies outside the federal OIG community to determine whether any differences exist for non-OIG agencies as compared to OIG agencies.

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