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Interorganizational Performance Comparisons Using Quality Assurance Audit Results

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INTERORGANIZATIONAL PERFORMANCE COMPARISONS USING QUALITY ASSURANCE AUDIT RESULTS

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ABSTRACT

Interorganizational Performance Comparisons
Using Quality Assurance Audit Results

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The Government Performance and Results Act (GPRA) of 1993 requires government agencies to conduct performance measurements of their contractors for purposes of evaluation and comparison. To be most meaningful, performance comparisons need to consider all relevant characteristics that are of importance to the agency. Yet, bounded rationality theory states that managers of complex programs may have insufficient time and resources to consider all potentially relevant factors. Therefore, metrics used for decision making need to incorporate all relevant factors before the information is provided to decision makers.

Over the last several decades, government agencies have increasingly identified Quality Assurance compliance as a characteristic of concern for government contractors. Nevertheless, government agencies, such as the United States Department of Energy (DOE), infrequently conduct quantitative performance comparisons of their contractors with respect to quality assurance compliance. When agencies do conduct the comparisons, the agencies generally use results from quality assurance audits. However, while audit results are quantitative and readily available, they generally do not address all relevant factors. Providing these incomplete data to decision makers increases the risk of making less than optimal decisions.

This research investigated the feasibility of using statistical regression techniques to transform raw audit results into more meaningful data that government decision makers could use to meet the intent of the GPRA's performance comparison requirements. The research used existing data from 398 DOE audits of 60 government contractors to develop fixed-effects models of quality assurance compliance.

The research results show that using raw audit results for contractor performance comparisons may lead to inappropriate ranking of contractors. In order to ensure more accurate ranking of contractors, comparison metrics that use audit results must account for audit-specific variables that increase the depth of the audit. Audit-specific variables such as *audit duration*, *audit team size*, *number of audit modules*, and *the time between successive audits* contribute to the number of issues found during an audit and need to be accounted for in relative performance metrics.

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CHAPTER 1

INTRODUCTION

As part of the New Public Management (NPM) movement of the 1990s, advocates successfully introduced a number of public policy reforms that were "founded on themes of disaggregation, competition, and incentivization" (Dunleavy, Margetts, Bastow, & Tinkler, 2005, p. 476). Compared to previous reform measures, these reforms "generally put a greater emphasis on strategic planning; on performance measurement, especially the measurement of program outcomes; on customer satisfaction as one of the desired outcomes; [and] on results-oriented objectives" (Swiss, 2005, p. 592). These reforms were intended to make government more efficient and effective.

The NPM reforms of the 1990s included the Government Performance and Results Act of 1993 (GPRA). This legislation required government agencies to produce annual performance plans that included "performance indicators to be used in measuring or assessing the relevant outputs, service levels, and outcomes of each program activity" and to "provide a basis for comparing actual program results with the established performance goals" (GPRA, 1993). On January 4, 2011, President Barak Obama signed into law the GPRA Modernization Act of 2010 (2011a) amending the GPRA and requiring "quarterly performance assessments of Government programs for purposes of assessing agency performance and improvement."

These laws compel government agencies to identify the important aspects of their programs and to measure and evaluate performance indicators for each program activity. However, some important aspects of program activities are inherently difficult to measure. In these situations, the GPRA Modernization Act of 2010 (2011b) provides an exemption if it “is not feasible to express the performance goals for a particular program activity in an objective, quantifiable, and measurable form.” Nevertheless, in keeping with the stated purpose of the law, federal agencies have a responsibility to establish suitable metrics for evaluating the performance of the agency and its activities, contractors, and suppliers.

The assumption that public officials and administrators behave as rational actors underpins GPRA reform measures. The classical rational actor model assumes decision makers use their cognitive abilities to evaluate information and make optimal decisions (Doucouliagos, 1994, p. 877). Thus, if government agencies are to function efficiently and effectively, the decision makers of those agencies must have all necessary, pertinent information available to them. The intent of the GPRA was to ensure that decision makers had the requisite information. In theory, if managers have the requisite performance information, they can conduct benchmarking or performance comparisons between competing contractors to ensure receiving the best value for budget expenditures (Thompson, 1994).

However, University of Connecticut researchers Kravchuk and Schack (1996) contended that the requirements of the GPRA combined with the complexities of many government organizations caused government decision makers to move away from the traditional rational actor role. Kravchuk and Schack contended that “the more… administrators come to rely upon formal measurement devices and systems, the more they will tend to operate in a cybernetic-decision mode, rather than a rational-actor mode” (p. 349). “To buffer themselves from the overwhelming complexity of the internal and external environments, decision makers establish mechanisms to screen out certain information selectively, in advance (whether or not potentially pertinent). This implicitly violates the rational actor's assumption of sensitivity to all pertinent information" (p. 352). Thus, paradoxically, the provisions of the GPRA were intended to improve the decision-making process, but may have actually undermined the integrity of the process.

Nevertheless, the performance comparison requirements of the GPRA will likely remain. As prominent researchers such as Patrick Dunleavy have acknowledged, "NPM practices are extensively institutionalized and will continue" (Dunleavy, et al., 2005, p. 476). As such, public administrators and agency officials are sometimes faced with the challenge of implementing past NPM innovations (such as GPRA-mandated performance comparisons) even though "their strongest advocates now expect [the innovations] to have little impact on altering the overall effectiveness of government" (Dunleavy, et al., 2005, p 468). The challenge, therefore, is for government agencies to implement the performance measurement requirements of the GPRA in such a way that agency officials operating in cybernetic decision-making mode (Kravchuk & Schack, 1996) have sufficient information to make good decisions.

> Effective management requires a system of measurement that provides a balanced, multifacteted [sic] view of performance, yet slices through the noise and complexity pulsing through the channels of measurement, to indicate when real change is occurring … Ultimately, a system of performance measures does no good if it does not inform decision makers. Worse, it can do great harm if it misrepresents, misleads, or introduces perverse behavioral incentives. Decision makers must understand and take account of the limitations of measurement

systems when interpreting the reported results. (Kravchuk & Schack, 1996, p. 349)

The requirement for a measurement system to provide a balanced, multifaceted view of performance necessitates metrics for all major objectives of the organization. “The highly structured nature of performance-feedback channels will mean that, unless preprogrammed into the channel, many factors that might otherwise affect decisions substantially will have little or no effect on the decision process” (Kravchuk & Schack, 1996, p. 352). In other words, a single measure, such as cost, is not sufficient to determine the relative value of a product or service when isolated from other critical measures, such as quality, timeliness, or functionality.

The difficulty of evaluating performance is compounded when the agency goes outside its own organization to assess its contractors. To compare two or more contractors, like data need to be available from each of the assessed contractors. For example, if an agency desires to compare cost and schedule performance of two of its contractors, the agency needs both cost data and schedule data from each contractor. The agency cannot effectively compare the two contractors if one provides only cost data and the other provides only schedule data.

Problem Statement

Government agencies and their stakeholders have many goals and objectives, and one organizational objective is *quality*. As used herein, quality refers to the “condition achieved when an item, service, or process meets or exceeds the user’s requirements and expectations” (DOE Quality Assurance Requirements, 2001). In this sense, quality is a nearly universal goal of all government agencies. The prominence of quality is such that government agencies frequently mandate quality requirements in contracts, grants, and cooperative agreements (DOE 414.1D).

Given the prominence of quality in government programs and contracts, Kravchuk and Schack's (1996) research suggested that quality may be an important factor to include in the performance-feedback process. Yet, including quality in the performance measurement process can be problematic because quality is, by its very nature, a qualitative characteristic, whereas performance measurement programs tend to favor quantitative measurements (Hatry, 2006). Moreover, challenges measuring quality increase when the government agency needs to use the information to compare the relative performance of multiple organizations, such as when the agency must evaluate the relative performance of multiple competing contractors.

The problem, therefore, is to identify a means to measure quality performance quantitatively in such a way that the measurement results are meaningful for effective decision makers operating in bounded rationality-induced, cybernetic-decision mode. To be meaningful, the results must not misrepresent, be misleading, or provide perverse incentives to the decision maker, government agency, or evaluated contractor (Kravchuk & Schack, 1996). The results must also be timely—"the more timely the feedback, the more useful it is for program managers and staff" (Hatry, 2006, p. 140)—and defensible; the data must be "complete, accurate, and consistent enough to document performance and support decision making" (Wholey, 2006, p. 269).

This exploratory study used data from one government agency to determine if a method for quantitatively measuring quality could be developed that allowed for interorganizational comparisons of government contractors. In accordance with Kravchuk and Schack's (1996) framework, the method needed to slice through the noise and complexity of quality compliance data in order to express real differences between contractors. Moreover, the method needed to work within the existing realities of complex government agencies.

Organization-Specific Challenges

One government agency that has experienced challenges conducting effective performance comparisons of its contractors is the U.S. Department of Energy (DOE). According to the Government Accountability Office (GAO), the DOE is the largest civilian contracting agency of the federal government: "Approximately 90 percent of DOE's [$26 billion] budget is spent on contracts and large capital asset projects" (GAO, 2013, p. 218). As such, measuring and monitoring contractor performance is crucial for the DOE. Yet, the DOE has repeatedly faced challenges monitoring contractor performance. Since 1990, the GAO has designated the DOE program elements as high-risk because the DOE's "record of inadequate management and oversight of contractors has left the department vulnerable to fraud, waste, abuse, and mismanagement" (GAO, 2013, p. 218). Although the GAO's 2013 report to Congress acknowledged that the DOE had made improvements in contract management, the GAO stressed that the DOE needed to sustain these improvements by "receiving and validating accurate and reliable information from contractors that can be used to make decisions and to hold [the contractors] and the department accountable for performance" (p. 222).

The DOE has numerous field offices and prime contractors that subcontract with numerous analytical laboratories throughout the United States. These laboratories conduct a wide range of chemical, radiological, and industrial hygiene analyses. In accordance with the recommendations of the GAO and the requirements of the GPRA, the DOE's contracting organizations need to evaluate the performance of these contracted laboratories.

Each contracting organization establishes its own requirements and priorities for contracted laboratories. Requirements may include analysis turn-around-time (TAT), cost, analytical capacity, certifications, technical capabilities, or quality. Contracting organizations may easily quantify some of these requirements for the purpose of performance comparisons. Prices are established, TATs can be measured, and certifications can be verified and counted. However, quality requirements are much more difficult to quantitatively measure.

Quality holds different meanings. The DOE has defined quality as the "condition achieved when an item, service, or process meets or exceeds the user's requirements and expectations" (DOE Quality Assurance Requirements, 2001). The DOE mandates quality requirements for a wide range of program activities. The DOE document *Quality Systems for Analytical Services* (QSAS) is a quality standard designed for and imposed upon analytical laboratories that conduct work for DOE projects. The DOE defines quality for these laboratories as the degree to which the laboratories comply with the QSAS.

Compliance with the QSAS is generally determined by conducting audits or assessments of a laboratory or the laboratory's work products. The DOE has a consolidated audit program (DOECAP) that regularly assesses commercial and government laboratories against the requirements of the QSAS. The only metrics available for benchmarking laboratories in terms of compliance to quality standards are the results from these audits. However, raw audit results are not especially useful for quantitative comparisons of interlaboratory performance.

Audits are snapshots in time and examine only a sample of a laboratory's work products. As such, the number of incidents found during an audit is just a fraction of the total number of nonconformances within the laboratory. The total number of nonconformances is unknown, and the detected fraction may vary from audit to audit. Moreover, the detected fraction may depend heavily on audit-specific factors such as how, when, and how frequently the audits are conducted. Thus, audit results are not readily useable for interlaboratory comparison of quality compliance because factors not directly related to a laboratory's conformance to requirements can greatly influence the results of an audit. It simply is not justifiable to conclude that a laboratory that has more detected issues during an audit is less complaint than a laboratory with far fewer detected issues.

To illustrate the problem, consider the following. Suppose two nearly identical laboratories violated requirements 100 times each in a given period. Furthermore, suppose that a three-person audit team audited one laboratory over a two-day period and detected six issues; in addition, a six-person audit team audited the other laboratory over a four-day period and detected 24 issues. Based on audit results alone, one might assume that the first laboratory was more compliant with quality requirements because it had far fewer *detected* issues. Yet in reality, the difference in numbers reflected how effectively the audit *detected* issues, not how many issues there actually were.

Providing raw audit results to a cybernetic-decision maker can be counterproductive. Quantitative metrics used for benchmarking multiple contractors against one another must reflect the contractors' performance, not the assessing agency's performance. Raw audit results used for benchmarking do not account for the agency's contribution to the observed results. As such, the uncorrected composite data could mislead decision makers.

Historically, the DOE and its prime contractors have not had a method to quantitatively compare their laboratory contractors against each other based on conformance to the quality requirements in the QSAS. Without an effective method, performance comparisons can be misleading. Moreover, the DOE and its prime contractors are not the only organization with this challenge. Many government agencies and private organizations audit or assess contractors and vendors to quality standards. Identifying a method to account more accurately for audit-specific factors could benefit multiple organizations.

Purpose of the Study

The purpose of this study was to investigate whether a quantifiable relationship existed between audit-specific factors and the number of issues detected during an audit. If the relationship between audit-specific factors could be quantified, then the contribution to the number of detected findings attributable to the contracted organization could be more accurately estimated. More accurate estimations should permit audit results to be used more accurately for performance comparisons of organizations with respect to quality requirements.

Significance of Study

Audits have long been used to evaluate compliance, "Quality audits are prominent and proven management tools for assessing compliance and effectiveness of quality systems” (Karapetrovic &Willborn, 2000, p. 679). Quality audits have proven to be “powerful management tool[s] for quality improvement” (Karapetrovic &Willborn, 2000, p. 679), and trends in data from quality audits have effectively detected changes or perturbations in quality systems (Taylor, 1997). This study adds to the body of public administration and quality assurance (QA) literature by demonstrating that government and private contracting agencies can use QA audit results from different organizations as quantitative metrics for performance comparisons by accounting for nonuniformity in the audit process.

Prior to this study, audit results had been used for performance comparisons. However, these performance comparisons used raw audit results, which implicitly assumed that audit-specific factors did not have a significant impact on the number of issues detected. However, results from a preliminary pilot study of results from 113 government audits indicated that as much as 30% of the observed variation in the number of detected audit issues may be attributable to only three audit-specific factors: (a) the length of the audit, (b) the number of auditors, and (c) the number of audit questions. These preliminary results cast considerable doubt on the appropriateness of using raw audit results for benchmarking of quality performance.

One DOE prime contractor that had subcontracts with two analytical laboratories illustrates the problem of using raw audit results. Records indicated that the first laboratory averaged 23.2 detected issues per audit since 2001. The second laboratory averaged 19.1 issues per audit during the same period since 2001. Ignoring audit-specific factors, the second laboratory appeared to have a better record of compliance based on the raw scores alone. However, records showed that audits of the first laboratory were, on average, 14% longer in duration and 16% greater in scope; in addition, audits were conducted by teams that were, on average, 80% larger. It is quite possible that the first laboratory had 21% more detected issues because the audits were more efficient and not because the existing issues were more numerous.

The results of the current study indicated it was overly simplistic to assume that all variation in the number of detected audit issues was attributable to the laboratory's performance. Nevertheless, audit results could be used for interorganizational performance comparisons of quality provided the statistical analyses accounted for key audit-specific variables such as audit scope, audit team size, and audit frequency. Although the research focused on data from laboratory contractors to the DOE, the challenges faced by the DOE are not unique. Other government agencies, prime contractors, and nongovernment agencies with similar audit programs may adapt this same technique for their own use.

Background of Study

Five years after the passage of the GPRA, the DOE commissioned the National Research Council (NRC) of the National Academies of Science to "conduct a study to review the policies, procedures, and practices used by DOE to identify, plan, design, and manage its portfolio of projects" (NRC, 1999, p. *v*.). In 2004, members of the NRC special committee reported the results of their three-year study. That report concluded the "DOE [did] not have a uniform set of objective measures for assessing the quality of project management" (NRC, 2004, p. 31). In 2005, the NRC issued a follow-up report titled "Measuring Performance and Benchmarking Project Management at the Department of Energy" (NRC, 2005). This follow-up report stressed the need for collecting and using data “to assess, compare, and analyze performance” (NRC, 2005, p. 2). Moreover, the report emphasized that performance data are more useful if collected and “used at the project level” rather than at the senior management level (NRC, 2005, p. 4).

In an effort to implement the NRC’s recommendations, the DOE began directing its contractors to provide performance data that could be used for benchmarking contractors against one another. The DOE issued a revision to its contractor oversight order, the Implementation of Department of Energy Oversight Policy, which required contractors to have an assurance system that included “[m]etrics and targets to assess the effectiveness of performance, including benchmarking of key functional areas with other DOE contractors, industry, and research institutions” (DOE, 2011a). This requirement effectively put the burden on DOE contractors to provide the DOE with data for performance comparisons. However, the order did not specify what data the contractor should provide or how the contractor or government administrator should conduct the performance comparisons.

The DOE and its numerous prime contractors manage programs and projects that require the services of analytical laboratories. These programs include toxic and radioactive waste management studies, environmental restoration efforts, facility decommissioning, and environmental monitoring. These studies often require laboratories to analyze soil, water, vegetation, air, and material samples for composition or contamination.

Numerous laboratories provide analytical services to the DOE and its contractors. Some of these laboratories have highly specialized capabilities, perhaps analyzing only a single chemical, while others analyze multiple chemicals or offer a broad range of radiological services. Some laboratories are government-owned, while others are for-profit private businesses; some are small "mom and pop" businesses, while others are multinational corporations.

The DOE requires many of its contractors to adopt and comply with formal QA requirements. Applicable QA requirements are generally stipulated in contracts or procurement documents (DOE, 2011b). Compliance with these requirements is a condition of funding. Contractually mandated compliance with standards necessitates audits. Because many DOE field offices and contractors subcontract analytical services, individual laboratories may have contracts with multiple DOE projects. Each of these projects requires compliance audits. In the past, these QA requirements resulted in inefficiencies. Each field office and prime contractor audited laboratories separately. Moreover, there was not a consistent QA standard applied. This meant that a single laboratory might have to implement multiple QA programs and might be audited by several DOE organizations in a single year.

To reduce redundant audits, DOE established the DOE Consolidated Audit Program (DOECAP).

> The DOECAP is a program of annual audits of environmental analytical laboratories and commercial waste treatment, storage and disposal facilities (TSDFs). First formulated in the mid-1990s and currently administered by the [DOE] Office of Health, Safety and Security, Office of Corporate Safety Programs (HS-23)[,] the intent of this corporate Departmental program is to eliminate redundant audits previously conducted independently by DOE field

element sites throughout the Department's Complex, and achieve standardization in audit methodology, processes and procedures. (DOE, 2013, ¶1)

The DOECAP provides laboratories with a single QA standard for all DOE work and a single audit program, which eliminates redundancies.

DOECAP's QA standard is the QSAS, an upper-level requirement document for all DOE contracted laboratories. The QSAS follows a total quality management approach addressing a wide range of issues that could potentially impact the quality of a laboratory's products or services. These include technical requirements such as sample handling, equipment calibration, and method evaluations as well as managerial or administrative requirements such as document control, organizational lines of authority, and customer complaints.

DOECAP audits assess laboratories' compliance with the requirements of the QSAS. Typically, the DOECAP conducts one audit annually at each laboratory facility. Auditors may be federal employees or contractors, and audit teams may have as many as 15 auditors or as few as one. Although the typical DOECAP audit is conducted over three consecutive days, other audits may range from one to seven days and need not be consecutive.

The audit team usually produces a draft audit report on the last day of the on-site portion of the audit. Over the weeks following the on-site portion of the audit, the DOECAP operations team, the audit team members, and the audited organizations review and finalize the audit report. Once the audit report is finalized, the DOECAP operations team extracts the audit results and enters them into a database along with key audit-specific factors,. The DOE's Oak Ridge Office (ORO) maintains the database and makes the data available on-line for all DOE organizations that participate in DOECAP. ORO currently maintains the audit results and metadata from all the DOECAP audits conducted during and after federal fiscal year (FY) 2000.

Theoretical Framework

Traditional economic theory treats decision makers as rational actors. The primary characteristics of the classical rational actor are: "(1) maximizing (optimizing) behavior; (2) the cognitive ability to exercise rational choice; and (3) individualistic behavior and independent tastes and preferences" (Doucouliagos, 1994, p. 877). More neoclassical conceptions of the rational actor incorporate concepts, such as *bounded rationality,* which acknowledges that the economic actor's ability to optimize outcomes is constrained because of limited time information, etc…Therefore, rational actors are constrained to "use heuristics, rules of thumb and simplifications; they rely on traditions, organizational routines and formal hierarchies" (Grossler, 2004, p. 320).

The research of Kravchuk and Schack suggested that the constraints of the GPRA and the complexities of government organizations bind the rationality of decision makers to such an extent that the heuristics, organizational routines, and formal hierarchies dominate the decision-making process (1996). As such, if vital information is not preprogrammed into the metrics and feedback channels, it will not be included in the decision-making process. Therefore, if quality is a characteristic of concern for the agency, the agency must formally include quality evaluations or measurements in the decision feedback mechanisms. The feedback mechanisms should employ quantitative means for assessing quality performance, but the metrics must not mislead or misrepresent. Moreover, if the goal is to rank or compare two or more organizations, the quantitative means must be either an absolute measure or a relative, interorganizational measure. A relative, *intra*organizational measure may be useful for measuring changes within an organization, but it cannot be used for comparing organizations.

This study demonstrated a feasible means for quantitatively measuring quality across organizations by using quantitative results from quality assurance audits. The quantitative method employed was a fixed-effects statistical model. In addition to independent variables outside the control of the assessed organization, the fixed-effects model also included dummy variables to account for the audited organizations' unknown contributions to the dependent variable of interest. Thus, the model results were less likely to mislead or misinform an agency decision maker operating in cybernetic-decision mode.

Analytical Approach

For comparison purposes, this study used two distinct quantitative analytical methods. Both approaches used statistical regression techniques to rank government contracted analytical laboratories based on the results of quality performance audits. One approach assumed that variations in the way an audit was conducted did not significantly impact the audit results and, therefore, could be omitted from the statistical analyses. This traditional approach served as the control case.

The other approach used in this study assumed the impacts of audit-specific factors were not negligible and had to be accounted for in the model. This approach incorporated audit-specific variables into fixed-effects, ordinary least squares (OLS) regression models. Approaches using least squares regression analyses have been a staple of QA analyses since the early days of Deming and Juran (Martin, 2000). Least squares regression analyses are used to “estimate average systematic error (bias) and its confidence interval in method-comparison studies” (Martin, 2000, p. 100).

The fixed-effects approach for this work followed the approach that Naveh and Erez (2004) used for previous quality assurance effectiveness research. Naveh and Erez investigated the causal relationship between quality assurance practices and outcomes in 18 different organizations over a 20-month period. Given that unknown factors unique to each of the 18 organization could have influenced outcomes, Naveh and Erez had to account for variation between the 18 distinct organizations. Consequently, they assumed that the unknown influential characteristics of the 18 organizations were relatively constant over the period of the investigation. This assumption allowed them to use a fixed-effects statistical approach. Specifically, in this approach, the researchers used an OLS regression model that incorporated a separate dummy independent variable for all but one of the organizations of interest. The organization without a dummy variable was the reference organization. The fixed-effects model produced a slope coefficient for each of the dummy variables. Each slope coefficient represented the additional contribution to the results that were attributable to the corresponding organization.

Although this dissertation study used the same basic approach that has been used by QA researchers such as Naveh and Erez, (2004) and Palmer et al. (1996), the purpose for the approach was quite different. Incorporating dummy variables allowed the previous researchers to better quantify the relationship between the quality assurance practices of interest and the dependent variables of interest. For this study, the dummy variables were the variables of primary concern. The models incorporated other independent variables in order to better quantify the relationship between the dummy variables and the dependent variables of interest.

The fixed-effects models incorporated two broad categories of related factors: audit-specific factors and laboratory characteristics. Audit-specific factors included

- the length of the audit,
- the number of auditors on the team,
- the number of audit observers,
- time since the previous audit,
- the type of audit, and
- the number of audit modules.

Laboratory characteristics included

- the type of laboratory and
- the laboratory's performance.

Overview of Methodology

This dissertation study used secondary data originally collected and compiled by the DOE from 398 separate DOECAP audits of 61 different laboratories over a 13-year period. These data were downloaded from the ORO's DOECAP website. Using these data, I conducted a series of regression analyses using multiple dependent and independent variables.

The source dataset contained numerical audit results of three types of audit issues: (a) Priority 1 findings, (b) Priority 2 findings, and (c) observations. The DOECAP audit reports also distinguished between different categories of issues. Thus, it was possible to distinguish between technical issues and general management or QA issues. Four variations of a general regression model were developed, and each variation used a different dependent variable. These four dependent variables were (a) technical findings, (b) technical issues, (c) findings, and (d) issues. I examined four laboratory types: (a) chemistry laboratories, (b) radiation laboratories, (c) multipurpose laboratories, and (d) nonchemistry, nonradiation laboratories (e.g., industrial hygiene laboratories). I used dummy independent variables for the laboratory type and selected the nonchemistry, nonradiation laboratory type as the reference type for the regression analyses.

In addition to the four variations of the general model, I also developed specific laboratory-type models. For these models, I omitted the laboratory type dummy variables and ran the models on subsets of the data consisting solely of the laboratory types of concern. I developed model variations for each of the four dependent variables for chemistry laboratories, radiation laboratories, and multipurpose laboratories, for a total of 12 additional model variations.

Research Questions

The study assumed that audit-specific factors outside the control of the contracted laboratory affected audit results. In order to use audit results to benchmark contractors fairly in performance comparisons, relevant audit-specific factors needed to be identified. To achieve the objectives of this study, I sought answers to the following questions:

1. Is there a statistically significant relationship between the number of issues detected during an audit and the audit duration, the audit team size, the audit frequency, the audit scope, or the presence of oversight during an audit?
2. Does the relationship between independent and dependent variables differ depending on the type of laboratory?

3. Does the relationship between independent and dependent variables differ depending on the selected definition of audit issue?

Limitations

This study was limited by the quality and quantity of source data, which were obtained from the DOECAP website and limited to results from audits conducted between January 2000 and August 2012. The study did not examine data from other auditing organizations (i.e., nonDOECAP). I considered only the variables identified in the audit reports and contained in the source data. Many independent variables may affect audit results, but most of these may not be included in the available source data. As such, it was anticipated that the models would account for significantly less than 100% of the observed variation in the numerical results.

Some laboratories work to multiple standards, such as ISO 9001, or ISO 14001. The study did not examine compliance with most of these standards. The study examined only laboratory compliance with the DOE QSAS.

Delimitations

The study was delimited in the following ways. First, the decision to study only DOECAP audit results limited the ability to generalize the data. As such, quantitative results applied only to DOECAP. Qualitatively, the results may apply to a much larger set of organizations. However, the ability to generalize the results to other organizations is limited to organizations with structure and stability similar to DOECAP's. Second, the study was delimited to data from laboratories that participated in DOECAP from FY 2000 through FY 2012. Significant changes in DOECAP's structure or implementation after FY 2012 may have affected the applicability of the models.

Assumptions

The study relied on secondary data that I obtained from the DOECAP website. Also available on the website were the original audit reports from which the data were extracted. During the study, I detected a few minor discrepancies between the extracted data and the audit reports. In general, it was not possible to determine if the discrepancies were data entry errors or if the data had changed sometime after DOECAP finalized the audit reports. For the study, I assumed that the data in the database were accurate.

DOECAP has revised the QSAS 10 times since it was initially issued. The study assumed that changes in QSAS requirements did not influence the systematic bias from audit-specific factors. No attempt was made to investigate the statistical relationship between specific auditors and the dependent variables of interest; only the relationship between the number of auditors and the dependent variables was investigated. For the study, I assumed that bias due to the number of auditors could be estimated without taking into account the identity of any specific auditor.

Summary

In chapter 1, I introduced the research problem, provided a cursory overview of the research methods, and provided background information that helps put the research into context. Chapter 1 also included brief discussions and references to work conducted previously by other researchers. In chapter 2, I examine the work of these researchers, and others, in more detail in order to better demonstrate how the current research fits into the larger body of performance assurance research.

CHAPTER 2

LITERATURE REVIEW

To understand the importance of the research, it is helpful to understand the following, which comprise the four parts of this chapter: (a) the purpose and history of QA programs with an emphasis on QA research related to laboratories and their importance for government agencies supporting science and research, (b) the purposes and motivations behind comparative performance measurements, (c) the requirements and challenges of comparative performance measurements, and (d) how the proposed study fits within current research.. This chapter begins with a brief history of quality assurance programs..

Quality Assurance

QA lacks a single, universally accepted definition but is generally described as the collection of planned or systematic actions necessary to provide adequate confidence that a product or service meets its intended purpose or fulfills customer expectations (adapted from ASQ, 2010b; DOE, 2005, p. 12; DOE Quality Assurance Requirements, 2001).

Historical Context of QA

QA principles have been integral components of science and engineering for thousands of years (ASQ, 2010a). However, QA, as a separately recognized discipline, has its origins in the post-World War II work of researchers Deming and Juran. Prior to Deming, quality research focused on identifying optimum conditions for production. Researchers, such as Taylor (1967), studied methods, conditions, and physical configurations that would optimize production while minimizing costs. However, these quality concepts adopted by early manufacturers were primarily based on deterministic models of production. These models had a fatal flaw: They did not account for variation in the production process. As a result, a typical assembly line may have minimized the per item cost of production; however, statistical variation resulted in the introduction of product defects. Quality control at these production facilities consisted of identifying product defects and either reworking the defective items, disposing of them, or passing them on to the customer. As a statistician, Deming showed that when the associated costs of defects were factored into the overall costs of production, the results were less than optimal.

Deming's seminal contributions to quality were his 14 key points of management that, in large part, formed the foundation of modern QA programs. Underlying these 14 principles was the concept that quality should be engineered into products (or services) at the outset rather than accommodated later after defects have occurred. Deming showed that the costs associated with preventing defects were more than compensated for by reducing the costs of re-work, redundant inspections, and customer dissatisfaction (Deming, 2000).

A contemporary of Deming, Juran was likewise influential in establishing QA as a separate discipline. Juran established a threefold managerial process known as the Juran Trilogy®, which consisted of (a) quality planning, (b) quality control, and (c) quality improvement (Juran, 1988, p. 12). The concepts of the Juran Trilogy® were not new, but Juran's structured systematic approach for applying these concepts was, in many ways, revolutionary. Juran focused on the human dimension of quality, and because humans are complex beings, he reasoned that quality had to be evaluated by means other than simple statistics, such as production numbers or profit margins: " [E]valuation of performance necessarily involves a good deal of sensing and judging by human beings. The goals and plans are too broad to permit evaluation solely by the numbers" (1988, p. 263).

The Japanese auto industry was the first to apply Deming and Juran's QA principles. Although Deming (2000) and Juran's (1988) work was originally met with a considerable degree of skepticism in western nations, the success experienced by the Japanese was so significant that manufacturers in the United States and elsewhere around the world soon followed suit and implemented their own QA programs with similar success. In the decades that followed, governments and industries standardized QA principles and methodologies in regulations and consensus standards, such as the International Organization for Standardization's ISO 9001 for Manufacturing, ISO 14001 for environmental industries, and the American Society of Mechanical Engineers' ASME NQA-1 for nuclear facilities.

QA in Science and Laboratories

Although the work of both Deming (2000) and Juran (1988) originated in the domain of manufacturing, the quality principles they espoused were management philosophies not manufacturing methods. As such, the application of these philosophies cut across organizational types and could be readily applied to nonmanufacturing disciplines. However, the efficacy of QA programs outside the sphere of manufacturing tended to be more difficult to measure in some respects, especially in the area of laboratory research. Objectively assessing the relative quality of a tangible product was relatively straightforward: the product could be measured, tested, and compared to established standards. In contrast, assessing the adequacy of QA controls in a nonproduction laboratory tended to be more difficult because these organizations defined quality in more subjective terms, such as “Are we asking the right scientific questions?” “Are we using the most effective methods?” “Are we making enough progress?” Metrics for evaluating these types of goals may be difficult to define. Moreover, even if an individual organization could successfully develop adequate metrics, the metrics might be so organizationally dependent that comparing across organizations would be difficult.

Relatively recent studies by diverse researchers around the world, such as Du (2002), Dizadji and Anklam (2004), Vogt (2001), and Barak, Younes, and Froom (2003), have sought to bridge this knowledge gap by specifically looking at QA in scientific research laboratories to determine whether QA programs were value-added and cost effective. Israeli researchers Barak, Younes, and Froom (2003) investigated commercial medical research laboratories that implemented ISO 9001 compliant QA programs. Their research sought to measure the quality of the laboratories by using customer complaints as a surrogate inverse measure of laboratory quality. The results of their five-year study showed that QA programs were only marginally effective at reducing the overall number of customer complaints. However, their study also showed that “the proportion of justified complaints had decreased by nearly 80% . . . to only 10.9% of the total complaints” (p. 282). Barak et al. concluded that the QA program effectively improved quality in “that the use of the ISO 9000 along with good laboratory practice resulted in a significant decrease in the proportion of justified complaints” (p. 282).

In a three-year study jointly conducted by the European Commission and Belgium’s Institute for Reference Materials and Measurements, researchers Dizadji and Anklam (2004) demonstrated that QA controls, if properly implemented, could be cost effective. However, their research indicated that the level of success in making QA controls cost effective depended somewhat on the strategic approach used by the laboratory. Dizadji and Anklam concluded that laboratories should tailor their QA approach to fit the predisposition of the target institution. Furthermore, to implement a QA program properly, the institution should "identify and classify different groups of activities in [the] laboratory into separate business domains" (p. 317). The institution should then "assess for each business domain, the approach, the benefits, costs and implications of working with a systematic QA and then design *a priori* appropriate working systems tailored to the real needs of each business" (p. 317).

Although previous research has demonstrated that QA could be cost effective, research by the German scientist Vogt (2001) showed the value of implementing QA in the laboratory when "perfect production is a prerequisite for services at the highest quality level" (p. 398). Pre-Deming quality control measures allowed an institution to recognize and correct errors, but this approach may be insufficient for laboratories where perfect production is a prerequisite. Vogt's research showed that a total quality management program could increase the technical quality of a laboratory's products. Moreover, Vogt's research also demonstrated that QA principles added the benefit of containing overall costs. Thus, a properly selected and applied QA program could bridge the gap between researchers who were primarily concerned with product quality and administrators who were primarily concerned with financial aspects.

Funk, Dammann, and Donnevert (2007) extended QA research to identify processes and techniques specific to analytical laboratories. They identified four QA components of particular importance to laboratories that must produce "reliable analytical results, the accuracy of which is determined, regularly verified, and documented" (p. 4).

Those four components were (a) determining quality objectives, (b) establishing quality control measures, (c) executing the quality assurance measures, and (d) conducting audits and confirmatory testing of results. Funk et al. noted, "Only by tying together all analytical activities into a closed system of both internal and external laboratory quality assurance can the reliability of analytical results be guaranteed" (p. 7).

Reminiscent of Juran's studies, work conducted by Llorens and Ruiz (2005) extended the study of laboratory QA to include sociological factors. They investigated "how externalizing the process of implementing ISO 9001 influences the dissemination of cultural values and practices of quality management in laboratories involved in chemical measurement" (p. 304). Laboratories required to comply with QA constraints have resisted QA programs in many instances. Llorens and Ruiz wanted to identify the factors that contributed to increased compliance with QA controls. In particular, they wanted to determine if outsourcing QA functions would have a measurable impact on the level of compliance. In order to improve efficiency, some laboratories have moved towards external QA controls that allow laboratory personnel to focus on core functions. According to Llorens and Ruiz, the economically driven belief is that "organizations can manage [their] capacity more efficiently and enhance their flexibility by focusing on their core activities and externalizing their noncore activities to an external, contingent workforce of independent consultants" (p. 304). However, results obtained by Llorens and Ruiz demonstrated that the effectiveness of QA programs increased and the associated challenges diminished when the QA program was largely implemented by individuals within the laboratory organization. Furthermore, due to emotional and sociological factors, "the greater the degree of internalization of the implementation process, the greater the dissemination of [Quality Management] culture among the workers" (p. 307). When laboratories implement QA programs that are externally developed and administered, the perception of ownership decreases and the internal desire to comply diminishes.

Collectively, the results of these and similar studies worldwide confirm that proper implementation of QA in the laboratory research setting can result in levels of success comparable to those observed in more traditional settings, such as the automotive industry. Although a laboratory's work products may be very different from the products of a manufacturing plant, QA controls positively influence numerous commonalities, such as customer satisfaction, costs, and employee attention.

QA in Government

Motivated by the success of private sector QA programs, the United States federal government soon adopted QA standards and programs for high-risk applications, particularly applications directly related to public safety. These included the U.S. Nuclear Regulatory Commission's Quality Assurance Criteria for Nuclear Power Plants and Fuel Reprocessing Plants (2007) and the U.S. Department of Energy's Quality Assurance Requirements (2001) for nuclear safety management. The government's application of QA, however, soon broadened to include high-risk, nonpublic safety applications, such as the U.S. Environmental Protection Agency's Quality Assurance and Quality Control Procedures (2011).

Although government agencies recognized QA's potential for ensuring the production of high quality products, they also viewed QA as expensive. The time workers spend implementing QA programs is a substantial opportunity cost to the government.

Moreover, QA programs require managers, engineers, and other QA specialists to oversee and assess the programs. These activities and personnel cost money. Thus, the federal government initially reserved these ostensibly expensive QA programs for fields where quality issues trumped financial considerations (Government Contract Quality Assurance, 2010).

As time progressed, forces combined to place pressure on the government to apply QA to lower risk applications. These factors included economic pressures, political and societal trends, and institutional momentum. Notwithstanding the considerable costs associated with QA programs, businesses found their application to be an effective means for achieving business goals, staying on schedule, and reducing overall costs. They found that the expense of QA was not just a cost of doing business, but a business investment that paid measurable dividends (Deming, 2000). Thus, even though costs were a prime factor for limiting early applications of QA, as time progressed, government agencies began to perceive QA as a means for controlling costs. In the end, elected officials and government administrators, faced with having to do more with less, increasingly adopted QA programs for lower risk applications as a means for leveraging limited resources (Deming, 2000).

Measuring Quality

Given the aim of QA programs to assure the quality of products or services, a large body of research has attempted to define ways of measuring quality. Early researchers, including Flynn, Schroeder, and Sakakibara (1994), attempted to develop a framework for measuring quality management practices within organizations. These early researchers often focused on defining dimensions of quality management that statistically correlated with achieving and sustaining high quality output in manufacturing settings. Flynn et al. (1994) successfully demonstrated that a scale they developed to measure management practices was statistically valid as a surrogate measure of quality performance. However, the scale had little practical value for interorganizational comparisons because it did not provide an absolute measure of quality compliance; rather, it was designed to be an indicator of the effectiveness of QA strategies. Moreover, the "instrument [was] designed for use at the plant level allowing measurement of plant level initiatives" (p. 361). As a survey of employee perceptions and management philosophies, the instrument was not designed for assessing quality initiatives at the division or corporate levels, much less at the industry level. Although these types of instruments may be used within organizations, they do not lend themselves to interorganizational comparison studies. Furthermore, Flynn et al. developed their instrument in a manufacturing setting, and some of the parameters used to validate their model do not apply to service industries, such as laboratories.

Florida State University researchers Yang and Hsieh (2007) using data from Taipei, Taiwan, attempted to build a theory-driven performance measure specifically for government agencies. Their results confirmed their model was well grounded in theory. However, the narrow scope of their research prevented extrapolation of their results to other government agencies. Moreover, the performance measures developed by Yang and Hsieh (2007) were based on data obtained from a survey instrument like the instrument developed by Flynn et al. (2007). Survey instruments do not lend themselves to interorganizational comparison studies of the type required to meet the intent of the GPRA. Research has shown that survey responses "that are perceived by the respondents as undesirable tend to be underreported" (Groves et al., 2004, p. 52). If a government agency desires to use a survey instrument to compare its contractors' relative compliance with QA requirements, there is little that the agency can do to ensure that the contractor does not intentionally bias the results.

Researchers such as Du (2002); Dizadji and Anklam (2004); Vogt (2001); Barak, Younes, and Froom (2003); and Funk, Dammann, and Donnevert (2007) attempted to measure quality more directly. However, they selected quality measurements that demonstrated the effectiveness of QA programs—measures such as efficiency, productivity, and customer satisfaction. The results of these studies and the studies conducted by Flynn et al. (2007) were not absolute measures. They could show improvement in quality, efficiency, or customer satisfaction, but they did not provide an absolute measure that government contracting agencies could use to compare one government contractor against another. This type of data, if provided to a decision maker operating in Kravchuk and Schack's cybernetic-decision mode, could mislead and misdirect when used for interorganizational benchmarking.

The body of research has shown that compliance with QA standards is an important factor related to efficiency, effectiveness, and product quality. As such, government agencies have a stake in measuring a contractor's degree of compliance with QA standards. Yet, measures developed to date have generally provided organizations with methods for measuring only their own internal level of quality and changes therein. Existing research has not identified adequate methods for outside entities, such as government contracting agencies, to quantitatively measure and compare the degree of QA compliance of one contracted laboratory against another contracted laboratory.

Proficiency Testing

One widely used QA technique for comparing laboratories is the proficiency test (PT). “An interlaboratory [PT] study is a planned series of analyses of a common test material performed by a number of laboratories, with the goal of evaluating the relative performances of the laboratories, the appropriateness and accuracy of the method used, or the composition and identity of the material being tested” (Hibbert, 2007, p. 136).
In a PT, a sample of known composition is prepared and distributed to participating laboratories. The laboratories then perform blind analyses on the sample. If a laboratory’s analytical results are within predefined acceptance limits, the laboratory passes the PT.

Although the PT is effective for determining a laboratory’s ability to perform a specific analytical test, it is severely limited as a tool for interlaboratory comparison. According to the Royal Society of Chemistry’s Analytical Methods Committee (AMC, 2005),

> The primary purpose of proficiency testing is to help laboratories detect and cure any unacceptably large inaccuracy in their reported results. In other words, it is designed as a self-help system to tell the participants whether they need to modify their procedures. Proficiency tests are not ideally designed for any other purpose.(5)

Failing a PT sample is an indicator that a particular laboratory procedure may be inadequate. However, this may or may not be an indicator of larger QA issues. Moreover, passing a PT is only an indicator that a laboratory can get the right number; is not an indicator of the laboratory’s ability to achieve any other contract quality requirement.

Furthermore, although the composition of a PT sample may be unknown, the fact that it is a PT sample *is* usually known. Because laboratories know the importance of PT samples, there is an incentive for laboratories to conduct PT sample analyses with greater than normal care. Indeed, Hibbert (2007) contended, “it is inevitable that laboratories may take more care with their proficiency testing samples” (p. 148). PT sample results, therefore, are not necessarily a measure of how well a laboratory performs on a regular basis but a measure of how well a laboratory performs at its best. Thus, proficiency testing has limited usefulness for interlaboratory performance comparisons of overall laboratory quality compliance.

QA Audits

According to the American Society for Quality (ASQ, 2013), an audit is defined as follows:

> On-site verification activity, such as inspection or examination, of a process or quality system, to ensure compliance to requirements. An audit can apply to an entire organization or might be specific to a function, process or production step. (p. 1)

Although each agency conducts audits somewhat differently, a typical audit consists of a team of individuals that visits a contractor’s facilities, examines records, observes work in progress, and interviews contractor employees and management. During the effort, auditors may compare observed work practices against approved procedures or accepted industry standards; auditors may look for documentation to corroborate compliance with regulatory or contractual requirements; or an auditor may examine equipment to ensure it functions as intended. As a rule, if auditors identify a violation of a requirement, they will try to determine if it is an isolated instance before documenting the violation in the audit report. However, other than trying to determine if the issue is an isolated instance, the auditors will not attempt to determine the extent of condition. In other words, the audit write-up will record the number of requirements the contractor violated, but not the *number* of times the contractor violated those requirements.

The federal government conducts audits “to determine and document whether items, processes, systems, or services meet specified requirements and perform effectively” (DOE, 2011b, §6.c). According to the U. S. Environmental Protection Agency (EPA, 2000):

> Effective technical audits and assessments contribute to a reduction in the occurrences of questionable data, faulty conclusions, and inappropriate practices. Key purposes of technical audits and assessments include the discovery and characterization of sources of measurement error, the reduction of deficiencies, and the safeguarding of EPA’s decision-making process. Audits and assessments help to ensure that approved QA Project Plans are being followed and that the resulting data are sufficient and adequate for their intended use. Proper use of technical audits and assessments can provide increased confidence that the collected environmental data are defensible and properly documented. Audits and assessments can uncover deficiencies in physical facilities, equipment, project planning, training, operating procedures, technical operations, custody procedures, documentation, QA and QC activities, and reporting. (p. 14)

Auditors in general, and DOECAP auditors in particular, must be qualified or certified before they may conduct audits unsupervised (DOE, 2009). Certification is based on a combination of factors including training, experience, and demonstration of capability. Many organizations base their certification programs on voluntary standards promulgated by organizations such as the American National Standards Institute (ASME, 1978).

Auditors generally work to a checklist or a line of inquiry based on legal or contractual requirements. When auditors identify apparent deviations from requirements, they provide the audited organization an opportunity to clarify or dispute the issue. If the deviation from the requirement is verified, the issue is formally documented in the audit report. Verified issues are then tracked through closure, and records are generally maintained for trending or other purposes.

Audit Effectiveness

The literature is replete with research on how to conduct effective audits. Willborn (1990) examined the need for audits to adapt to changing operational environments in order to be effective. Gardner (1997) examined the importance of applying standard principles when conducting audits. Russell (2010) looked at audit organization and preparation. Copeland, Espersen, and Grobler (2013) emphasized the effect that audit scope can have on results (p. 34). Johnston, Crombie, Davies, Alder, and Millard (2000) reviewed findings from 93 studies of individual audit projects to identify facilitators and barriers to conducting the audit process.

The body of literature suggests that the way an audit is conducted profoundly impacts the results of the audit. Because of this, emphasis has been placed on consistency of the audit process. Handzo (1990), a professional quality assurance auditor of corporate suppliers, stated the following:

> One auditing system should be developed for the entire company, providing a uniform measuring/rating criteria for each area of discussion during the audit. This ensures that audits are conducted the same way and provides identical training for the audit team members. (p. 54)

Although Dalhousie University researcher Karapetrovic and University of Manitoba researcher Willborn (2000), did not dismiss the importance of consistency, they did recognize that perfect consistency is not always possible: “Audits are open and dynamic systems, meaning that the parameters and constraints under which they operate inevitably change…” (p. 683). Moreover, “Audits are adaptive systems, being able to accustom themselves to changing operational environments” (p. 683).

Thus, the body of research has suggested that audits must change to be effective. Moreover, changes in the way audits are conducted impact the results. Traditional methods for using audit results for benchmarking implicitly assume that the way an audit is conducted does not significantly affect the results and can, therefore, be ignored in performance comparison studies. I conducted this study to determine if changes to the audit process do significantly affect the results and, therefore, must be explicitly included in performance comparison studies.

Purpose for Measuring and Comparing Performance

Numerous researchers have identified management uses for performance measurements (Ammons, 1995; Kopczynski and Lombardo, 1999; Osborne & Plastrik, 2000; Wholey & Newcomer, 1997). Noted Harvard University researcher Behn (2003) grouped these various uses into eight major reasons that public managers measure performance:

> As part of their overall management strategy, the leaders of public agencies can use performance measurement to (1) evaluate; (2) control; (3) budget; (4) motivate; (5) promote; (6) celebrate; (7) learn; and (8) improve. (p. 588)

Each of these reasons can provide some motivation for measuring and assessing an analytical laboratory's level of compliance with QA requirements. However, four of these reasons have particular relevance to the current study.

Program Evaluation

A principle motivation for measuring performance is simply to evaluate an organization's status towards meeting its goals and how that status changes in time.

> Performance measurement of program outputs and outcomes provides important, if not vital, information on current program status and how much progress is being made towards important program goals. It provides needed information as to whether problems are worsening or improving, even if it cannot tell us why or how the problem improvement (or worsening) came about. (NAPA 1994, p. 2)

Likewise, as stated by Hatry of the Urban Institute:

> . . . performance data do not reveal the extent to which the program caused the measured results. . . . Performance measurement is designed primarily to provide data on outcomes. . . . But to be most helpful . . . performance measurement systems also need to have built into them opportunities to analyze the details of program performance and steps to seek explanations for the outcome data such systems produce. (2006, p. 5)

Understanding the story behind the numbers is a key challenge associated with using QA audit results for performance measurements. The number and types of detected audit issues can be readily tabulated, but the raw numbers do not tell why the audit team was able to detect the identified issues. “[T]o evaluate performance, public managers need some kind of desired result with which to compare the data, and thus judge performance” (Behn, 2003, p. 598).

Motivation and Control

Performance measurement is a standard tool used by management for asserting control. As stated by Lancaster University Management School’s David Otley, a “major function of accounting performance measurement lies in its internal use as a means of motivating and controlling the activities of managers so that they concentrate on increasing the overall value of the business . . .” (Otley, 2003, p. 12).

> Indeed, the controlling style of management has a long and distinguished history. It has cleverly encoded itself into one of the rarely stated but very real purposes behind performance measurement. “Management control depends on measurement.” (Behn, 2003, p. 589)

QA compliance measurements may be used for influencing laboratories to change for the better. If a contracting organization, like DOE or one of its prime contractors, has unbiased QA performance data, those data may provide incentives for a subpar laboratory to improve its level of performance. However, if the laboratory has reason to believe its relative ranking is based on biased data, the laboratory may have little or no incentive to change its level of performance.

Budget

Federal acquisition requirements mandated by Government Services Administration require that cost comparisons be included in contract award decisions (GSA Contract Pricing, 2005). However, cost comparisons require more than data on the cost of the item or service being procured. Purchasing personnel and contract managers must also consider the provider's ability to deliver a product or service that meets all the customer's needs. These customer needs may include a host of other requirements such as security requirements, schedule requirements, production requirements, and quality compliance standards.

Contracting organizations' requests for proposals (RFPs) typically identify minimum requirements that all bidders must meet in order to win a contract. Additionally, RFPs include weighted factors that permit the awarding agency to rank and differentiate eligible bidders. Cost is a required differentiating factor. If two or more bidders are equal on all other factors, the low bidder will win the contract.

DOE's emphasis on QA compliance suggests that past QA performance is a potential factor that DOE could use to rank bidders, but this requires data about each bidding organization's compliance with QA requirements. Results from effectively conducted QA audits can provide past compliance data. However, if compliance metrics use raw audit results, uncorrected for audit-specific factors, the results may detrimentally affect the award process by unjustifiably favoring one contractor over another.

Requirements for Effective Performance Measurements

The National Research Council (NRC, 2005) recommends that performance measures for implementing the GPRA meet the following ten characteristics:

- Measureable, objectively or subjectively;
- Reliable and consistent;
- Simple, unambiguous, and understandable;
- Verifiable;
- Timely;
- Minimally affected by external influence;
- Cost effective;
- Meaningful to users;
- Related to mission outcome; and
- Drive effective decisions and process improvement (p. 10).

Identifying or developing performance measures that meet these 10 requirements can be challenging for an organization. Moreover, although the list is broad, it is not comprehensive. The following subsections examine additional performance measure requirements and challenges.

Measurement Framework

UK researchers Propper and Wilson (2003) showed the importance of using multiple metrics for measuring performance. A single organization may have multiple stakeholders, and each stakeholder may have a distinct set of values and priorities. A single metric or set of metrics that may be used to measure success towards meeting one stakeholder's desired outcome may not be adequate to measure another stakeholder's desired outcome. Propper and Wilson concluded,

> [A] single [performance measure] is not sufficient. Public sector organisations often have multiple stakeholders who have differing, and sometimes conflicting,

> goals. One [performance measure] cannot adequately address all these actors' objectives. Instead a range of [performance measures] should be employed, both in terms of what they measure and also in terms of their form. (p. 19)

Similarly, researchers Kravchuk and Schack (1996) suggested using a framework of performance measures:

> What is needed, then, is a framework for system-wide performance measurement that acknowledges the diversity of the system's goals, while providing information on aggregate efficiency and effectiveness. Ideally, this framework should measure inputs, processes, outputs, and outcomes as well as client satisfaction. Further, the system should serve the purposes of both continual performance assessment and long-term evaluation. (p. 354)

More recently, researchers Nicholson-Crotty, Theobald, and Nicholson-Crotty (2006) identified additional dangers associated with using single performance measures. They found that managers often have multiple, plausible metrics available to them to measure a single concept (p. 101). Unfortunately, these metrics can sometimes provide conflicting results. Nicholson-Crotty et al. asserted that "differing measures can provide starkly different feedback to managers about their organizations" (p. 110).

The danger of selecting a single metric for measuring performance increases if the metric is used to compare different organizations. One metric may unfairly benefit one organization to the detriment of another organization. Selecting a different metric may reverse the perceived results, even though there has been no change in the organizations. Nicholson-Crotty et al. showed that if measurements and comparisons of organizational performance were to be fair and effective, they "must be sensitive to the real differences among multiple measures of performance" (Nicholson-Crotty, et al., 2006, p. 110).

Quantitative Measurements

Performance data can come in the form of both qualitative and quantitative data. Evaluators may appropriately use both types of data for comparative measurements of performance; however, they have tended to prefer quantitative data. "Qualitative evidence is, in general, considerably less convincing than quantitative evidence of progress" (Hatry, 2006, p. 79).

Recent research from Heinrich (2012) at the University of Texas at Austin demonstrated the importance of using credible quantitative data. In 2002, the George W. Bush administration introduced the Program Assessment Rating Tool (PART) to meet the goals of the GPRA more effectively. PART is a management tool that

> looks at all factors that affect and reflect program performance including program purpose and design; performance measurement, evaluations, and strategic planning; program management; and program results. (OMB, 2013, ¶ 1)

Heinrich's research examined data submitted to the Office of Management and Budget in support of the PART process. Heinrich hypothesized, and her research confirmed, that favorable PART scores were positively correlated with the rigor of the data used for evaluating performance. Organizations that provided only qualitative evidence had lower PART scores overall (Heinrich, 2012, p. 132).

In addition to credibility issues, problems arise when using qualitative measures in conjunction with other measures. For instance, it is common for the government to issue requests for proposals that include provisions for evaluating potential contractors according to both quality of service and cost. However, if one potential contractor is judged highest in its quality of service, but charges twice as much as the other contractor, how can the government determine if the superior service is worth the additional cost? If it were possible to determine that the agency was getting three times the service for only twice the cost, perhaps the additional cost may be justified, but that requires quantification of the quality of service. If the amount of additional quality cannot be quantified, it may not be possible to justify awarding a contract to the more expensive contractor, even if they do better work.

Organizational Fit

Hatry (2006) contended that all service-providing organizations, "small or large, public or private, … should be intensely concerned with the quality, outcomes, and efficiency of those services and should measure performance" (p. 7). Nevertheless, performance measures need to be developed that are consistent within the organization and understood by stakeholders (NRC, 2005, p. 29). "Establishing a performance measurement process begins with identification of a program's . . . mission and its basic objectives" (Hatry, 2006, p. 39).

Larger Political Climate

Research from Yang and Hsieh (2007) illustrated the importance of selecting performance measures that have an appropriate institutional fit within a broader political climate. Their research results indicated "that the implementation of performance measurement is inseparable from the evolution of politics and democratic governance" (p. 872). The successful adoption and implementation of measurement programs is more likely to occur if an organization has the support and participation of external stakeholders.

> In order to institutionalize performance measurement and make it work, public managers must ensure top management commitment, middle manager support, stakeholder involvement, continuous training, and external political support. (Yang & Hsieh, 2007, p. 872)

Existing Data

For contracting organizations to compare one laboratory against another, they must either make the measurements themselves or have the laboratories make the measurements and provide the data to the contracting agency. Researchers such as Colledge and March (1993), Flynn et al. (1994), and Nevalainen, Berte, Kraft, Leigh, Picaso, and Morganza (2000) developed methods or instruments for measuring performance. Their methods depended on the assessed organization collecting most, if not all, the data. Researchers Galloway and Nadin (2001) investigated interlaboratory performance benchmarking and noted that “the more data that were collected [for benchmarking] the greater the workload for participating laboratories” (p. 591). “Participation does take time and resources” (Yang & Hsieh, 2007, p. 871).

Moreover, in some cases, the contractor may have never collected the required data. Quantitative performance measurements require a sufficiently large dataset to make statistically valid inferences. If the contractor never collected the data, they may need years to collect a dataset large enough to be assembled. For this reason and others, organizations such as the NRC (2004, 2005) have recommended that government agencies use existing datasets, where possible, for performance measurements and benchmarking. However, beyond audit results, government contracting organizations may have very little QA compliance data available.

Literature Summary

For quality metrics to be effective, the current literature on comparative performance measurements has suggested that measurements should

- be system-wide performance measurements (Kravchuk & Schack, 1996),
- be quantitative to facilitate accurate cross-organizational comparisons (Hatry, 2006),
- fit the needs of the organizations' stakeholders (NRC, 2005),
- fit within the larger political climate (Yang & Hsieh, 2007),
- be based on existing datasets so as to reduce data acquisition burdens and expedite meaningful analyses (Yang & Hsieh, 2007), and
- accurately measure performance (Kravchuk & Schack, 1996; Nicholson-Crotty, et al., 2006; NRC, 2005).

QA audit results meet many of these criteria. Kravchuk and Schack (1996) stated a need for "a framework for system-wide performance measurement that acknowledges the diversity of the system's goals, while providing information on aggregate efficiency and effectiveness" (p. 354). QA program requirements, such as those contained within the QSAS, are systemwide, total quality management requirements. They encompass a broad range of requirements that address efficiency and effectiveness issues, administrative and technical issues, legal and contractual issues, internal and external issues.

QA audit results are also quantitative. Although requirements and audit programs differ from agency to agency, the agencies almost universally tabulate audit results numerically. Thus, numerical audit results are available for performance comparisons. Quantitative performance comparisons are more convincing than qualitative comparison (Hatry, 2006, p. 79).

In general, audit results do not need to be adapted for organizational fit. There are many different QA compliance standards. These standards tend to be industry specific. The government agency generally selects the compliance standard that is specific for the contracted work. For instance, DOE identifies the QSAS, a standard specifically developed for analytical laboratories, as the contractually mandated QA standard for analytical laboratories. As such, audits, by default, only measure compliance to the requirements that fit the audited organization. Thus, the audit results data meet Hatry's requirement for organizational fit.

QA audits also fit within the larger political climate as required by Yang and Hsieh's (2007) research results. Formal QA programs have increased in popularity over the last several years (Sidney, 2003). Even skeptics of quality assurance auditing, such as University of Wisconsin researchers Ehrmeyer and Laessig (2007) acknowledge that auditing is a recognized component of quality assurance practices and are promoted by government agencies and international organizations. In the words of Peter Vermaercke of the Belgian Nuclear Research Centre:

> Nowadays, quality assurance (QA) is a common feature in a production or service environment such as a routine analytical laboratory…. Any research laboratory performing work for external customers or the community at large, must, at some

point, guarantee its competence to its clients. This competence can no longer be based on the promises of the general management or on a reputation built up over the years, but on a well-structured quality system (QS) that preferably has proven its competence, e.g. by certification or accreditation. (Vermaercke, 2000, p. 11)

QA audit results also meet the existing data criterion. Because data generating activities take time and resources (Yang and Hsieh, 2007), data for performance comparisons either need to be obtained from existing data generating activities (for which resources have already been allocated) or from new activities which require new resources. Since QA audit programs already exist, the data are available for use without requiring significant new resource allocations. This can be critical during times of fiscal constraint.,

While QA audit results meet many of the bulleted criteria listed above, they have not been shown to meet the last criterion—accurately measure performance. QA audit results have not been shown to accurately measure performance because contrary to the National Research Council's recommendations, raw audit results are not "[m]inimally affected by external influence" (NRC, 2005, p. 10). Raw audit results are a composite measure of both the audited organization's performance and the auditing organization's performance.

The current study fills a noticeable gap at the convergence of both QA and performance assessment research. Previous QA literature describes methods for assessing quality within organizations using QA audits. Performance measurement literature describes ways of comparing performance across organizations. This study aimed to bridge the gap by determining if contracting agencies, such as the DOE, could use audit results to measure performance with QA requirements accurately and quantitatively across organizations by statistically compensating for bias introduced by the audit process. If that could be demonstrated, QA audit results could form the basis of an effective and efficient system-wide framework for cross-organizational performance measurements as called for by Kravchuk and Schack (1996).

CHAPTER 3

METHODS

The purpose of this chapter is to present an overview of the methods used for conducting the study. The chapter restates the research questions addressed during the study and the procedures that were implemented.

Research Questions

To successfully achieve the objectives of the study, answers to the following questions were sought:

1. Is there a statistically significant relationship between the number of issues detected during an audit and the audit duration, the audit team size, the audit frequency, the audit scope, or the presence of oversight during an audit?
2. Does the relationship between independent and dependent variables differ depending on the type of laboratory?
3. Does the relationship between independent and dependent variables differ depending on the selected definition of audit issue?

If the research results indicated that there was a significant relationship between the audit-specific independent variables and the quantitative audit results, this would suggest the need for audit-specific factors to be incorporated into performance comparison metrics. If the research results indicated that there was a significant relationship between the audit-specific independent variables and the type of laboratory, this would suggest the need for contractor type to be incorporated into performance comparison metrics. If the research results indicated that the relationship between the independent variables and the dependent variables change depending on the choice of dependent variable, this would suggest the need for the contracting agency to consciously determine which quality metric should be used for assessing quality performance. Failing to incorporate significant variables into performance metrics could result in data being provided to decision makers that could mislead or misinform.

Unit of Analysis

The unit of analysis for the study was the quality assurance compliance audit. A unit of analysis is the focus or major entity that is analyzed during a study. As stated by researcher Babbie (2012), it is the “what or whom being studied” (p. 560). This study uses the audit as the unit of analysis because the goal is to investigate how audit results vary according to changes in the way audits are conducted.

Research Variables

The study examined the relationship between three classes of variables. These classes are *dependent variables*, *independent variables*, and *control variables*. Each variable class is discussed below.

Dependent Variables

As stated by Creswell (2003), “*Dependent variables* are variables that depend on the independent variables; they are the outcomes or results of the influence of the independent variables” (p. 94). The study examined four dependent variables: identified technical findings, identified technical issues, identified findings, and identified issues.

The QA community uses a variety of terms to denote audit results. These terms include *deficiency, nonconformity, nonconformance, noncompliance, finding, observation, condition, opportunity for improvement, event,* and *issue*—to name a few. Organizations may also assign priority or severity levels to some of these terms.

DOECAP audits report results in two broad categories: (a) findings and (b) observations. DOECAP defines a *finding* as

> a factual statement issued from a DOECAP audit to document . . . [a] failure to adequately establish or document requirements consistent with applicable regulations, industry standards, or contract(s); or a deviation from established requirements. (DOE Deficiency, 2009; DOE Findings, 2009)

There are two severity levels for DOECAP findings: Priority I and Priority II. "A Priority I finding constitutes the highest censure the DOECAP can issue against an audited facility" (DOE Priority I Findings, 2009).

> A Priority I finding [is] issued for a significant item of concern, or significant deficiency regarding key management/programmatic control(s) or practice(s), which represents a concern of sufficient magnitude to potentially render the audited facility unacceptable to provide services to the DOE, or present substantial risk and liability to DOE if not resolved via immediate and expedited corrective action(s). (Priority I Findings 2009)

A Priority II finding is any violation of a requirement that does not meet the threshold of a Priority I finding. DOECAP defines an *observation* as "a deficiency of an isolated nature, a deviation from Best Management Practices, or an opportunity for improvement, which may warrant attention by the audited facility" (DOE, Observations, 2009). DOECAP does not define the term *issue*. However, the proposed study uses the term *issue* as a generic reference to either a finding or an observation.

Although DOECAP and the larger QA community define a finding as a violation of a requirement, the number of findings identified in an audit report generally does not reflect the number of violations committed by the audited organization. This occurs for two reasons. First, findings are tallied by the number of requirements violated, not the number of times requirements are violated. For instance, if a laboratory worker violated a single requirement 20 times, auditors typically would issue a single finding, not 20 separate findings. Second, the audit reports reflect the number of violations identified by the auditors, not the number of violations that actually occurred. Auditors have a limited amount of time and a limited amount of evidence to review. Given these constraints, it is generally not possible to identify all violations that may have occurred since the previous audit.

DOECAP organizes its audits in terms of modules that correspond to technical disciplines, plus additional modules for general laboratory and information management requirements. Each module has a separate audit checklist that lists requirements to be verified by the auditors. When an audit team member identifies an issue, they also identify and record the associated audit module. As such, in the study I was able to distinguish between issues that were technical in nature, and more general, or administrative, issues.

In the study, I examined four dependent variables: (a) Technical Findings, (b) Technical Issues, (c) Findings, and (d) Issues. No distinction was made between Priority I and Priority II findings. The pilot study conducted in preparation for the proposed study showed that Priority I findings were rarely detected during audits and did not significantly contribute to the total number of audit findings. Therefore, I grouped both severities of findings into a single measure.

Figure 1 is a Venn diagram showing the relationship between the various types of dependent variables examined in the study. Issue refers to anything in the chart. Technical *issues* are everything in the left set. Findings are those issues in the right set. *Observations* are the compliment of the set of findings. Technical Findings are the intersection of the Findings and Technical Issue*s* sets.

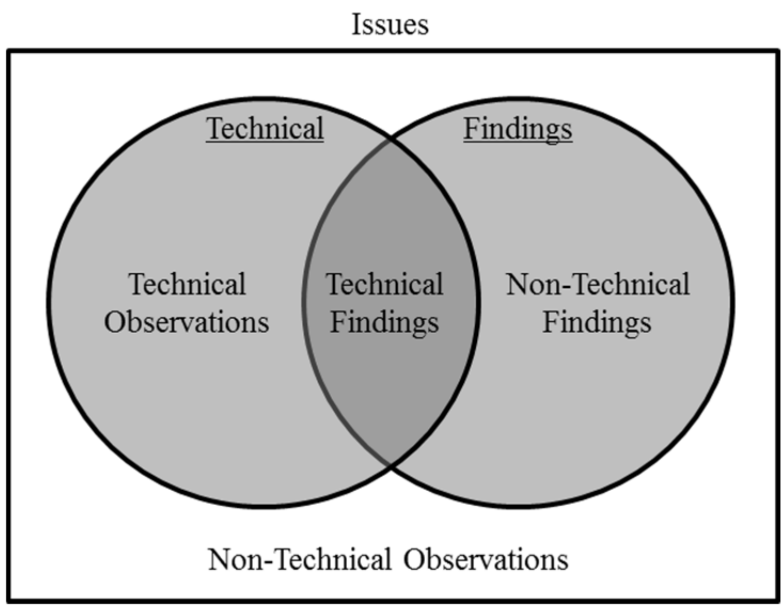

Figure 1. Venn diagram of issue (dependent variable) types.

Independent Variables

Creswell (2003) defined independent variables as "variables that (probably) cause, influence, or affect outcomes. They are also called treatment, manipulated, antecedent, or predictor variables" (p. 94). Quality assurance research literature has suggested that how an audit is conducted will affect how many underlying issues are detected (Karapetrovic & Willborn, 1999). Three factors in particular affect the results: audit depth, audit team expertise, and the number of underlying issues. In this study, I investigated five independent variables for their influence on the number and type of detected audit issues. Each of these five variables relates either directly or indirectly to one of the three factors above. These five are:

- Audit duration
- Audit team size
- Number of audit modules
- Time between successive audits
- Audit oversight

Audit duration. (Duration*)* Audit duration directly relates to audit depth. The longer the audit, the more time auditors have to examine records, interview personnel, read procedures, and observe operations. Each of these provides additional opportunities to detect issues. I hypothesized that a positive relationship would exist between the duration of an audit and the number of identified audit issues.

Audit duration was calculated as the number of business days on-site during an audit. No attempt was made to estimate the time spent on pre- or post-audit activities. Because the source dataset did not record the start time or end time of daily audit activities, only whole numbers were used for audit duration. This may have affected the statistical significance of some of the audit results. I discuss this in more detail in Chapter 4.

Audit team size. (AuditorsPerMod) The size of an audit team directly relates to audit depth. If an audit team has more auditors, then more interviews can be conducted, more records can be reviewed, more procedures can be read, and more activities can be observed. I hypothesized that a positive relationship would exist between the size of the audit team and the number of identified audit issues.

The audit team size was measured in terms of number of auditors per module. The ratio of auditors per module, rather than the number of auditors, was used because the number of auditors generally increases as the number of modules increases. This increases the potential for collinearity of independent variables. Using the ratio of auditors per module corrects for this collinearity.

Number of audit modules. (NumMods) The number of audit modules directly relates to audit depth. Different laboratories have different requirements. Audits only assess compliance with applicable requirements. The DOECAP audit process groups requirements into lines of inquiry called modules. The more modules included in an audit, the more auditors are required to assess. I hypothesized that as the number of modules increased so would the number of identified audit issues.

Although the number of audit questions varies from module to module, no attempt was made to examine the relationship between the number of audit questions and the number of audit issues. Only the number of modules was used for statistical analyses.

Time between successive audits. (YearFrac) The elapsed time between successive audits indirectly relates to the number of underlying issues. Auditors typically concentrate their efforts on reviewing activities that have occurred and records that have been generated since the most recently conducted previous audit. As the time between successive audits increases, the number of opportunities for violating requirements may also increase. I hypothesized that, if there was a statistically significant relationship between the audit interval and the number of detected issues, it would to be a positive relationship. However, as a rule, the DOECAP operations team tries to schedule successive audits 12 months apart. This meant that there was not much variability in the independent variable, so it was not clear if a statistically significant relationship could be determined.

Audit oversight. (Oversight) The presence or absence of managerial oversight could indirectly affect audit scope. Auditors may be influenced by sociological factors. While most of these factors are not recorded in the available source dataset, one possible factor is recorded: many audits have an oversight person observing the audit. These oversight individuals may be officials from Washington, high-level DOECAP managers, or other stakeholders. The presence of these individuals may influence how diligently an auditor works, how lenient an auditor may be when confronted with a borderline situation, or how broadly an auditor interprets a requirement. To account for this, audit oversight was treated as a dummy variable. One (1) was used to represent audits with one or more audit observers and zero (0) was used for audits with no observers.

This study examined only independent variables directly related to the audit process. Numerous independent variables potentially influence the number of identified issues. Most of these variables are not directly related to the audit process. Variables such as laboratory size, personnel training programs, workload, and corporate oversight may cause, mitigate, or prevent issues. However, these variables are related to the laboratory, not the audit process. In this study, I sought to determine the bias caused by the audit process. As such, I focused on audit-specific attributes.

No attempt was made to determine the influence of any individual audit team members on the number or types of detected audit issues. Research from other nonQA auditing disciplines has shown a relationship between individual auditors and the overall effectiveness of audits (Adeyemi, Okpala, & Dabor, 2012). Factors such as an auditor's skill, familiarity with requirements, familiarity with the audited organization, and general disposition can influence the number of issues an auditor detects and reports. Unfortunately, due to constraints with the source dataset, these factors were not investigated as part of the proposed study. However, the DOECAP maintains a relatively large cadre of certified auditors. Moreover, DOECAP auditor certification requirements are relatively stringent. Therefore, in the study I assumed that the audit team expertise was relatively constant across the audits and could be omitted from the analyses without significantly affecting the results.

It was assumed that excluding the influence of individual auditors did not seriously affect the validity the results. With such a large pool of auditors (over 50 in any given year), there is continual change in the makeup of DOECAP audit teams. Because the audit teams are continually changing, the effects of any one auditor should be minimal. To test this assumption, I examined the audit history of individual auditors. That examination indicated that, on average (both mean and mode), each auditor audits only one laboratory once in a ten-year period, and only 5% of auditors audit a single laboratory more than three times in a ten-year period. This was an indicator that the influence of any single auditor should be negligible.

Control Variables

The type of work a laboratory conducts can affect the number of occurrences of noncompliances as well as the ease of their detection. A full service laboratory has more requirements that are applicable. Each additional requirement represents another opportunity for noncompliance. In order to perform meaningful interlaboratory comparisons, I needed to account for laboratory type in the analyses.

In the study, I identified four laboratory types: chemistry laboratories, radiation laboratories, multipurpose laboratories, and nonchemistry, nonradiation laboratories (*e.g.* industrial hygiene laboratories). This grouping corresponds to the modules that DOECAP uses for conducting audits and reporting issues. Because a multipurpose laboratory is both a chemistry laboratory and a radiation laboratory, only two control variables were necessary. The study did not attempt to address why one laboratory type had more or fewer detected issues than another.

Controlling for laboratory type is important for comparison studies. Suppose an agency needs to send samples to a laboratory for radionuclide analyses and the agency has a choice between a radiation-only laboratory and a full service laboratory. In this situation, the agency may not care how well a laboratory performs chemistry analyses, but if the laboratory type is not accounted for in the performance comparison, the full service laboratory's irrelevant chemistry performance will contribute to the performance score.

A chief objective for conducting statistical analyses of audit results is to enable the government agency to compare its contractors based on their own performance, not the performance of the audit team. A fixed-effects model assumes that the performance of a contracted laboratory is relatively constant. Given that assumption, each laboratory, excluding a reference laboratory, was assigned its own dummy control variable.

Hypotheses

Using the five independent variables described above, five hypotheses were tested and, where possible, quantified:

H_1: There is a positive relationship between the number of identified audit issues and the duration of an audit.

H_2: There is a positive relationship between the number of identified audit issues and the number of auditors on an audit team.

H_3: There is a positive relationship between the number of audit modules and the number of detected audit issues.

H_4: There is a positive relationship between the elapsed time between successive audits and the number of detected audit issues.

H_5: The number of detected audit issues is affected by the presence of audit oversight.

Research Design

This study is a nonexperimental correlational design using statistical modeling. Statistical modeling of the relationship between the independent variables and the dependent variables is appropriate because no fixed, functional relationship exists between the two sets of variables. As expressed by Cacuci (2003) of the University of South Carolina,

> A statistical model is used when the system's output cannot be expressed as a fixed function of the input variables. Statistical models are particularly useful for representing the behavior of a system based on a limited number of measurements

> and for summarizing and/or analyzing a set of data obtained experimentally or numerically. (pp. 40-41)

A quantitative nonexperimental design is appropriate because the variables of interest are not manipulable in ex post facto research (Johnson, 2001). “The purpose of a correlational study is to determine relationships between variables or to use these relationships to make predictions. . . .” (Gay & Airasian, 2000, p. 321). The research used OLS regression analyses to quantify the correlation between the independent variables of interest and the dependent variable.

Bivariate Linear Least Squares Regression

Before conducting multiple regression analyses, each of the five independent variables was examined separately using simple linear least squares regression to evaluate their relative impact on the dependent variables. Bivariate linear regression is an OLS approach for modeling the relationship between two variables. This approach assumes that the relationship between two variables, X and Y can be described by the following formula:

$$Y = aX + b + e.$$

In the formula, a and b are constants and e represents the presence of error (Lewis-Beck, 1980). Using paired sample data, the technique adjusts the constants so that the total sum of the squares of the errors is minimized. Of particular interest from these regression tests is the sign of the slope coefficient (a) of the regression curve and the degree of statistical significance.

Collinearity Testing

Independent variables were tested for multicollinearity before conducting multiple regression analyses. OLS assumes that each independent variable is independent of each and every other independent variable. However, this often is not the case. If two or more variables are collinear, or highly correlated, they may actually be measuring substantially the same thing. This tends to inflate standard errors and decrease confidence in slope coefficients.

In the current study, I used two methods for testing collinearity: the Pearson correlation matrix and the Lewis-Beck test. The Pearson correlation matrix is a quick method that reveals problematic correlations between any two independent variables. The result of this test is displayed in Table 1 for all variables excluding the laboratory dummy variable. As can be seen in Table 1, the method did not reveal problematic correlations between any two independent variables. The variable pair with the highest absolute value was the NumMods/isChemLab pair which had a value of 0.627; most other pairs were correlated at much lower levels. However, this method has a weakness in that it does not indicate if a variable is correlated with a linear combination of other variables. The Lewis-Beck test addresses this concern.

Table 1

Pearson Correlation Matrix

Variable	Issues	Duration	Auditors PerMod	Num Mods	Year Frac	Over-sight	isRadLab	isChemLab
Issues	1.000	0.413	0.153	0.505	0.017	-0.129	0.125	0.212
Duration		1.000	0.172	0.559	0.009	0.005	0.346	0.341
AuditorsPerMod			1.000	-0.132	-0.084	-0.009	0.175	-0.217
NumMods				1.000	-0.071	0.041	0.186	0.627
YearFrac					1.000	-0.013	0.040	-0.034
Oversight						1.000	0.014	0.038
isRadLab							1.000	-0.174
IsChemLab								1.000

The Lewis-Beck test is performed by regressing each independent variable against the other independent variables to see if any variable is correlated with a linear combination of the other variables. Thus, to conduct the test, a separate regression model must be performed for each independent and control variable. Table 2 displays the results. The coefficient of determination (R^2) values for the seven model runs ranged from a low of 0.007 for the Oversight variable to a high of 0.568 for the NumMods variable. These values were all sufficiently lower than 1, suggesting that collinearity was not a problem

Table 2

Lewis-Beck Test Results

Dependent Variable	R^2	Sig. (p)
Duration	0.430	0.000
AuditorPerMod	0.150	0.000
NumMods	0.568	0.000
Oversight	0.007	0.897
YearFrac	0.025	0.206
IsRadLab	0.262	0.000
IsChemLab	0.500	0.000

Multiple Regression Analyses

I developed 18 multiple regression models during the study: five variations of a general model, four variations of a chemistry laboratory model, four variations of a radiation laboratory model, four variations of a multipurpose laboratory model, and one control model. The model variations corresponded to the four different dependent variables of interest. The general model had one additional variation that used the number of observations as the dependent variable. I discuss the reason for this additional model variation in Chapter 4. Each model used multiple regression analysis. Multiple regression analysis is an extension of bivariate linear regression that incorporates multiple independent variables into the equation (Berry & Feldman, 1985; Lewis-Beck, 1980).

The study examined four dependent variables because contracting agencies have different priorities. Contracting agencies conducting basic research may be primarily concerned with a laboratory's compliance with technical requirements. Contrariwise, agencies trying to address regulatory issues or facing possible litigation may be concerned with more general compliance. Model variations were required to determine whether the choice of dependent variable affected performance comparison results and, therefore, needed to be accounted for during benchmarking of contractors.

Analytical Assumptions

The research design incorporated four assumptions:

1. The causal relationship is one-way.
2. There have been no temporal changes in the relationship between the independent and dependent variables.

3. The performance of the individual laboratories is the primary causal factor for the observed audit results.

One-way causal relationship. The methodology assumed that the listed independent variables influence the listed dependent variables, but that the listed dependent variables do not significantly influence the listed independent variables.

No temporal changes. The DOECAP program is dynamic; changes to the program are constantly occurring. Requirements are added or changed according to programmatic needs. The study made the simplifying assumption that these changes do not significantly impact the relationship between the variables of interest.

Laboratory performance. The underlying assumption of this work is that two primary factors contribute to detected audit issues: laboratory performance and audit-specific factors. If the impact of audit-specific factors can be statistically compensated for, then the contracted laboratory's contribution can be more accurately assessed. There are undoubtedly factors external to both the laboratory and the audit process that influence the number of detected audit issues. However, the study assumes that a laboratory's ability to manage or cope with these external factors is a component of laboratory performance.

Source Data

The DOECAP Operations Team maintains an electronic data system (EDS) for archiving and making available the results of all audits conducted since FY 2000. Information available on the EDS includes the following for each audit:

- List of audit team members
- List of audit observers

- Audit start and end dates
- Facility names
- Modules audited
- Priority I findings listed by module
- Priority II findings listed by module
- Observations listed by module
- Corrective action plans for findings

Data Confidentiality, Acquisition, and Security

DOE treats DOECAP audit results as *official use only* (OUO) information. DOE defines *OUO* information as

> unclassified information that may be exempt from public release under the Freedom of information Act (FOIA) and has the potential to damage government, commercial, or private interest if disseminated to persons who do not need to know the information to perform their jobs or other DOE authorized activities. (DOE, 2009, §5.20)

The current study is a DOE authorized activity. As such, the research had to comply with the requirements for using OUO information.

In order to use the DOECAP audit results, the dataset was culled to remove all potentially OUO information. Any information that could potentially identify a laboratory was deleted from the source data and was not used for the study. Laboratory names were deleted and a numeric designator assigned by the DOECAP Operations Team was used for laboratory identification. This numeric designator is available via the EDS to government contracting agencies, so the results of the proposed study may be used for meaningful interlaboratory comparisons. Audit dates also were also deleted from the source data. Although the study examined temporal components of audits and their impacts on audit results, only the elapsed time since the previous audit and the duration of audits were necessary for the study; there was no need for the absolute start or end date of any audit.

The protection of potentially OUO information was maintained at all times throughout the study. The unscrubbed source data were not made available to any individual who had not signed a confidentiality agreement with DOECAP. Once potential OUO information was culled from the dataset, two independent, OUO-trained individuals reviewed the dataset before it was made public. This ensured that all potentially OUO information was removed from the dataset. All analyses were conducted on a government-owned, secure system.

Summary

The current study used OLS regression models to investigate the impacts that audit specific factors can have on audit results. Audit specific factors used as independent variables included the duration of audits, the frequency of audits, the number of auditors participating on audits, the scope of audits, and the presence or absence of audit oversight. The variables were regressed against four different dependent variables of possible interest to government organizations.

The source data for the OLS regression models were obtained from an audit program run by the United States DOE. These data were managed in accordance with strict protocols for OUO information. The data were analyzed using statistical methods, such as the Lewis Beck Test, to assess their suitability for OLS regression models.

CHAPTER 4

FINDINGS

In Chapter 1 of this work, I discussed the background, purpose, and significance of this study. In Chapter 2, I discussed the context of this study within the larger body of quality assurance and government performance research. Chapter 3 addressed the methods and design of the research. In this chapter, I restate the research questions and present the results of the research.

Because the study involved multiple types of laboratories, I present the results from each type of laboratory in a separate section with subsections devoted to the results for each of the four independent variables of interest. I discuss the variations of the general model in greatest detail. My discussions of the laboratory-specific models focus only on statistically significant variables and major differences between models.

I calculated the statistical results using IBM SPSS Statistics (SPSS). SPSS is a computational software program that is widely used in the social sciences. The software is capable of performing simple linear regression, multiple regression, and descriptive statistical analyses. I selected and used SPSS to perform the statistical analyses because of SPSS's capabilities and the need for a statistical tool capable of handling multiple independent variables.

Research Questions

To achieve the objectives of the study, I sought answers to the following questions.

1. Is there a statistically significant relationship between the number of issues detected during an audit and the audit duration, the audit team size, the audit frequency, the audit scope, or the presence of oversight during an audit?
2. Does the relationship between independent and dependent variables differ depending on the type of laboratory?
3. Does the relationship between independent and dependent variables differ depending on the selected definition of audit issue?

Methodology Summary

Using existing data from the DOECAP, I developed 18 fixed-effects, OLS regression models for the study. Five models were variations of a general model that incorporated dummy variables to account for laboratory type. Each variation of the general model investigated the relationship between the independent variables and one of five different dependent variables. Twelve models examined the relationship between three specific laboratory types and four dependent variables. These 12 models were run on subsets of the data; therefore, the models did not require control variables for the laboratory type. One additional model was developed that did not account for audit-specific factors or laboratory type. This model served as a control model.

General Model

The general model is a fixed-effects model using a separate dummy variable for each laboratory. I selected Laboratory 62 as the reference laboratory for the general model and all subsequent models. I assigned all other laboratories a dummy variable consisting of the prefix "isLab" followed by the laboratory ID number. For example, the dummy variable I assigned to laboratory number 31 was isLab*31*. I chose laboratory 62 as the reference laboratory in part because it was a full-service laboratory and therefore would appear in all model runs. Moreover, during the pilot study for this research, laboratory 62 appeared to be a high performer. Using laboratory 62 as the reference laboratory resulted in model runs wherein the majority of laboratory dummy variables had positive slope coefficients. Positive slope coefficients were not necessary for the analyses, but they did facilitate rapid visual comparison of the resulting data.

The general model also incorporated two dummy variables for laboratory type: isRadLab and isChemLab. The value of isRadLab equaled “1” for radiation laboratories, and “0” for nonradiation laboratories. The value of isChemLab equaled “1” for chemistry laboratories, and “0” for nonchemistry laboratories. Laboratories that were neither radiation laboratories nor chemistry laboratories served as the reference laboratory type.

The time between successive audits was denoted by the independent variable YearFrac. The value of YearFrac for a given audit is the fractional number of years since the previous audit. Since a laboratory’s first audit was not preceded by an earlier audit, the YearFrac variable could not be calculated for initial audits. Therefore, the audit results for laboratories that had only been audited once fell out of the analyses. This reduced the number of laboratories available for comparison down from 61 to 51.

Dropping initial audits from the analyses also resulted in a reduction of the mean number of issues found per audit from 17.86 to 16.28. Descriptive statistics show that, on average, audit teams identify 28.0 issues per initial audit—72% more issues on average than are identified during subsequent audits. Although the initial audits represented only 11% of the total number of audits in the source dataset, their omission from the analysis had a measureable impact due to the relatively high number of issues detected during initial audits.

The relatively high number of issues found during initial audits suggests that the first audit is not representative of the contractor's true performance. The results from the first audit are identified during the learning period of the laboratory, and, thus, are not reflective of the long-term performance of laboratories and may appropriately be omitted from the statistical analyses.

I created four variations of the general model—one variation for each of the dependent variables of interest. Table 3 displays the coefficient of determination (R^2) for each of the four variations of the general model. I present the results of each variation of the general model in the following subsections. Following these four subsections, I include a subsection that compares these results to the raw results.

Table 3

Coefficients of Determination for the General Models

Model Run	Dependent Variable	R^2
General Model Variation 1	*Issues*	0.554
General Model Variation 2	*Findings*	0.451
General Model Variation 3	*Technical Issues*	0.499
General Model Variation 4	*Technical Findings*	0.388

Issues

The first variation of the general model used the number of detected audit issues as the dependent variable. No attempt was made to distinguish between findings and observations. Findings and observations were counted equally regardless of severity. Model results are presented in Appendix B, Table B1.

The model results show a statistically significant correlation between the number of issues detected during an audit and the number of audited modules ($p < 0.001$), the number of auditors per module ($p < 0.001$), the elapsed time since the previous audit ($p < 0.1$), and the presence of audit oversight ($p < 0.01$). The slope coefficient for the number of modules per audit was 4.63 issues per module. This suggests that, on average, holding all other variables constant, for each additional module included in an audit, you can expect auditors to detect 4.63 additional issues.

The slope coefficient for the number of audit modules per audit was 4.63 detected issues per module. This suggests that increasing an audit's scope by one additional module, say from three modules to four, should result in four or five additional detected issues if all other variables are unchanged. This implies that performance metrics need to account for the scope of the audit.

The slope coefficient for the number of auditors per modules was 6.877 detected issues per auditor per module. This suggests that increasing an audit team size by one additional auditor per module should result in the detection of nearly seven additional issues. Since the mean number of issues detected per audit is only 16.28, you can expect to detect approximately 42% more issues by increasing the number of auditors per module by just 1. This increase represents an increase in issue detection, not a decrease in contractor performance.

This coefficient has implications outside the initial scope of this study. It suggests that the detection of issues is highly dependent on the size of an audit team. Due to budget constraints, the DOECAP operations team has had to reduce the number of auditors on some audits. This coefficient suggests that the reduction in team size allows existing issues to go undetected by the audit teams.

The coefficient for the YearFrac variable was 1.647 issues per year. This suggests that for about every 7 months of elapsed time between successive audits, the DOECAP audit team will find, on average, 1 additional issue. Like the number of auditors per module variable, this variable has particular importance during times of budget constraints. Like many agencies, DOECAP attempts to audit its contractors on a yearly basis. However, during times of fiscal constraints, the DOECAP may decrease the audit frequency. Since the mean number of issues detected per audit is 16.28, 2 successive annual audits should detect a total of about 32 or 33 issues at an average laboratory. However, this slope coefficient suggests that if the time between successive audits increases by 1 year, the total number of issues detected during the 2 year period is only expected to be about 18 (0 the first year and 16.28 + 1.647 the second year). Thus, although biannual audits may detect more issues per audit, the total number of issues detected over time may decrease by as much as 45%.

Unfortunately, there is no way to determine from the available data if these issues undetected by the audit team would get detected and addressed through some other means. The laboratory's internal assessment program may identify and address these issues independent of the DOECAP audit program. Nevertheless, the large number of detectable issues that may go undetected should be considered before instituting a decrease in audit frequency. In addition, although this result is specific to the DOECAP, it may very well apply to other agencies.

The slope coefficient for the Oversight variable is negative. This suggests that each time an audit team includes external oversight, the audit should result in 6.649 fewer detected issues on average. There are multiple ways to explain the observed results. First, the correlation does not imply causality. Although an overseer could cause a decrease in the mean number of detected issues, the causal relationship could actually go the other direction. For instance, the dataset does not indicate how audits are selected for oversight. It is possible that an overseer is sent to an audit when there is reason to expect that the audit team is not adequately prepared. It may be that an overseer is sent when there is reason to believe a laboratory has made significant improvement in its level of compliance. In either case, it would be *Audit* that affects the Oversight, not the reverse.

There are, of course, ways that the presence of oversight could cause a reduction in detected issues. It is possible that overseers somehow influence in the audit process. Auditors may be more conservative when identifying issues in the presence of oversight, or may be distracted by the overseer. The overseer may also affect the performance of the laboratory. If the laboratory receives advance warning of oversight, it may better prepare for the audit and thus avoid some issues. Unfortunately, the results from this model variation alone do not support a definitive conclusion regarding causality.

The slope of the Duration variable is only 0.168 issues per day and is not statistically significant. The source dataset only records the start date and end date of the audits; the daily start and end times are not recorded. This meant that only whole numbers could be used for the values of the independent variable Duration, whereas the true audit duration was an interval value. Moreover, the dataset only recorded the duration of the on-site portion of the audits. However, actual audit activities generally start before the audit team arrives on site. As such, the accuracy of the calculation of audit Duration was dubious; this made the Duration variable a poor independent variable and may have contributed to its statistical insignificance. AppendixTableB1 lists the dummy variables for the laboratories in ascending order of the slope coefficients. Because laboratory 62 was the reference laboratory, it is not shown, but would have a slope coefficient of 0. Because all the other laboratories have positive slope coefficients, this implies that laboratory 62 is the highest ranked laboratory using this model variation.

Of particular interest is the fact that it is only the lowest ranking laboratories that have statistically significant slope coefficients. A fixed-effects model assumes that the dummy variable represents a stable characteristic. In this case, the dummy variables represent the performance of the individual laboratories. The statistical significance of the lower ranking laboratories implies that these laboratories are consistently lower performers. Whereas the statistical insignificance of the slope coefficients of the higher ranking laboratories indicates that they are not consistently the highest ranking. In other words, the better laboratories will occasionally have audits with high numbers of detected issues, whereas poorer laboratories frequently have audits with higher numbers of detected issues.

The variables isChemLab and isRadLab are control variables that denote whether or not a laboratory does chemical analyses or radiation analyses. Both of the variables have statistically insignificant slope coefficients. This indicates that the laboratory type may be a poor predictor of audit performance.

Findings

The second variation of the general model used the number of detected audit findings as the dependent variable. Because findings are actual violations of requirements, they are generally considered to be more serious than other detected issues, such as observations. Because of this, some agencies may only be concerned about findings when conducting performance comparisons. This variation of the general model is most appropriate for agencies that only track findings or requirement violations. I present the results of this regression model in Appendix Table B2.

The results from this model variation are comparable to those from the previous model variation. The model results show a statistically significant correlation between the number of finding detected during an audit and the number of audited modules ($p < 0.001$), the number of auditors per module ($p < 0.01$), and the elapsed time since the previous audit ($p < 0.01$). However, it does not show a statistically significant relationship between the number of audit findings and the presence of audit oversight or the laboratory type.

The slope coefficient for the number of modules per audit was 1.728 findings per module. This suggests that for each additional module included in an audit you can expect auditors to detect 1.728 additional findings on average. This slope coefficient is a little less than half the coefficient for the model when *issues* is the dependent variable. Given that findings account for approximately half of all issues, this slope coefficient is not unreasonable.

Likewise, the slope for the number of auditors per module is what might be expected given the results of the previous model variation. The slope coefficient for the number of auditors per modules was 3.216 findings per auditor per module—a little less than half the slope coefficient for this variable when regressed against *issues*. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of approximately three additional findings. Since the mean number of findings detected per audit is only 7.66, you can expect to detect approximately 42% more issues by increasing the number of auditors per module by just 1. This increase represents an increase in issue detection, not a decrease in contractor performance.

The slope coefficient for the YearFrac variable was 1.556 findings per year. This suggests that for about every 8 months of elapsed time between successive audits, the DOECAP audit team will find, on average, 1 additional finding. Since the mean number of findings detected per audit is 7.66, 2 successive annual audits should detect a total of about 15 findings at an average laboratory. However, this slope coefficient suggests that if the time between successive audits increases by 1 year, the total number of findings detected during the 2-year period is only expected to be about 9 (0 the first year and 7.66 + 1.556 the second year). Thus, although biannual audits may detect more findings per audit, the total number of findings detected over time may decrease by as much as 40%.

The slope coefficient for the independent variable Duration was 0.601 findings per day. However, like the results from the previous model variation, this slope coefficient was not statistically significant. Imprecision in recording the daily start and end times of the audits hindered precise determination of the independent variable.

Unlike the results from previous model variation, the coefficient for the *oversight* variable was not statistically significant when regressed against findings only. To investigate why this variable may be significant for issues in general, and not for findings, I developed a new model variation with the number of observations as the dependent variable. Those model results are shown in Table B3. Those results show that there is a statistically significant relationship between the number of observations and the presence of oversight.

To understand why oversight might affect the likelihood of identifying an observation, but not a finding, it is helpful to recall the differences between the two types of audit issues. A finding is either a deviation from a requirement, or a failure to document compliance with a requirement (DOE Deficiency, 2009; DOE Findings, 2009). Findings are relatively objective. However, an observation is “a deficiency of an isolated nature, a deviation from Best Management Practices, or an opportunity for improvement, which may warrant attention by the audited facility” (DOE, Observations, 2009). Observations are more subjective than findings. Since the model shows a significant correlation between oversight and observation, but no significant correlation between Oversight and Findings, this may suggest that the presence of oversight may impact subjective determinations, but have less impact on more objective results.

As seen in the results of model variation 1, the slope coefficients for the laboratory dummy variables are only significant for the poorer performing laboratories. What is noticeably different for the results of this model is the number of laboratories with negative coefficients. As with the previous model, laboratory 62 was the reference laboratory. Therefore, a slope coefficient less than zero signifies how many fewer findings the model predicts a laboratory will have compared to laboratory 62, assuming all other variables are equal. The fact that there are six laboratories with coefficients less than zero means that laboratory 62 dropped in ranking from first place, to seventh place.

Technical Issues

The variation 3 of the general model used the number of detected technical issues as the dependent variable. Total quality management programs incorporate a wide range of requirements. Many of these requirements are administrative in nature. Some agencies may be less concerned about administrative issues and more concerned about technical issues when conducting performance comparisons. This variation of the general model tested the fixed-effects model for applicability when only technical issues are of concern. I present the results of this regression model in Appendix-TableB4.

The results from this model variation are comparable to those from the model variation 1. The model results show a statistically significant correlation between the number of technical issues detected during an audit and the number of audited modules ($p < 0.001$), the number of auditors per module ($p < 0.001$), and the presence of audit oversight ($p < 0.05$). The slope coefficient for the NumMods variable was 2.027 technical issues per module. This suggests that for each additional module included in an audit you can expect auditors to detect around two additional technical issues on average. The slope coefficient for the number of AuditorsPerMod variable was 4.548 technical issues per auditor per module. This suggests that for each additional auditor per module included in an audit you can expect auditors to detect four or five additional technical issues. The slope coefficient for the Oversight variable was -3.600 technical issues per audit. This implies that an audit with external oversight will have three or four fewer issues than a similar audit without oversight. However, as with model variation1, variation 3 does not show a statistically significant relationship between the dependent variable and the elapsed time since the previous audit or the laboratory type.

The ranking of individual laboratories using this model differs from both the previous two model variations, although it more closely resembles variation 1. In this model variation, the reference laboratory, laboratory 62, rose to the third position from the top. This may imply that issue category (i.e. finding versus observation) more heavily influences overall performance ranking than issue type (i.e. administrative versus technical).

Technical Findings

Variation 4 of the general model used the number of detected technical findings as the dependent variable. This variation of the general model tested the fixed-effects model for applicability when only technical finding are of concern. I present the results of this regression model in Appendix-Table B5.

The results from this model variation are comparable to those from the model variation 2. The model results show a statistically significant correlation between the number of technical findings detected during an audit and the number of audited modules ($p < 0.05$), the number of auditors per module ($p \leq 0.001$), and the elapsed time since the previous audit ($p < 0.05$). It does not show a statistically significant relationship between the number of technical findings and the duration of the audit or the presence of audit oversight. However, unlike model variation 2, model variation 4 show a statistically significant relationship between the dependent variable and the laboratory type ($p < 0.05$ for isChemLab and $p < 0.1$ for isRadLab). This is likely due to additional requirements that apply to these two types of labs that are above basic requirements.

The ranking of individual laboratories using this model differs substantially from the previous 3 model variations. In this model variation, the reference laboratory,

laboratory 62, dropped from first position to 19th position. The selection of dependent variable clearly affects the relative ranking of a contractor when benchmarking against quality compliance.

Comparison to Raw Results Model

In order to determine the impact of conducting contractor performance comparisons using the general model, it was necessary to compare performance scores using the model against performance scores based on raw audit results. To do this, I generated a fixed-effects regression model using laboratory dummy variables as the only independent variables and audit issues as the dependent variable. This model produced the Raw Slope values displayed in Table B6. This model assumes that all the observed variation in the number of detected audit issues is attributable to the audited laboratory.

Based on the dummy variables' coefficients, I calculated a raw performance score by using the following formula which is a variant of the standard unit normalization formula (Etzkorn, 2012):

$$score = \{1 - [(m_i - m_{min}) \div (m_{max} - m_{min})]\} \times 100\%,$$

where m_i is the slope of the dummy variable for the individual laboratory, m_{min} is the slope of the best performing laboratory, and m_{max} is the slope of the worst performing laboratory. The resulting values are displayed in the Raw Score column of TableB6 in Appendix B. Similarly, I calculated the performance comparison scores for model variation 1 using the same formula and the laboratory dummy variables for m_i. Those results are displayed in the Model Score column of Table B6. The final column displays the simple difference between the two scores.

The results in Table B6 indicate the importance of accounting for audit-specific factors in performance comparison metrics. Table B6 displays as much as a 61% difference between the raw benchmarking score and the score adjusted based on audit-specific factors. This difference can be substantial when it comes time for contract renewals. In highly competitive situations, only a few percentage points may separate award recipients from nonrecipients.

Even when regression analyses do account for audit-specific factors, performance scores can be substantially impacted by the selection of dependent variable. Table B7 displays the results of the laboratory performance scores based on the four variations of the general model. As can be seen in the table, the choice of dependent variable can have a major impact on the performance score. After correcting for audit-specific factors, laboratory 30 was the best performing laboratory in terms of technical findings and findings. However, it was the 2nd worst performing laboratory when judged on technical issues.

Laboratory Type 1: Chemistry Laboratories

I developed four model variations for chemistry laboratories—one model variation for each dependent variable of interest. These models differ from the general model in two respects. First, they do not include control variables for laboratory type. Second, they used a subset of the source data: only audits from laboratories that do chemical analyses were included in the statistical analyses. The subset of the data included 250 audits of 40 laboratories. As with the general model, laboratory 62 was selected as the reference laboratory. Model results corresponding to each of the four dependent variables are presented in the following subsections.

Issues

The first variation of the chemistry laboratory model used the number of detected audit issues as the dependent variable. No attempt was made to distinguish between findings and observations. Findings and observations were counted equally regardless of severity. The mean number of issues detected per audit was 19.65. Model results are presented in Table C1.

The results from this model variation show a statistically significant correlation between the number of issues detected during an audit of a chemistry laboratory and the number of audited modules ($p < 0.001$), the number of auditors per module ($p < 0.001$), and the presence of audit oversight ($p < 0.05$). The slope coefficient for the number of modules per audit was 4.345 issues per module. This suggests that, on average, holding all other variables constant, for each additional module included in an audit, you can expect auditors to detect 4.345 additional issues.

The slope coefficient for the number of AuditorsPerMod variable was 10.278 detected issues per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of approximately 10 additional issues. The value of this coefficient is noticeably higher than its counterpart in variation 1 of the general model. This may suggest that, for some reason, the effectiveness of chemistry laboratory audits is more sensitive to the number of auditors.

The slope coefficient for the NumMods variable was 4.345 detected issues per module per audit. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of about four additional issues on average. The value of this coefficient is noticeably higher than its counterpart in variation 1 of the general model.

The coefficient for the YearFrac variable was 1.653 issues per year. This suggests that for about every 7 months of elapsed time between successive audits, the DOECAP audit team will find, on average, 1 additional issue. However, the slope does not appear to be statistically significant. Nevertheless, the value does imply that agency administrators should carefully consider the possible consequences of reducing audit frequencies in response to fiscal constraints.

The slope coefficient for the Oversight variable is -6.434. This coefficient is significant at the $p < 0.05$ level. This suggests that each time an audit team includes external oversight, the audit should result in 6.434 fewer detected issues on average.

The slope of the Duration variable is only 0.223 issues per day and is not statistically significant.

Table C1 lists the dummy variables for the laboratories in ascending order of the slope coefficients. Because laboratory 62 was the reference laboratory, it is not shown, but would have a slope coefficient of 0. The difference between the highest and lowest value for laboratory dummy coefficients is nearly identical to that of variation 1 of the general model. As seen previously in the results from all the other model runs, only the lower ranking laboratories have statistically significant slope coefficients

Findings

The second variation of the chemistry laboratory model used the number of detected audit findings as the dependent variable. This variation of the model is most appropriate for agencies that want to compare chemistry laboratories and only is concerned about issues that are actual violations of requirements. The mean number of findings per audit was 9.61. I present the results of this regression model in Table C2.

The results from this model variation only show a statistically significant `correlation between the number of findings detected during an audit of a chemistry laboratory and two independent variables (not including the laboratory dummy variables). The coefficient for the NumMods variable was significant at the $p < 0.01$ level. The coefficient for the AuditorsPerMod variable was significant at the $p \leq 0.001$ level.

The slope coefficient for the AuditorsPerMod variable was 5.792 detected findings per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of approximately 5 or 6 additional findings on average. The value of this coefficient is noticeably higher than its counterpart in variation 2 of the general model. Again, this may suggest that, for some reason, the effectiveness of chemistry laboratory audits is more sensitive to the number of auditors.

The slope coefficient for the NumMods variable was 1.484 detected findings per module per audit. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of 1 or 2 additional issues on average. The value of this coefficient is only slightly lower than its counterpart in variation 2 of the general model.

The values of the coefficients for the YearFrac, Oversight, and Duration variables were similar to the values from Variation 2 of the general model. YearFrac's value was 1.136 findings per year. Oversight's value was -1.078 findings per audit. Duration's value was 0.808 findings per day. However, none of these independent variables were statistically significant.

Table C2 lists the dummy variables for the laboratories in ascending order of the slope coefficients. Because laboratory 62 was the reference laboratory, it is not shown, but would have a slope coefficient of 0. The difference between the highest and lowest value for laboratory dummy coefficients is comparable to that of variation 2 of the general model. As seen previously in the results from all the other model runs, only the lowest ranking laboratories have statistically significant slope coefficients.

Technical Issues

In variation 3 of the chemistry laboratory model, I used the number of detected technical issues as the dependent variable. This variation of the model is most appropriate for agencies that want to compare chemistry laboratories and are only concerned about technical issues, as opposed to administrative issues. The mean number of technical issues per audit was 9.55. I present the results of this regression model in Table C3.

The results from this model variation are comparable to those from the ChemistryLlaboratorieM modVl variation 1. The model results show a statistically significant correlation between the number of technical issues detected during an audit and the NumMods variable ($p < 0.001$) and the AuditorsPerMod variable ($p < 0.001$). However, the statistical significance of the Oversight variable was weak, at best ($p < 0.1$). As with model variation1, it does not show a statistically significant relationship between the dependent variable and the YearFrac or the Duration variables.

The ranking of individual laboratories using this model differs from both the previous two model variations, although it more closely resembles variation 1. In model variation 1, the reference laboratory, laboratory 62, was in the third position from the top. In model variation 2, laboratory 62 dropped to 15th position. In this model variation, laboratory 62 rose to 9th position.

Technical Findings

In Variation 4 of the chemistry laboratory model, I used the number of detected technical finding as the dependent variable. This variation of the model is most appropriate for agencies that want to compare chemistry laboratories and is only concerned about violations of technical requirements. The mean number of Technical Findings was 4.47. I present the results of this regression model in Appendix and TableC4.

The results from this model variation only show a statistically significant correlation between the number of technical findings detected during an audit of a chemistry laboratory and one independent variable. The coefficient for the AuditorsPerMod variable was significant at the $p < 0.001$ level. All other variables were statistically insignificant.

The ranking of individual laboratories using this model differs substantially from the previous 3 model variations. In this model variation, the reference laboratory, laboratory 62, dropped to the 31st position. The selection of dependent variable clearly impacts the relative ranking of a contractor when benchmarking against quality compliance.

Laboratory Type 2: Radiation Laboratories

I developed four model variations for radiation laboratories—one model variation for each dependent variable of interest. Like the chemistry laboratory models, these models differ from the general model in two respects. First, they do not include control variables for laboratory type. Second, they used a subset of the source data: only audits from laboratories that do radioisotope analyses were included in the statistical analyses. The subset of the data included 179 audits of 27 laboratories. As with the general model, laboratory 62 was selected as the reference laboratory. Model results corresponding to each of the four dependent variables are presented in the following subsections.

Issues

The first variation of the radiation laboratory model used the number of detected audit issues as the dependent variable. No attempt was made to distinguish between findings and observations. Findings and observations were counted equally regardless of severity. The mean number of issues per audit was 19.27. Model results are presented in Table D1.

The results from this model variation show a statistically significant correlation between the number of issues detected during an audit of a radiation laboratory and the number of audited modules ($p < 0.001$), and the number of auditors per module ($p < 0.01$). The slope coefficient for the NumMods variable was 5.555 issues per module. This suggests that, on average, holding all other variables constant, for each additional module included in an audit, you can expect auditors to detect 5.555 additional issues. This coefficient does not differ greatly from the coefficient from the general model.

The slope coefficient for the AuditorsPerMod variable was 8.041 detected issues per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of approximately eight additional issues. The value of this coefficient is noticeably higher than its counterpart in variation 1 of the general model, but lower than in variation 1 of the chemistry laboratory model.

The value of the coefficients for the YearFrac, Oversight, and Duration variables were similar to the values from variation 1 of the general model. YearFrac's value was 1.854 findings per year. Oversight's value was -6.292 findings per audit. Duration's value was 1.763 findings per day. However, the significance of Oversight's slope coefficient was only borderline at p=0.054 while YearFrac's and Duration's coefficients were not statistically significant.

Table D1 lists the dummy variables for the laboratories in ascending order of the slope coefficients. Because laboratory 62 was the reference laboratory, it is not shown, but would have a slope coefficient of 0. As was the case for variation 1 of the general model, positive slope coefficients for all the laboratory dummy variables indicate that laboratory 62 is the highest ranked laboratory. Although the number of radiation laboratories is much lower than the total number of laboratories, the relative ranking of the radiation laboratories is substantially the same as in variation 1 of the general model. Also, as seen all previously models and variations, only the lower ranking laboratories have statistically significant slope coefficients.

Findings

The second variation of the radiation laboratory model used the number of detected audit findings as the dependent variable. This variation of the model is most appropriate for agencies that want to compare radiation laboratories and is only concerned about issues that are actual violations of requirements. The mean number of findings per audit was 9.19. I present the results of this regression model in Table D2.

The results from this model variation only show a statistically significant correlation between the number of findings detected during an audit of a radiation laboratory and three independent variables (not including the laboratory dummy variables). The coefficient for the NumMods variable was significant at the $p < 0.01$ level. The coefficient for the YearFrac variable was significant at the $p < 0.01$ level. The coefficient for the AuditorsPerMod variable was significant at the $p \leq 0.05$ level.

The slope coefficient for the YearFrac variable was 2.015 findings per year. This suggests that for about every 6 months of elapsed time between successive audits, the DOECAP audit team should find one additional finding, on average.

The slope coefficient for the number of modules per audit was 2.062 detected findings per module per audit. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of approximately two additional issues on average. The value of this coefficient is slightly lower than its counterpart in variation 2 of the general model. This may suggest that, as was the case for chemistry laboratories, the effectiveness of radiation laboratory audits is more sensitive to the number of auditors.

The slope coefficient for the number of auditors per modules was 3.256 findings per auditor per module—a little less than half the slope coefficient for this variable when regressed against *issues*. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of approximately three additional findings.

The value of the coefficients for the Oversight, and Duration variables were noticeably different from the values from variation 2 of the general model and variation 1 of the radiation laboratories model. Oversight's value was -0.659 findings per audit. Duration's value was 2.223 findings per day. However, neither of these independent variables were statistically significant.

Table D2 lists the dummy variables for the laboratories in ascending order of the slope coefficients. Because laboratory 62 was the reference laboratory, it is not shown, but would have a slope coefficient of 0. As seen previously in the results from all the other model runs, only the lowest ranking laboratories have statistically significant slope coefficients.

Technical Issues

In variation 3 of the radiation laboratory model I used the number of detected technical issues as the dependent variable. This variation of the model is most appropriate for agencies that want to compare radiation laboratories and is only concerned about technical issues, as opposed to administrative issues. The mean number of technical issues per audit was 9.93. I present the results of this regression model in Table D3.

The results from this model variation show a statistically significant correlation between the number of technical issues detected during an audit and the NumMods variable ($p < 0.001$) and the AuditorsPerMod variable ($p \leq 0.001$). The model does not show a statistically significant relationship between the dependent variable and the YearFrac, Duration, or Oversight variables.

The slope coefficient for the NumMods variable was 3.027 detected findings per module per audit. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of around additional technical issues on average. The value of this coefficient is only somewhat higher than its counterpart in variation 3 of either the general model or the chemistry laboratory model.

The slope coefficient for the AuditorsPerMod variable was 5.958 detected technical issues per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of approximately six additional technical issues. The value of this coefficient is slightly smaller than its counterpart in variation 3 of the chemistry laboratories model, but somewhat higher than in variation 3 of the general model.

Technical Findings

In Variation 4 of the radiation laboratory model, I used the number of detected technical finding as the dependent variable. This variation of the model is most appropriate for agencies that want to compare radiation laboratories and is only concerned about violations of technical requirements. The mean number of technical findings per audit was 4.67. I present the results of this regression model in Table D4.

The results from this model variation show a statistically significant correlation between the number of technical findings detected during an audit and the NumMods variable ($p < 0.05$) and the AuditorsPerMod variable ($p \leq 0.05$). The YearFrac variable was only borderline significant with $p = 0.076$. The model does not show a statistically significant relationship between the dependent variable and the Duration, or Oversight variables.

The slope coefficient for the NumMods variable was 1.128 detected technical findings per module per audit. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of around one additional technical finding on average. The value of this coefficient is only noticeably higher than its counterpart in variation 4 of either the general model or the chemistry laboratory model.

The slope coefficient for the AuditorsPerMod variable was 2.549 detected technical findings per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of around 2 or 3 additional technical issues. The value of this coefficient is similar to its counterpart in variation 4 of the general model.

Laboratory Type 3: Full-Service Laboratories

I developed four model variations for full-service laboratories—one model variation for each dependent variable of interest. Like the chemistry and radiation laboratory models, these models do not include control variables for laboratory type and only use a subset of the source data. Only results from audits of laboratories that do both chemical and radioisotope analyses were included in the statistical analyses. The subset of the data included 120 audits of 19 laboratories. As with the general model, laboratory 62 was selected as the reference laboratory. Model results corresponding to each of the four dependent variables are presented in the following subsections.

Issues

The first variation of the full-service laboratory model used the number of detected audit issues as the dependent variable. No attempt was made to distinguish between findings and observations. Findings and observations were counted equally regardless of severity. The mean number of issues per audit was 20.53. Model results are presented in Table E1.

The results from this model variation show a statistically significant correlation between the number of issues detected during an audit of a radiation laboratory and the number of audited modules ($p < 0.001$), and the number of auditors per module ($p < 0.01$). The slope coefficient for the NumMods variable was 5.558 issues per module. This suggests that, on average, holding all other variables constant, for each additional module included in an audit, you can expect auditors to detect 5 or 6 additional issues. This coefficient is nearly identical in value to the coefficient from variation 1 of the radiation laboratories model (5.555).

The slope coefficient for the AuditorsPerMod variable was 11.585 detected issues per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of around 11 or 12 additional issues. The value of the coefficient for this model variation is the highest of all the model runs..

The value of the coefficients for the YearFrac, Oversight, and Duration variables were similar to the values from variation 1 of the general model. YearFrac's value was 1.184 issues per year. Oversight's value was -6.090 issues per audit. Duration's value was 2.277 issues per day. However, slope coefficients for these variables were not statistically significant.

Findings

The second variation of the radiation laboratory model used the number of detected audit findings as the dependent variable. This variation of the model is most appropriate for agencies that want to compare radiation laboratories and is only concerned about issues that are actual violations of requirements. The mean number of findings per audit was 9.67. I present the results of this regression model in Table E2.

The results from this model variation only show a statistically significant correlation between the number of findings detected during an audit of a full-service laboratory and one independent variable. The coefficient for the AuditorsPerMod variable was significant at the $p < 0.001$ level. All other variables were statistically insignificant.

The slope coefficient for the AuditorsPerMod variable was 6.596 detected findings per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of around 11 or 12 additional findings. The value of the coefficient for this model variation is only slightly higher than slope coefficient for the AuditorsPerMod variable of the Chemistry Laboratories Model Variation 2.

Technical Issues

In variation 3 of the full-service laboratory model I used the number of detected technical issues as the dependent variable. This variation of the model is most appropriate for agencies that want to compare full-service laboratories and is only concerned about technical issues. The mean number of technical issues per audit was 11.65. I present the results of this regression model in Table E3.

The results from this model variation show a statistically significant correlation between the number of technical issues detected during an audit of a full-service laboratory and the number of audited modules ($p < 0.01$), and the number of auditors per module ($p < 0.05$). The value of the coefficients for the YearFrac, Oversight, and Duration variables were not statistically significant.

The slope coefficient for the NumMods variable was 3.776 technical issues per module. This suggests that, on average, holding all other variables constant, for each additional module included in an audit, you can expect auditors to detect about four additional technical issues. The value of the coefficient for this model variation is the highest of all the model runs for technical issues.

The slope coefficient for the AuditorsPerMod variable was 7.561 detected technical issues per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of around 7 or 8 additional issues. The value of the coefficient for this model variation is the highest of all the model runs.

Technical Findings

In variation 4 of the full-service laboratory model, I used the number of detected technical finding as the dependent variable. This variation of the model is most appropriate for agencies that want to compare laboratories that have both analytical chemistry and radioisotope capabilities and is only concerned about violations of technical requirements. The mean number of technical findings per audit was 5.30. I present the results of this regression model in Table E4.

The results from this model variation only show a statistically significant correlation between the number of findings detected during an audit of a full-service laboratory and one independent variable. The coefficient for the AuditorsPerMod variable was significant at the $p < 0.01$ level. All other variables were statistically insignificant. The slope coefficient for the AuditorsPerMod variable was 4.775 detected technical findings per auditor per module. This suggests that increasing an audit team size by one additional auditor per module, should result in the detection of around five additional technical findings. The value of the coefficient for this model variation is only slightly higher than slope coefficient for the AuditorsPerMod variable of the Chemistry Laboratories Model Variation 2. The value of the coefficient for this model variation is the highest of all the model runs.

Summary

The results presented in this chapter show that the number of issues detected during contractor audits is significantly influence by the way auditing agency conducts the audits. As such, contractor rankings based on raw audit results may not accurately reflect a contractor's true performance. Variables such as the frequency of audits, the number of auditors conducting the audit, and audit scope may need to be accounted for statistically in order to accurately measure a contractor's true relative performance. Likewise, the data indicate that the choice of dependent variables also impacts the relative ranking of a contractor. Thus, the government agency conducting the comparison must carefully determine which issue types have the greatest importance to the agency.

CHAPTER 5

SUMMARY AND DISCUSSION

In this final chapter, I restate the research problem, review the research questions, summarize the results, and discuss the implications of the results. As stated in Chapter 1, traditional rational-choice theory assumes decision makers use their cognitive abilities to evaluate information to make optimal decisions. However, the GPRA forces government decision makers to rely heavily on metrics when making decisions. The complexities of government agencies and the legislative mandate to rely on metrics practically ensure that decision makers will not work in ideal rational-choice mode. Rather, decision makers operate in cybernetic-decision mode—decision makers do what the data tell them to do (Kravchuk & Schack, 1996).

Under these circumstances, it is imperative that the data provided and used by decision makers to evaluate contractors actually address the issues of concern to the agency. Moreover, the data need to accurately reflect the relative performance of the contractors who were being evaluated. Failing to use metrics that actually measure characteristics of importance could result in the agency not receiving the services it needs. Failing to fairly assess a contractor's performance could result in less-than-optimal contractors winning contract awards.

One characteristic that is increasingly becoming important to government agencies is quality. However, contractor data on quality has been difficult to quantify for inclusion in performance metrics. The results of quality assurance audits hold promise as a quantitative measure of quality; however, factors external to the contractors' performance may contribute to the quantitative results. Failing to account for these external factors results in contractors being assessed, in part, on the performance of the government agency.

I conducted this study to determine if it were possible to account for some of the agency's contribution to quality assurance audit results. Accounting for the agency's contribution allows for more accurate estimates of the contractors' contributions. Having these corrected numbers allows government agencies to more accurately incorporate quality into overall contractor performance assessments.

Summary of Results

To achieve the objectives of the study, answers to the following questions were sought.

1. Is there a statistically significant relationship between the number of issues detected during an audit and the audit duration, the audit team size, the audit frequency, the audit scope, or the presence of oversight during an audit?
2. Does the relationship between independent and dependent variables differ depending on the type of laboratory?
3. Does the relationship between independent and dependent variables differ depending on the selected definition of audit issue?

To answer Question1, I tested the five hypotheses from Chapter 3:

H_1: There is a positive relationship between the number of identified audit issues and the duration of an audit.

H_2: There is a positive relationship between the number of identified audit issues and the number of auditors on an audit team.

H_3: There is a positive relationship between the number of audit modules and the number of detected audit issues.

H_4: There is a positive relationship between the elapsed time between successive audits and the number of detected audit issues.

H_5: The number of detected audit issues is affected by the presence of audit oversight.

Audit Duration

H_1: There is a positive relationship between the number of identified audit issues and the duration of an audit.

The results of the regression models did not support this hypothesis. Although the slope coefficients were positive for all model runs, none of the 17 model variations showed a statistically significant relationship between the Duration independent variable and the dependent variable of interest. Audit Duration directly relates to audit depth. The longer the audit, the more time auditors have to examine records, interview personnel, read procedures, and observe operations. However, the Duration variable in the source dataset only represents a portion of the time spent on the audit; only the number of days on site is recorded in the dataset. Neither the number of hours per day on site nor the time spent conducting off-site audit activities, are recorded in the dataset. Variations in the unaccounted for components of the audit duration may have contributed to the statistical insignificance of this variable.

Audit Team Size

H_2: There is a positive relationship between the number of identified audit issues and the number of auditors on an audit team.

The results of the regression models support this hypothesis. The size of the audit team, in terms of number of auditors per audited module, was significant for all 17 model variations. Moreover, the coefficients were positive for all model variations. The size of an audit team directly relates to audit depth. If an audit team has more auditors, more interviews can be conducted, more records can be reviewed, more procedures can be read, and more activities can be observed.

Audit Scope

H_3: There is a positive relationship between the number of audit modules and the number of detected audit issues.

The results of the regression models support this hypothesis. Audit scope refers to the number of requirements against which an organization is assessed. The slope coefficients were positive for all model runs. Moreover, 13 of the 16 model variations showed a statistically significant ($p < 0.05$) relationship between the NumMods independent variable and the dependent variables of interest.

Audit Frequency

H_4: There is a positive relationship between the elapsed time between successive audits and the number of detected audit issues.

The results of the regression models did not support this hypothesis. Although the slope coefficient for the YearFrac variable was positive for all 17 model variations, coefficient was statistically significant ($p < 0.05$) for only three variations. In the general model, there was a statistically significant relationship ($p < 0.01$) between YearFrac and the number of findings, but no statistically significant relationship between YearFrac and the number of observations. This led to a borderline significance (p=0.075) between YearFrac and issues in general.

There are multiple reasons why the frequency of audits may be more likely to impact the detection of findings than the detection of observations. A finding is either a deviation from a requirement, or a failure to document compliance with a requirement (DOE Deficiency, 2009; DOE Findings, 2009). However, an observation is “a deficiency of an isolated nature, a deviation from Best Management Practices, or an opportunity for improvement, which may warrant attention by the audited facility” (DOE, Observations, 2009). Because observations are either one-off events or minor in nature, they may be more difficult to detect than findings as time elapses. On the other hand, more serious infringements or failure to document compliance may have more permanency. Thus, an auditor may be able to detect a finding much longer after it occurs than an observation. This makes findings less sensitive to audit frequency.

Audit Oversight

H_5: The number of detected audit issues is affected by the presence of audit oversight.

Overall, the results of the regression models were inconclusive for this hypothesis. For all but 1 of the 17 model variations, the slope coefficient for the Oversight variable was negative. Additionally, the significance of the slope coefficients for findings was consistently lower than for issues in general. This was particularly noticeable in the general model where the relationship between Oversight and findings was statistically insignificant ($p = 0.320$), while the relationship between Oversight and

Observations was $p < 0.001$. This would seem to indicate that the presence of Oversight tends to reduce the number of observations identified by auditors.

Observations are more subjective than findings. Although the general model shows a significant correlation between oversight and observation, but no significant correlation between oversight and Findings, this may suggest that the presence of oversight may impact subjective determinations, but have less impact on more objective results.

Laboratory Type

Does the relationship between independent and dependent variables differ depending on the type of laboratory?

The results of the 12 laboratory specific regression models indicate that the relationships between the independent variables and dependent variables do differ depending on the type of laboratory. Although the general behavior of the models is consistent for all model variations, the minor differences have noticeable impact on the ranking of laboratories. This is particularly noticeable when the dependent variable is TechnicalFindings. This is not surprising given that different types of laboratories have different technical requirements. It may be that some technical requirements are inherently more difficult to comply with, or may be more difficult to understand. In either case, those types of laboratories that have to comply with these technical requirements will have more issues than those laboratories that have a different set of technical requirements.

Issue Type

Does the relationship between independent and dependent variables differ depending on the selected definition of audit issue?

The results of the regression models indicate that the choice of dependent variable has a significant impact on performance comparison results. In this study, I primarily investigated four dependent variables: (a) technical findings, (b) technical issues, (c) findings, and (d) issues. However, the selection of these four dependent variables was somewhat arbitrary. I could have selected Priority I findings or Priority II findings. I could have selected administrative issues or observations related to organic chemistry. The study results show that this choice of dependent variables impacts the relative ranking of contractors.

The purpose of contractor performance comparisons, or benchmarking, is to rank, measure, or compare outcomes or traits between contractors (Hatry, 2006). However, in order for the performance comparisons to be most meaningful to the assessing agency, the agency must determine what outcomes or traits are most desirable or worth comparing. While quality as a general concept is important, when it comes to achieving agency objectives, agency decision makers need to decide what dependent variable needs to be the basis of the quality measurement.

Discussion of Results

Quality assurance audit results hold promise as a potential metric for performance comparisons. The data are quantitative, tend to fit the organization being assessed, and fit within the larger political climate. Moreover, audit data are obtained from existing programs, which eliminates or reduces the need for new data gathering efforts.

However, audit results are affected by external influence. The results of this study indicated that audit results were significantly affected by external factors related to the way the auditing agency performed the audit. These external factors included the scope of the audit, the number of auditors, the audit frequency, and the degree of audit oversight. As such, audit results were a composite measure of both the audited organization's performance and the auditing agency's performance.

If quality assurance audit results are to be used for contractor performance comparisons, proper metrics must be developed. These metrics must account for the auditing agency's contribution to the results. The metrics must also measure the most appropriate dependent variable. The results of the current study indicate that failure to account for audit-specific variables and the improper selection of dependent variable can dramatically affect contractor performance scores.

Implications of the Study

The requirements of the GPRA and the growing prominence of quality assurance contract requirements puts pressure on government agencies to conduct quality assurance performance comparisons of government contractors. Quality assurance is a key component of many government contracts. Contractor performance comparisons that address some contract requirements, while ignoring quality, do not address all the salient needs of the agency. Failing to incorporate quality in performance metrics undermines the purpose of performance comparisons.

However, the metrics used for quality performance comparisons must be carefully crafted or risk being counterproductive. The complexity of government agencies and the realities of bounded rationality theory suggest that agency decision makers will increasingly "rely upon formal measurement devices and systems," rather than the traditional rational-actor decision-making process (Kravchuk & Schack, 1996, p. 349). As such, the measurement devices upon which these decision makers rely must accurately reflect the most important aspects of the contract. A decision-making system that provides inaccurate data does little good and can even "do great harm if it misrepresents, misleads, or introduces perverse behavioral incentives" (Kravchuk & Schack, 1996, p. 349). If quality assurance audit results are to be used for performance comparison efforts, the metrics based on these results must accurately represent the characteristic being measured.

In this research, I identified variables that have a statistically significant relationship to audit results. These variables and their associated regression slope coefficients are particular to the DOECAP. Their values and statistical significances cannot be extrapolated to other organizations. Nevertheless, the fact that there are audit-specific variables that have statistical significance has broader implications.

The research results imply that audit-specific factors affect audit results. Raw audit results are not an accurate interorganizational measure of a contractor's quality performance. Audit factors outside the control of the contractor, such as the size of the audit team, the number of audit questions, and the frequency of the audit, can affect the quantitative results of the audit. This implies that if an agency desires to use audit results for performance comparison studies, the agency must account for audit-specific factors. In this research, I demonstrated a method that can be used to account for audit-specific factors by identifying relevant audit-specific independent variables and incorporating them into fixed-effects regression models that use dummy variables for each of the contractors of interest.

Relationship to Prior Research

Previous research indicates that government agencies need to include accurate quality metrics in feedback loops to decision makers. Research from Kravchuk and Schack (1996) suggested that the requirements of the GPRA and the complexities of modern organizations bind the rationality of decision makers to such an extent that decisions tend to be based primarily on numbers. If the numbers do not incorporate all relevant information, the decision makers are likely to make sub-optimal decisions. Since QA requirements are an increasingly important component of government contracts, performance to the requirements is a key component of overall contractor performance. Therefore, metrics for quality should be included in the feedback loops.

Propper and Wilson (2003) and Nicholson-Crotty, et al. (2006) showed the importance of using metrics that measure a range of stakeholder goals and objectives. Moreover, they concluded that "accuracy of the information is essential" (Propper & Wilson, 2003, p. 19). The current study showed that QA audit results, which measure compliance with a wide range of technical, administrative, and regulatory requirements, may be used for performance comparisons. However, the accuracy of QA audit results for measuring performance is dependent on correcting the data for audit-specific factors.

Previous research, such as that conducted by Nevalainen, et al. (2000), Flynn et al. (1994), and Colledge and March (1993), developed methods and instruments for measuring performance. However, research from Yang and Hsieh (2007) and the NRC have indicated the impracticality of these methods due to the resource burdens they place on the assessed contractors. This study provides a means for measuring contractor performance that is based on existing programs and, therefore, does not further burden contractors with any new resource demands.

Hatry (2006) and Yang and Hsieh (2007) investigated the importance of performance metrics that fit the values of the organization being assessed as well as the values of other stakeholders. Since QA audit results generally measure compliance with requirements that are defined by the contractor's industry, compliance with these requirements is generally valued by the assessed contractors. The current study shows how performance metrics can be developed that are based on these contractor-accepted values.

Propper and Wilson (2003), Hatry (2006), Heinrich (2012), and the NRC stressed the importance of using quantitative metrics that accurately measure the actual performance of the contractor. Metrics that are significantly affected by external influences are poor tools for benchmarking. The current study showed that QA audit results are significantly affected by external influences. Therefore, raw audit results are not suitable for interorganizational performance comparisons. Nevertheless, the study demonstrated how agencies could use statistical techniques to account for many of the externalities that would otherwise make QA audit results unsuitable for performance comparison measurements.

Unanticipated Findings

Finding a statistically significant relationship between Oversight and Issues, but not between Oversight and Finding was unanticipated. Findings are subsets of Issues. Consequently, if the presence of Oversight were to influence an auditor to upgrade an observation to a finding, or downgrade a finding to an observation, it would affect the total number of findings, but it would not affect the overall number of issues. Therefore, it would not be surprising to observe a statistically significant relationship between Oversight and Findings, but not Oversight and Issue*s*. Nevertheless, the results showed the opposite. In context of the current study, this unanticipated result (a) further supports the need to control for audit-specific factors when ranking contractors by using audit results and (b) illustrates the importance of properly selecting the most appropriate dependent variable. If Findings is the dependent variable of choice, including Oversight in the statistical analysis may not be important. However, if the agency is concerned with the total number of audit issues, Oversight may need to be included in performance score calculations.

This unanticipated result may actually be a very positive result for the DOECAP in particular. The result suggests that an auditor's determination of what is and what is not a finding is relatively insensitive to the presence of Oversight. Since DOECAP findings are supposed to be objective (DOE Deficiency, 2009; DOE Findings, 2009), it would be disconcerting to see a significant relationship between Oversight and the number of findings. However, a statistically significant relationship between Oversight and the number of relatively subjective Observations is not troubling.

It was not anticipated that the slope coefficients for the YearFrac variable would be so small compared to the mean number of issues detected per audit. DOECAP auditors identify about 16 issues per audit, on average. The average DOECAP-contracted laboratory is audited once a year. The low values of the slope coefficients suggest that if the audit frequency is reduced to once every two years, a significant percentage of detectable issues, as much as 45%, may not be detected by DOECAP.

The results of this study do not prove that these issues will never be identified or resolved. It is possible that the laboratories could identify and resolve these issues themselves, independent of the DOECAP auditors. Nevertheless, this is something worthy of additional consideration when determining audit frequency.

Recommendations

Government agencies should incorporate quality performance metrics in evaluations of contractor performance. In order for contractor performance comparisons to be most meaningful, performance measurements should include metrics that address all performance elements of importance. The increasing prominence of total quality management requirements in government contracts suggests that quality is an element of importance, and it should be measured and included in contractor benchmarking.

QA audit results uniquely meet many of the requirements for performance measurements and should be used to measure historic quality performance. The data are quantitative, tend to fit the organization being assessed, and fit within the larger political climate. Moreover, these data are obtained from existing programs, which eliminates or reduces the need for new data gathering activities.

However, agencies that elect to use QA audit results for performance comparisons need to corrected the data for audit-specific factors. Raw audit results are significantly impacted by audit-specific factors. These factors do not reflect the performance of the audited contractor. Failing to adjust for these audit-specific factors impacts performance scores and jeopardizes accurate ranking of contractors.

In order to be most accurate, audit programs should record audit data that potentially biases raw audit results so that the raw results can be corrected. This study showed that there is a statistical relationship between DOECAP audit results and both the number of auditors and the number of audit modules in a DOECAP audit. Recording this information allows the raw audit results to be corrected for these variables. Different audit programs may have different independent variables that significantly affect audit results. Failing to maintain information on these variables makes them unavailable for inclusion in statistical analyses. If agencies wish to maximize the accuracy of their performance comparisons, they must collect and maintain the source data needed for the analyses.

The results suggest that agencies may be wise to use multiple dependent variables when conducting quality performance comparisons. In some instances, the total number of issues may be the best measure for an agency. In other cases, perhaps due to specific program project requirements, the agency may only be concerned with technical findings. Given that contractor performance scores depend on the selection of dependent variables, a contractor may score high with one dependent variable and low with another. Using multiple dependent variables can help identify contractors that are consistently high ranking.

Implications

Current contractor performance comparison studies that do not include quality metrics may be misleading. Although cost, schedule, production, and other common measures of contractor performance are undoubtedly important, the quality of contracted products and services is also important. The research of Kravchuk and Schack (1996) suggested that failing to include important information in the feedback mechanism results in decisions based on incomplete information. In other words, the decision is still likely to be made even if the information is incomplete or inadequate.

Agencies may use audit results for performance comparisons; however, current quality performance metrics that use raw audit results may be misleading. The results of this study show a marked difference between performance scores based on raw audit results and performance scores adjusted for audit-specific factors. Although the analytical results of this study are specific to DOECAP audits and cannot be extrapolated to other programs, they do demonstrate differences can occur if audit-specific factors are not accounted for. Failing to account for audit-specific factors can result in a high performing contractor appearing to be a poor performing contractor and can make a poor performing contractor appear to be a much better performing contractor, which undermines the purpose of performance comparisons.

Inaccurate ranking of contractors not only has implications for the government agency, but also for the contracted entities. Contractors should be concerned about how past performance is being scored. Auditing a contractor frequently, or with larger than average audit teams, or to a larger number of requirements as compared to its competitors, may unfairly disadvantage the contractor. Depending on how quality is scored against other requirements, such as cost and schedule, even minor decreases in a quality score can cause a contractor to lose a bid.

Recommendations for Future Research

The current study investigated the impact of laboratory type on the number of audit issues, but it did not investigate other contract specific variables that may impact the results. These variables may include contract size, contractor size, time in business, or time in the audit program. These factors may have unanticipated impacts that should be accounted for in the performance comparison process. Further research investigating these contract specific variables appear s warranted.

Additional research also seems needed to determine why oversight reduces the number of detected observations. This result may be isolated to DOECAP, or it may be a more fundamental effect of audit oversight. Similar analyses of data from other audit programs may shed light on the observed behavior. A better understanding of this behavior could be used to improve the audit process.

A study investigating contractor learnability may be worthwhile. The research showed that initial DOECAP audits result in 72% more issues, on average, than subsequent audits. This indicates that contractors are learning organizations. During times of change, it may be advantageous to contract with highly adaptable, quick-learning organizations. Identifying and including contractor learnability or adaptability in performance metrics may be advantageous.

Future research needs to investigate means for weighting issues. This study did not weigh dependent variables according to severity; Priority I and Priority II findings were treated equally. When Findings and Observations were combined into a single dependent variable, Issues, they were equally weighted. In reality, the severity is not constant over issue type. For performance scores based on audit results to be most meaningful, issues should be weighted by severity. Research investigating the impacts of weighting on performance scores would be enlightening.

Limitations

Slope coefficients and significance values in this study are DOECAP specific and cannot be extrapolated to other organizations. There is no reason to believe that the insignificance of the Duration variable in this study means that audit duration is always insignificant. Idiosyncrasies in the way DOECAP records audit duration may have contributed to its statistical insignificance. The slope value for YearFrac was small compared to the average number of issues detected per audit; this relationship might not hold true for other auditing organizations.

Some slope coefficients may be trivial, even if they are statistically significant. For instance, the small value for the YearFrac coefficient (1.556 findings per year) for the general model of this study is non-trivial if it is being used to determine how frequently to schedule audits. However, it may be quite trivial for performance comparison purposes if the elapsed time between successive audits is nearly the same for all contractors. Since the values of the coefficients are program dependent, the values should be evaluated for meaningfulness whenever the model is applied.

This study indicates that an agency can use this process for interorganizational comparisons of contractors only if one or more of the available dependent variables is important to the government agency. However, this may not always be the case. For some agencies, the number of violations of requirements may be more important than the number of requirements violated. For other agencies, the rate of violations per unit of work may be important. To use this method, an agency must carefully consider the appropriateness of the dependent variable selected and may need to adjust that variable for factors such as contractor size or volume of work.

The process needs to be modified to include contractors that have been audited only once. The YearFrac variable, which was used to determine the time between successive audits, requires a previous audit; initial audits are not preceded by earlier audits, so the value for YearFrac is null for initial audits and the audit records are excluded from the statistical analyses. If the YearFrac variable is omitted, initial audits can be incorporated into the analyses. However, if the contracted organizations, like DOECAP laboratories, display the same disparity between the number of issues detected in initial audits and the number detected in subsequent audits, the analyses would need to include a dummy variable for initial audit to adequately account for the steep learning curve.

Although the research indicates that it is possible to reduce the influence of external factors on the results of quality performance measurements, it does not indicate that the influence of external factors can be eliminated. The coefficient of determination for the general model's four variations was only about 0.5. This means there is a substantial amount of variation that is not attributable to any of the identified independent variables.

There are two types of variables that can affect the audit results. One type affects the number of issues that occur; the other type affects the fraction of issues that are detected. Unidentified variables that affect the number of issues that occur are not troublesome to performance comparisons. Although external issues such as illnesses, economic downturns, or power outages may affect a contractor's level of quality compliance, they are not supposed to; the contractor is supposed to comply with requirements at all times, regardless of external factors. If some variable impacts a contractor's level of compliance, that is a measure of the contractor's performance. However, unknown variables that affect the fraction of detected issues are worrisome. If the auditing agency does something different in one audit that allows the audit team to find a higher percentage of existing issues, the process unfairly impacts one contractor over another. For instance, if the contracting agency consistently sends it most thorough auditors to one contractor, and its least thorough auditors to another contractor, and does not account for this variation in the performance comparison analyses, the performance comparisons may be meaningless or misleading.

Summary and Conclusion

The NPM movement of the 1990s and beyond resulted in numerous government reforms that were designed to improve the efficiency and effectiveness of public agencies. These reforms put "emphasis on strategic planning; on performance measurement, especially the measurement of program outcomes; on customer satisfaction as one of the desired outcomes; [and] on results-oriented objectives" (Swiss, 2005, p. 592). An underlying assumption of these reform measures was that an agency could not claim success, without objective evidence that desired outcomes were being achieved.

The NPM movement is no longer popular. In fact, some researchers have gone so far as to declare NPM "dead" (Dunleavy, et al., 2006). The popularity of NPM reforms has waned, in some cases, because the reforms had "little impact on altering the overall effectiveness of government" (Dunleavy, et al., 2006, p. 468). Even worse, in other cases, NPM reforms led to "policy disasters" (Dunleavy, et al., 2006, p. 468).

However, the ineffectiveness of NPM reforms was not entirely unanticipated. Early NPM researchers such as Kravchuk and Schack (1996) recognized that some NPM reforms, like the performance comparison requirements of the GPRA, might be counterproductive because they move agency decision makers away from the traditional rational-actor role wherein decision makers use their cognitive abilities to evaluate information to make optimal decisions. NPM reforms that stress measurement pressure agency decision makers to do what the numbers tell them to do—with minimal rational skepticism.

Nevertheless, even some of the strongest critics of NPM recognize that the reforms have been widely entrenched and, consequently, will be around for a long time. "NPM practices are extensively institutionalized and will continue" (Dunleavy, et al., 2006, p. 468). The performance requirements of the GPRA are public law and are not likely to be repealed any time soon.

The permanency of these institutionalized reforms makes it imperative that methods be developed to make the reforms workable. The research of Kravchuk and Schack suggests that in order to make contractor performance comparison efforts effective, the metrics used must accurately reflect the true performance of the contractor. If accurate, representative metrics can be developed, the metrics can be used in a decision-making process that produces meaningful results—even if the agency decision maker is not operating in rational-actor mode.

The growing prominence of QA requirements for government programs illustrates the importance of these programs for government contracts. Given this importance, QA needs to be incorporated into the performance comparison process. However, this requires metrics to be identified for measuring QA compliance.

QA audit results are readily available metrics for QA compliance. Many government agencies already conduct QA audits of contractors. These audits are used to assess contractors' compliance with QA requirements. The results from these audits could be used for interorganizational comparisons of government contractors provided the data are accurate measures of the contractors' performance.

This study shows that uncorrected, raw audit results are not appropriate for interorganizational comparisons. Raw audit results are a composite measure of how many issues a contractor has as well as how effectively the audit team finds those issues. Using the uncorrected metric in interorganizational performance comparisons is inappropriate because a suitable metric should be relatively insensitive to factors external to the contractor's performance. If left uncorrected, audit results are unsatisfactory for interorganizational performance comparisons

However, the research shows that a significant portion of the auditing agency's contribution to the raw results can be compensated for statistically. Using OLS regression techniques, agencies can identify and compensate for audit-specific factors that would otherwise bias comparison results. The method does not entirely eliminate external factors, but it does diminish them.

QA is an important element of modern government contracts. The degree of compliance with QA is highly variable across contractors. Contractors that comply well with QA requirements should be recognized for their high degree of compliance. Contractors that comply poorly with QA requirements should not be unduly rewarded.

This research identifies a methodology that government agencies can use to compare contractors' compliance with QA requirements.

APPENDIX A

ABBREVIATIONS

DOE	U.S. Department of Energy
DOECAP	U.S. Department of Energy Consolidated Audit Program
GPRA	Government Performance and Results Act of 1993
NPM	New Public Management
NRC	National Research Council
OLS	Ordinary Least Squares
OUO	Official Use Only
QA	Quality Assurance
TAT	Turnaround Time

APPENDIX B

GENERAL MODEL RESULTS

Table B1

General Model Variation 1: Association between Independent Variables and the Number of Issues Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-24.936	6.62		-3.767	0.000
Duration	0.168	1.514	0.010	0.111	0.912
AuditorsPerMod	6.877	1.820	0.209	3.778	0.000
NumMods	4.630	0.765	0.495	6.049	0.000
Oversight	-6.949	2.278	-0.132	-3.051	0.003
YearFrac	1.647	0.921	0.084	1.788	0.075
isChemLab	1.714	2.871	0.067	0.597	0.551
isRadLab	1.226	2.628	0.055	0.467	0.641
isLab39	1.817	5.129	0.029	0.354	0.723
isLab35	1.825	4.445	0.029	0.411	0.682
isLab2	2.498	5.193	0.027	0.481	0.631
isLab33	4.390	5.961	0.043	0.736	0.462
isLab26	5.328	6.334	0.058	0.841	0.401
isLab23	5.511	4.517	0.084	1.220	0.223
isLab44	5.740	9.453	0.028	0.607	0.544
isLab19	6.188	4.725	0.107	1.310	0.191
isLab25	6.211	9.726	0.030	0.639	0.524
isLab48	6.516	9.690	0.032	0.672	0.502
isLab69	6.582	7.254	0.055	0.907	0.365
isLab7	6.824	5.145	0.113	1.326	0.186
isLab32	6.926	6.278	0.094	1.103	0.271
isLab43	7.458	4.724	0.108	1.579	0.115
isLab37	7.540	6.364	0.073	1.185	0.237
isLab4	8.105	4.667	0.135	1.736	0.084
isLab30	8.106	9.027	0.040	0.898	0.370
isLab46	8.250	5.253	0.125	1.570	0.117
isLab21	8.332	4.585	0.138	1.817	0.070
isLab59	8.349	5.796	0.090	1.441	0.151
isLab42	9.147	4.424	0.152	2.068	0.040
isLab11	9.149	4.438	0.146	2.062	0.040
isLab61	9.316	5.393	0.119	1.727	0.085

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab18	9.708	4.482	0.161	2.166	0.031
isLab70	9.711	9.883	0.047	0.983	0.327
isLab41	9.776	5.254	0.141	1.861	0.064
isLab5	10.601	4.468	0.176	2.373	0.018
isLab20	10.826	9.052	0.053	1.196	0.233
isLab24	10.850	5.771	0.173	1.880	0.061
isLab14	11.502	5.014	0.191	2.294	0.023
isLab65	12.350	7.323	0.085	1.686	0.093
isLab28	12.802	5.387	0.175	2.376	0.018
isLab60	12.868	9.337	0.063	1.378	0.169
isLab53	12.984	7.271	0.089	1.786	0.075
isLab9	13.155	4.492	0.218	2.929	0.004
isLab57	14.073	6.536	0.118	2.153	0.032
isLab13	15.013	5.152	0.249	2.914	0.004
isLab16	15.662	5.125	0.260	3.056	0.002
isLab49	16.031	5.606	0.190	2.860	0.005
isLab10	16.580	5.751	0.180	2.883	0.004
isLab66	16.873	7.836	0.116	2.153	0.032
isLab12	17.113	5.586	0.219	3.063	0.002
isLab40	17.202	5.084	0.274	3.383	0.001
isLab47	18.285	6.455	0.154	2.833	0.005
isLab54	18.755	5.862	0.203	3.199	0.002
isLab38	20.587	6.861	0.142	3.001	0.003
isLab17	21.721	6.562	0.183	3.310	0.001
isLab8	26.981	5.429	0.345	4.970	0.000
isLab36	27.510	7.334	0.189	3.751	0.000
isLab27	27.746	9.337	0.135	2.972	0.003

Table B2

General Model Variation 2: Association between Independent Variables and the Number of Findings Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-12.012	4.046		-2.969	0.003
Duration	0.601	0.926	0.064	0.649	0.517
AuditorsPerMod	3.216	1.113	0.177	2.890	0.004
NumMods	1.728	0.468	0.335	3.693	0.000
Oversight	-1.386	1.392	-0.048	-0.996	0.320
YearFrac	1.556	0.563	0.145	2.763	0.006
isChemLab	1.885	1.755	0.134	1.074	0.284
isRadLab	1.390	1.607	0.113	0.865	0.388
isLab30	-6.282	5.518	-0.055	-1.138	0.256
isLab44	-2.146	5.778	-0.019	-0.371	0.711
isLab35	-1.756	2.717	-0.051	-0.646	0.519
isLab23	-1.329	2.761	-0.037	-0.481	0.631
isLab39	-0.898	3.135	-0.026	-0.286	0.775
isLab2	-0.190	3.174	-0.004	-0.060	0.952
isLab19	0.369	2.888	0.012	0.128	0.898
isLab42	0.384	2.704	0.012	0.142	0.887
isLab4	0.531	2.853	0.016	0.186	0.853
isLab48	0.621	5.923	0.005	0.105	0.917
isLab11	0.730	2.713	0.021	0.269	0.788
isLab26	1.047	3.872	0.021	0.270	0.787
isLab43	1.196	2.887	0.031	0.414	0.679
isLab37	1.913	3.890	0.034	0.492	0.623
isLab25	2.243	5.945	0.020	0.377	0.706
isLab28	2.485	3.293	0.061	0.755	0.451
isLab7	2.516	3.145	0.076	0.800	0.424
isLab14	2.564	3.065	0.077	0.837	0.404
isLab60	2.825	5.708	0.025	0.495	0.621
isLab61	3.045	3.297	0.071	0.924	0.356
isLab20	3.056	5.533	0.027	0.552	0.581
isLab59	3.250	3.543	0.064	0.917	0.360
isLab33	3.365	3.644	0.059	0.923	0.357
isLab32	3.624	3.837	0.090	0.944	0.346
isLab57	3.711	3.996	0.057	0.929	0.354
isLab9	3.724	2.746	0.112	1.356	0.176
isLab18	3.936	2.740	0.118	1.436	0.152

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab46	3.982	3.211	0.110	1.240	0.216
isLab5	4.038	2.731	0.121	1.479	0.140
isLab69	4.052	4.434	0.062	0.914	0.362
isLab41	4.059	3.212	0.106	1.264	0.207
isLab24	4.109	3.528	0.119	1.165	0.245
isLab21	4.344	2.803	0.131	1.550	0.122
isLab27	4.710	5.708	0.042	0.825	0.410
isLab53	4.956	4.444	0.062	1.115	0.266
isLab70	5.926	6.041	0.052	0.981	0.328
isLab16	6.090	3.133	0.183	1.944	0.053
isLab66	6.272	4.790	0.078	1.309	0.191
isLab13	7.145	3.149	0.215	2.269	0.024
isLab65	7.448	4.476	0.093	1.664	0.097
isLab47	7.533	3.946	0.115	1.909	0.057
isLab40	7.829	3.108	0.226	2.519	0.012
isLab12	8.683	3.415	0.201	2.543	0.012
isLab38	8.806	4.194	0.110	2.100	0.037
isLab54	9.065	3.583	0.178	2.530	0.012
isLab49	9.640	3.427	0.207	2.813	0.005
isLab8	9.801	3.318	0.227	2.953	0.003
isLab10	10.423	3.516	0.205	2.965	0.003
isLab17	10.499	4.011	0.160	2.618	0.009
isLab36	13.402	4.483	0.167	2.994	0.003

Table B3

Association between Independent Variables and the Number of Observations Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-12.924	4.194		-3.081	0.002
Duration	-0.433	0.959	-0.042	-0.451	0.652
AuditorsPerMod	3.661	1.153	0.185	3.174	0.002
NumMods	2.902	0.485	0.515	5.984	0.000
Oversight	-5.563	1.443	-0.176	-3.855	0.000
YearFrac	0.091	0.584	0.008	0.156	0.876
isChemLab	-0.171	1.819	-0.011	-0.094	0.925
isRadLab	-0.164	1.665	-0.012	-0.098	0.922
isLab33	1.025	3.777	0.017	0.271	0.786
isLab69	2.530	4.596	0.035	0.551	0.582
isLab2	2.687	3.290	0.048	0.817	0.415
isLab39	2.715	3.250	0.072	0.835	0.404
isLab32	3.302	3.977	0.075	0.830	0.407
isLab35	3.582	2.817	0.095	1.272	0.205
isLab70	3.785	6.262	0.031	0.604	0.546
isLab25	3.968	6.162	0.032	0.644	0.520
isLab21	3.988	2.905	0.110	1.373	0.171
isLab46	4.268	3.328	0.108	1.282	0.201
isLab26	4.282	4.013	0.077	1.067	0.287
isLab7	4.308	3.260	0.119	1.322	0.187
isLab65	4.902	4.640	0.056	1.057	0.292
isLab59	5.099	3.672	0.092	1.389	0.166
isLab37	5.627	4.032	0.091	1.396	0.164
isLab41	5.717	3.329	0.137	1.717	0.087
isLab18	5.773	2.840	0.159	2.033	0.043
isLab19	5.819	2.994	0.167	1.944	0.053
isLab48	5.895	6.140	0.048	0.960	0.338
isLab10	6.158	3.644	0.111	1.690	0.092
isLab43	6.262	2.993	0.150	2.092	0.037
isLab61	6.270	3.417	0.133	1.835	0.068
isLab49	6.392	3.552	0.126	1.800	0.073
isLab5	6.563	2.831	0.181	2.319	0.021
isLab24	6.741	3.657	0.178	1.844	0.066
isLab23	6.840	2.862	0.173	2.390	0.018
isLab4	7.574	2.957	0.209	2.561	0.011

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab20	7.770	5.735	0.063	1.355	0.177
isLab13	7.868	3.264	0.217	2.411	0.017
isLab44	7.886	5.989	0.064	1.317	0.189
isLab53	8.028	4.607	0.092	1.743	0.082
isLab11	8.419	2.812	0.223	2.994	0.003
isLab12	8.430	3.540	0.179	2.382	0.018
isLab42	8.762	2.803	0.242	3.126	0.002
isLab14	8.937	3.177	0.246	2.813	0.005
isLab40	9.373	3.221	0.248	2.910	0.004
isLab9	9.431	2.846	0.260	3.314	0.001
isLab16	9.572	3.247	0.264	2.948	0.003
isLab54	9.690	3.714	0.174	2.609	0.010
isLab60	10.043	5.916	0.081	1.698	0.091
isLab28	10.317	3.413	0.234	3.023	0.003
isLab57	10.362	4.141	0.145	2.502	0.013
isLab66	10.601	4.965	0.121	2.135	0.034
isLab47	10.753	4.090	0.150	2.629	0.009
isLab17	11.222	4.157	0.157	2.699	0.007
isLab38	11.781	4.347	0.135	2.710	0.007
isLab36	14.090	4.647	0.161	3.032	0.003
isLab30	14.387	5.719	0.116	2.515	0.012
isLab8	17.180	3.440	0.365	4.995	0.000
isLab27	23.036	5.916	0.186	3.894	0.000

Table B4

General Model Variation 3: Association between Independent Variables and the Number of Technical Issues Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-12.497	4.170		-2.997	0.003
Duration	-0.605	0.954	-0.060	-0.635	0.526
AuditorsPerMod	4.548	1.147	0.231	3.966	0.000
NumMods	2.027	0.482	0.363	4.203	0.000
Oversight	-3.600	1.435	-0.115	-2.509	0.013
YearFrac	0.635	0.580	0.055	1.094	0.275
isChemLab	2.901	1.809	0.190	1.604	0.110
isRadLab	1.763	1.656	0.132	1.065	0.288
isLab39	-0.904	3.231	-0.024	-0.280	0.780
isLab33	-0.518	3.755	-0.008	-0.138	0.890
isLab35	0.079	2.801	0.002	0.028	0.978
isLab60	0.196	5.883	0.002	0.033	0.973
isLab25	0.942	6.127	0.008	0.154	0.878
isLab2	1.085	3.272	0.020	0.332	0.740
isLab20	1.463	5.703	0.012	0.256	0.798
isLab26	1.480	3.990	0.027	0.371	0.711
isLab48	1.623	6.105	0.013	0.266	0.791
isLab19	1.648	2.977	0.048	0.554	0.580
isLab44	2.406	5.955	0.020	0.404	0.686
isLab53	2.539	4.580	0.029	0.554	0.580
isLab46	2.637	3.310	0.067	0.797	0.426
isLab7	2.689	3.241	0.075	0.830	0.407
isLab32	2.711	3.955	0.062	0.686	0.494
isLab69	2.777	4.57	0.039	0.608	0.544
isLab65	3.109	4.613	0.036	0.674	0.501
isLab41	3.122	3.310	0.075	0.943	0.346
isLab14	3.194	3.159	0.089	1.011	0.313
isLab61	3.250	3.398	0.069	0.957	0.340
isLab24	3.627	3.636	0.097	0.998	0.319
isLab70	3.760	6.226	0.031	0.604	0.546
isLab5	4.038	2.815	0.112	1.435	0.153
isLab37	4.040	4.009	0.066	1.008	0.314
isLab23	4.056	2.846	0.103	1.425	0.155
isLab28	4.445	3.394	0.101	1.310	0.191
isLab21	4.941	2.889	0.137	1.711	0.088

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab43	4.982	2.976	0.120	1.674	0.095
isLab59	5.102	3.651	0.092	1.397	0.163
isLab42	5.249	2.787	0.146	1.883	0.061
isLab4	5.324	2.940	0.148	1.810	0.071
isLab11	5.371	2.796	0.143	1.921	0.056
isLab16	5.539	3.229	0.154	1.716	0.087
isLab18	5.574	2.824	0.155	1.974	0.049
isLab47	5.702	4.067	0.080	1.402	0.162
isLab49	5.728	3.532	0.114	1.622	0.106
isLab40	6.200	3.203	0.165	1.936	0.054
isLab12	6.221	3.519	0.133	1.768	0.078
isLab66	6.630	4.937	0.076	1.343	0.180
isLab57	6.665	4.118	0.094	1.618	0.107
isLab36	6.666	4.620	0.077	1.443	0.150
isLab54	7.242	3.693	0.131	1.961	0.051
isLab17	7.793	4.134	0.110	1.885	0.060
isLab13	7.948	3.246	0.221	2.449	0.015
isLab10	8.127	3.623	0.147	2.243	0.026
isLab9	8.875	2.830	0.247	3.136	0.002
isLab27	13.149	5.882	0.107	2.235	0.026
isLab38	13.242	4.322	0.153	3.064	0.002
isLab30	13.272	5.687	0.108	2.334	0.020
isLab8	13.407	3.420	0.287	3.920	0.000

Table B5

General Model Variation 4: Association between Independent Variables and the Number of Technical Findings Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-5.881	2.501		-2.352	0.019
Duration	0.009	0.572	0.002	0.015	0.988
AuditorsPerMod	2.356	0.688	0.219	3.426	0.001
NumMods	0.597	0.289	0.196	2.066	0.040
Oversight	-0.895	0.860	-0.052	-1.04	0.299
YearFrac	0.732	0.348	0.115	2.103	0.036
isChemLab	2.406	1.085	0.289	2.218	0.027
isRadLab	1.712	0.993	0.235	1.725	0.086
isLab30	-2.971	3.410	-0.044	-0.871	0.384
isLab20	-2.423	3.419	-0.036	-0.709	0.479
isLab39	-2.065	1.938	-0.101	-1.066	0.288
isLab60	-1.942	3.527	-0.029	-0.551	0.582
isLab44	-1.937	3.571	-0.029	-0.542	0.588
isLab23	-1.506	1.706	-0.070	-0.883	0.378
isLab35	-1.440	1.679	-0.070	-0.857	0.392
isLab19	-1.093	1.785	-0.058	-0.612	0.541
isLab53	-0.953	2.747	-0.020	-0.347	0.729
isLab25	-0.842	3.674	-0.013	-0.229	0.819
isLab2	-0.791	1.962	-0.026	-0.403	0.687
isLab42	-0.745	1.671	-0.038	-0.446	0.656
isLab26	-0.726	2.393	-0.024	-0.303	0.762
isLab48	-0.674	3.661	-0.010	-0.184	0.854
isLab28	-0.605	2.035	-0.025	-0.297	0.767
isLab33	-0.364	2.252	-0.011	-0.162	0.872
isLab5	-0.176	1.688	-0.009	-0.104	0.917
isLab61	-0.031	2.037	-0.001	-0.015	0.988
isLab37	0.005	2.404	0.000	0.002	0.998
isLab7	0.129	1.943	0.007	0.067	0.947
isLab65	0.178	2.766	0.004	0.064	0.949
isLab11	0.217	1.676	0.011	0.129	0.897
isLab41	0.386	1.985	0.017	0.195	0.846
isLab43	0.508	1.784	0.022	0.285	0.776
isLab46	0.581	1.984	0.027	0.293	0.770
isLab4	0.628	1.763	0.032	0.356	0.722

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab24	0.837	2.180	0.041	0.384	0.701
isLab14	0.863	1.894	0.044	0.455	0.649
isLab59	0.949	2.189	0.032	0.434	0.665
isLab27	1.004	3.527	0.015	0.285	0.776
isLab57	1.070	2.469	0.028	0.433	0.665
isLab32	1.323	2.371	0.055	0.558	0.577
isLab9	1.451	1.697	0.074	0.855	0.393
isLab70	1.469	3.733	0.022	0.393	0.694
isLab47	1.486	2.439	0.038	0.610	0.543
isLab69	1.537	2.740	0.040	0.561	0.575
isLab18	1.543	1.693	0.079	0.912	0.363
isLab16	1.798	1.936	0.091	0.929	0.354
isLab21	2.061	1.732	0.105	1.190	0.235
isLab40	2.078	1.921	0.101	1.082	0.280
isLab66	2.479	2.960	0.052	0.837	0.403
isLab12	2.512	2.110	0.098	1.190	0.235
isLab54	3.024	2.214	0.100	1.366	0.173
isLab36	3.240	2.770	0.068	1.170	0.243
isLab49	3.403	2.118	0.124	1.607	0.109
isLab10	4.015	2.173	0.133	1.848	0.066
isLab38	4.560	2.592	0.096	1.759	0.080
isLab13	4.566	1.946	0.232	2.346	0.020
isLab8	4.590	2.051	0.180	2.238	0.026
isLab17	4.643	2.479	0.120	1.873	0.062

Table B6

Comparison of Raw Performance Scores to Model-Adjusted Performance Scores Based on Audit Issues

Lab	Slope	Raw Score	Model Slope	Model Score	Diff
isLab48	-8.667	100.00%	6.516	76.52%	23.48%
isLab25	-7.167	96.39%	6.211	77.61%	18.77%
isLab70	-6.167	93.98%	9.711	65.00%	28.98%
isLab24	-5.667	92.77%	10.850	60.90%	31.88%
isLab32	-5.444	92.23%	6.926	75.04%	17.20%
isLab26	-4.167	89.16%	5.328	80.80%	8.36%
isLab66	-4.000	88.75%	16.873	39.19%	49.57%
isLab69	-3.167	86.75%	6.582	76.28%	10.47%
isLab37	-2.067	84.10%	7.540	72.82%	11.27%
isLab39	-1.750	83.33%	1.817	93.45%	-10.12%
isLab19	-0.524	80.38%	6.188	77.70%	2.68%
Lab 62	0.000	79.12%	0.000	100.00%	-20.88%
isLab43	0.933	76.87%	7.458	73.12%	3.75%
isLab33	1.533	75.42%	4.390	84.18%	-8.76%
isLab35	1.833	74.70%	1.825	93.42%	-18.72%
isLab46	2.152	73.93%	8.250	70.27%	3.66%
isLab23	3.970	69.55%	5.511	80.14%	-10.59%
isLab2	4.000	69.48%	2.498	91.00%	-21.52%
isLab59	4.667	67.87%	8.349	69.91%	-2.04%
isLab14	5.795	65.15%	11.502	58.55%	6.61%
isLab7	6.256	64.04%	6.824	75.41%	-11.36%
isLab61	6.583	63.25%	9.316	66.42%	-3.17%
isLab42	6.949	62.37%	9.147	67.03%	-4.66%
isLab41	7.433	61.20%	9.776	64.77%	-3.56%
isLab21	7.949	59.96%	8.332	69.97%	-10.01%
isLab40	9.917	55.22%	17.202	38.00%	17.22%
isLab10	10.167	54.62%	16.58	40.24%	14.37%
isLab18	10.564	53.66%	9.708	65.01%	-11.35%
isLab11	10.667	53.41%	9.149	67.03%	-13.61%
isLab28	11.222	52.07%	12.802	53.86%	-1.79%
isLab44	11.833	50.60%	5.740	79.31%	-28.71%
isLab57	14.583	43.98%	14.073	49.28%	-5.30%
isLab53	15.000	42.97%	12.984	53.20%	-10.23%
isLab47	15.083	42.77%	18.285	34.10%	8.67%
isLab4	15.103	42.72%	8.105	70.79%	-28.07%

Lab	Slope	Raw Score	Model Slope	Model Score	Diff
isLab54	15.500	41.77%	18.755	32.40%	9.36%
isLab16	15.641	41.43%	15.662	43.55%	-2.13%
isLab65	15.667	41.36%	12.350	55.49%	-14.13%
isLab13	15.949	40.68%	15.013	45.89%	-5.21%
isLab5	16.103	40.31%	10.601	61.79%	-21.48%
isLab49	16.476	39.41%	16.031	42.22%	-2.81%
isLab9	16.718	38.83%	13.155	52.59%	-13.76%
isLab30	17.833	36.14%	8.106	70.78%	-34.64%
isLab27	18.333	34.94%	27.746	0.00%	34.94%
isLab60	18.333	34.94%	12.868	53.62%	-18.68%
isLab8	19.958	31.02%	26.981	2.76%	28.27%
isLab12	21.958	26.20%	17.113	38.32%	-12.12%
isLab17	22.833	24.10%	21.721	21.71%	2.38%
isLab36	26.000	16.47%	27.510	0.85%	15.61%
isLab38	32.333	1.20%	20.587	25.80%	-24.60%
isLab20	32.833	0.00%	10.826	60.98%	-60.98%

Table B7

Comparison of Laboratory Performance Scores forFour Variations of the General Model (G1-G4)

Lab	G1	G2	G3	G4	Min	Max	Diff
isLab10	40.2%	15.2%	36.9%	8.2%	8.2%	54.6%	46.4%
isLab11	67.0%	64.4%	56.2%	58.1%	53.4%	67.0%	13.6%
isLab12	38.3%	24.0%	50.2%	28.0%	24.0%	50.2%	26.2%
isLab13	45.9%	31.8%	38.1%	1.0%	1.0%	45.9%	44.9%
isLab14	58.5%	55.1%	71.4%	49.6%	49.6%	71.4%	21.7%
isLab16	43.6%	37.2%	55.0%	37.4%	37.2%	55.0%	17.8%
isLab17	21.7%	14.8%	39.2%	0.0%	0.0%	39.2%	39.2%
isLab18	65.0%	48.1%	54.7%	40.7%	40.7%	65.0%	24.3%
isLab19	77.7%	66.2%	82.2%	75.3%	66.2%	82.2%	15.9%
isLab2	91.0%	69.1%	86.1%	71.4%	69.1%	91.0%	21.9%
isLab20	61.0%	52.6%	83.5%	92.8%	0.0%	92.8%	92.8%
isLab21	70.0%	46.1%	59.2%	33.9%	33.9%	70.0%	36.1%
isLab23	80.1%	74.9%	65.3%	80.8%	65.3%	80.8%	15.4%
isLab24	60.9%	47.3%	68.3%	50.0%	47.3%	92.8%	45.5%
isLab25	77.6%	56.7%	87.1%	72.0%	56.7%	96.4%	39.7%
isLab26	80.8%	62.8%	83.3%	70.5%	62.8%	89.2%	26.4%
isLab27	0.0%	44.2%	1.8%	47.8%	0.0%	47.8%	47.8%
isLab28	53.9%	55.5%	62.6%	68.9%	52.1%	68.9%	16.9%
isLab30	70.8%	100.0%	0.9%	100.0%	0.9%	100.0%	99.1%
isLab32	75.0%	49.7%	74.7%	43.6%	43.6%	92.2%	48.6%
isLab33	84.2%	51.0%	97.3%	65.8%	51.0%	97.3%	46.3%
isLab35	93.4%	77.0%	93.1%	79.9%	74.7%	93.4%	18.7%
isLab36	0.9%	0.0%	47.1%	18.4%	0.0%	47.1%	47.1%
isLab37	72.8%	58.4%	65.5%	60.9%	58.4%	84.1%	25.7%
isLab38	25.8%	23.4%	1.2%	1.1%	1.1%	25.8%	24.7%
isLab39	93.5%	72.7%	100.0%	88.1%	72.7%	100.0%	27.3%
isLab4	70.8%	65.4%	56.5%	52.7%	42.7%	70.8%	28.1%
isLab40	38.0%	28.4%	50.4%	33.7%	28.4%	55.2%	26.8%
isLab41	64.8%	47.5%	71.9%	55.9%	47.5%	71.9%	24.4%
isLab42	67.0%	66.2%	57.0%	70.8%	57.0%	70.8%	13.8%
isLab43	73.1%	62.0%	58.9%	54.3%	54.3%	76.9%	22.6%
isLab44	79.3%	79.0%	76.9%	86.4%	50.6%	86.4%	35.8%
isLab46	70.3%	47.9%	75.3%	53.3%	47.9%	75.3%	27.4%
isLab47	34.1%	29.9%	53.8%	41.5%	29.9%	53.8%	24.0%
isLab48	76.5%	65.0%	82.3%	69.8%	65.0%	100.0%	35.0%
isLab49	42.2%	19.2%	53.7%	16.3%	16.3%	53.7%	37.4%

Lab	G1	G2	G3	G4	Min	Max	Diff
isLab5	61.8%	47.6%	65.5%	63.3%	40.3%	65.5%	25.2%
isLab53	53.2%	43.0%	75.9%	73.5%	43.0%	75.9%	33.0%
isLab54	32.4%	22.1%	43.1%	21.3%	21.3%	43.1%	21.8%
isLab57	49.3%	49.3%	47.1%	46.9%	44.0%	49.3%	5.3%
isLab59	69.9%	51.6%	58.0%	48.5%	48.5%	69.9%	21.4%
isLab60	53.6%	53.8%	92.3%	86.5%	34.9%	92.3%	57.4%
isLab61	66.4%	52.7%	71.0%	61.4%	52.7%	71.0%	18.3%
isLab65	55.5%	30.3%	72.0%	58.6%	30.3%	72.0%	41.6%
isLab66	39.2%	36.3%	47.4%	28.4%	28.4%	88.8%	60.3%
isLab69	76.3%	47.5%	74.3%	40.8%	40.8%	86.7%	46.0%
isLab7	75.4%	55.3%	74.9%	59.3%	55.3%	75.4%	20.1%
isLab70	65.0%	38.0%	67.4%	41.7%	38.0%	94.0%	55.9%
isLab8	2.8%	18.4%	0.0%	0.7%	0.0%	31.0%	31.0%
isLab9	52.6%	49.2%	31.7%	41.9%	31.7%	52.6%	20.9%
Lab62	100.0%	68.1%	93.7%	61.0%	61.0%	100.0%	39.0%

APPENDIX C

CHEMISTRY LABORATORIES MODEL RESULTS

Table C1

Chemistry Laboratories Model Variation 1: Association between Independent Variables and the Number of Issues Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-23.519	7.577		-3.104	0.002
Duration	0.223	1.812	0.011	0.123	0.902
AuditorsPerMod	10.278	2.823	0.245	3.641	0.000
NumMods	4.345	0.905	0.362	4.803	0.000
Oversight	-6.434	2.657	-0.133	-2.421	0.016
YearFrac	1.653	1.698	0.065	0.974	0.331
isLab26	-1.825	9.191	-0.015	-0.199	0.843
isLab39	-0.462	4.659	-0.009	-0.099	0.921
isLab37	1.119	10.035	0.006	0.112	0.911
isLab35	1.290	4.619	0.024	0.279	0.780
isLab2	1.875	5.393	0.024	0.348	0.729
isLab33	2.167	6.440	0.021	0.337	0.737
isLab25	3.616	10.120	0.021	0.357	0.721
isLab7	3.754	4.740	0.072	0.792	0.429
isLab23	4.489	4.716	0.079	0.952	0.342
isLab46	4.735	5.043	0.079	0.939	0.349
isLab19	5.517	6.056	0.062	0.911	0.363
isLab4	5.612	5.139	0.108	1.092	0.276
isLab43	5.665	5.016	0.095	1.130	0.260
isLab44	5.686	9.955	0.032	0.571	0.568
isLab21	6.339	4.670	0.117	1.357	0.176
isLab59	6.485	5.423	0.082	1.196	0.233
isLab30	7.768	9.368	0.044	0.829	0.408
isLab41	8.019	4.759	0.134	1.685	0.093
isLab11	8.232	4.632	0.152	1.777	0.077
isLab18	8.285	4.597	0.159	1.802	0.073
isLab42	8.370	4.634	0.155	1.806	0.072
isLab24	8.636	6.495	0.119	1.330	0.185
isLab5	9.568	4.699	0.184	2.036	0.043
isLab20	9.921	9.414	0.056	1.054	0.293
isLab28	10.215	4.952	0.162	2.063	0.040

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab60	10.734	9.331	0.061	1.150	0.251
isLab65	11.123	7.096	0.089	1.568	0.119
isLab57	11.845	6.332	0.116	1.871	0.063
isLab9	12.014	4.742	0.231	2.534	0.012
isLab13	12.677	4.634	0.244	2.736	0.007
isLab16	13.552	4.586	0.261	2.955	0.003
isLab49	13.802	5.202	0.190	2.653	0.009
isLab12	14.211	5.210	0.211	2.728	0.007
isLab17	18.888	6.328	0.185	2.985	0.003
isLab38	19.963	7.116	0.160	2.805	0.006
isLab53	22.040	9.329	0.125	2.362	0.019
isLab54	23.221	6.198	0.228	3.746	0.000
isLab36	25.519	7.122	0.205	3.583	0.000
isLab27	25.612	9.327	0.146	2.746	0.007

Table C2

Chemistry Laboratories Model Variation 2: Association between Independent Variables and the Number of Findings Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-9.800	4.668		-2.100	0.037
Duration	0.808	1.116	0.068	0.724	0.470
AuditorsPerMod	5.792	1.739	0.247	3.331	0.001
NumMods	1.484	0.557	0.221	2.663	0.008
Oversight	-1.078	1.637	-0.040	-0.658	0.511
YearFrac	1.136	1.046	0.080	1.087	0.279
isLab30	-6.513	5.771	-0.066	-1.129	0.260
isLab37	-4.047	6.181	-0.041	-0.655	0.513
isLab26	-3.606	5.662	-0.052	-0.637	0.525
isLab39	-3.114	2.870	-0.103	-1.085	0.279
isLab44	-2.513	6.132	-0.026	-0.410	0.682
isLab35	-2.151	2.845	-0.071	-0.756	0.451
isLab23	-2.097	2.905	-0.066	-0.722	0.471
isLab4	-1.399	3.165	-0.048	-0.442	0.659
isLab2	-0.656	3.322	-0.015	-0.197	0.844
isLab7	-0.318	2.920	-0.011	-0.109	0.913
isLab19	-0.177	3.730	-0.004	-0.047	0.962
isLab43	-0.134	3.090	-0.004	-0.043	0.965
isLab42	-0.097	2.854	-0.003	-0.034	0.973
isLab11	-0.008	2.853	0.000	-0.003	0.998
isLab28	0.020	3.050	0.001	0.006	0.995
isLab25	0.055	6.234	0.001	0.009	0.993
isLab60	0.644	5.748	0.007	0.112	0.911
isLab46	0.961	3.106	0.029	0.309	0.757
isLab57	1.365	3.900	0.024	0.350	0.727
isLab59	1.446	3.341	0.033	0.433	0.665
isLab33	1.638	3.967	0.029	0.413	0.680
isLab41	2.337	2.931	0.070	0.797	0.426
isLab24	2.358	4.001	0.058	0.589	0.556
isLab20	2.429	5.799	0.025	0.419	0.676
isLab27	2.560	5.745	0.026	0.446	0.656
isLab18	2.655	2.832	0.091	0.938	0.350
isLab21	2.768	2.877	0.091	0.962	0.337
isLab9	2.847	2.921	0.098	0.975	0.331
isLab5	3.251	2.895	0.112	1.123	0.263

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab16	4.007	2.825	0.138	1.418	0.158
isLab13	4.916	2.855	0.169	1.722	0.087
isLab65	6.033	4.371	0.086	1.380	0.169
isLab12	6.036	3.209	0.160	1.881	0.061
isLab49	7.464	3.204	0.184	2.329	0.021
isLab17	7.799	3.898	0.137	2.001	0.047
isLab38	8.368	4.383	0.120	1.909	0.058
isLab53	9.167	5.747	0.093	1.595	0.112
isLab54	11.229	3.818	0.197	2.941	0.004
isLab36	11.373	4.387	0.163	2.592	0.010

Table C3

Chemistry Laboratories Model Variation 3: Association between Independent Variables and the Number of Technical Issues Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-9.999	4.973		-2.010	0.046
Duration	-0.631	1.189	-0.049	-0.531	0.596
AuditorsPerMod	6.642	1.853	0.262	3.585	0.000
NumMods	2.142	0.594	0.295	3.607	0.000
Oversight	-3.243	1.744	-0.111	-1.859	0.064
YearFrac	0.651	1.114	0.042	0.584	0.560
isLab39	-3.144	3.058	-0.096	-1.028	0.305
isLab33	-2.428	4.227	-0.039	-0.574	0.566
isLab60	-1.892	6.124	-0.018	-0.309	0.758
isLab37	-1.427	6.586	-0.013	-0.217	0.829
isLab25	-0.970	6.642	-0.009	-0.146	0.884
isLab26	-0.658	6.033	-0.009	-0.109	0.913
isLab35	-0.323	3.032	-0.010	-0.106	0.915
isLab7	-0.049	3.111	-0.002	-0.016	0.988
isLab46	0.012	3.310	0.000	0.004	0.997
isLab20	0.556	6.179	0.005	0.090	0.928
isLab2	0.643	3.540	0.013	0.182	0.856
isLab41	1.127	3.123	0.031	0.361	0.719
isLab19	1.373	3.975	0.026	0.345	0.730
isLab65	1.433	4.657	0.019	0.308	0.759
isLab28	1.932	3.250	0.051	0.594	0.553
isLab24	1.983	4.263	0.045	0.465	0.642
isLab44	2.434	6.534	0.023	0.373	0.710
isLab5	3.175	3.084	0.101	1.030	0.304
isLab59	3.175	3.560	0.066	0.892	0.373
isLab16	3.217	3.010	0.102	1.069	0.286
isLab21	3.328	3.065	0.102	1.086	0.279
isLab12	3.352	3.419	0.082	0.980	0.328
isLab49	3.531	3.414	0.080	1.034	0.302
isLab23	3.544	3.095	0.103	1.145	0.254
isLab4	3.551	3.373	0.113	1.053	0.294
isLab43	4.290	3.292	0.119	1.303	0.194
isLab18	4.353	3.017	0.139	1.443	0.151
isLab42	4.377	3.042	0.134	1.439	0.152
isLab36	4.521	4.675	0.060	0.967	0.335
isLab57	4.619	4.156	0.075	1.111	0.268

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab11	4.855	3.040	0.148	1.597	0.112
isLab17	5.178	4.153	0.084	1.247	0.214
isLab13	5.431	3.042	0.173	1.786	0.076
isLab53	6.835	6.123	0.064	1.116	0.266
isLab54	6.974	4.068	0.113	1.714	0.088
isLab9	7.922	3.112	0.252	2.545	0.012
isLab27	11.060	6.122	0.104	1.807	0.072
isLab30	12.716	6.149	0.120	2.068	0.040
isLab38	12.799	4.670	0.170	2.740	0.007

Table C4

Chemistry Laboratories Model Variation 4: Association between Independent Variables and the Number of Technical Findings Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-3.326	2.966		-1.121	0.263
Duration	0.206	0.709	0.029	0.290	0.772
AuditorsPerMod	4.043	1.105	0.288	3.659	0.000
NumMods	0.573	0.354	0.143	1.617	0.107
Oversight	-0.532	1.040	-0.033	-0.511	0.610
YearFrac	0.490	0.664	0.057	0.738	0.461
isLab39	-4.241	1.824	-0.234	-2.326	0.021
isLab37	-4.152	3.928	-0.071	-1.057	0.292
isLab60	-4.057	3.652	-0.069	-1.111	0.268
isLab30	-3.285	3.667	-0.056	-0.896	0.371
isLab20	-2.998	3.685	-0.051	-0.814	0.417
isLab28	-2.978	1.938	-0.141	-1.536	0.126
isLab25	-2.576	3.961	-0.044	-0.650	0.516
isLab7	-2.452	1.855	-0.141	-1.322	0.188
isLab26	-2.431	3.598	-0.058	-0.676	0.500
isLab44	-2.325	3.896	-0.039	-0.597	0.551
isLab23	-1.979	1.846	-0.104	-1.072	0.285
isLab19	-1.814	2.370	-0.061	-0.765	0.445
isLab33	-1.765	2.521	-0.052	-0.700	0.485
isLab35	-1.726	1.808	-0.095	-0.955	0.341
isLab46	-1.722	1.974	-0.086	-0.872	0.384
isLab65	-1.509	2.777	-0.036	-0.543	0.588
isLab41	-1.494	1.863	-0.075	-0.802	0.423
isLab2	-1.123	2.111	-0.042	-0.532	0.595
isLab42	-1.106	1.814	-0.061	-0.610	0.543
isLab57	-1.102	2.478	-0.032	-0.445	0.657
isLab27	-1.094	3.651	-0.019	-0.300	0.765
isLab59	-0.933	2.123	-0.035	-0.440	0.661
isLab24	-0.806	2.542	-0.033	-0.317	0.751
isLab4	-0.798	2.011	-0.046	-0.397	0.692
isLab5	-0.795	1.839	-0.046	-0.432	0.666
isLab16	-0.397	1.795	-0.023	-0.221	0.825
isLab53	-0.263	3.651	-0.004	-0.072	0.943
isLab11	-0.242	1.813	-0.013	-0.133	0.894
isLab43	-0.154	1.963	-0.008	-0.079	0.937

Variable	B	Std. Error	Beta	t	Sig. (p)
isLab12	-0.031	2.039	-0.001	-0.015	0.988
isLab18	0.436	1.799	0.025	0.243	0.809
isLab21	0.667	1.828	0.037	0.365	0.716
isLab9	0.762	1.856	0.044	0.411	0.682
isLab36	1.143	2.788	0.027	0.410	0.682
isLab49	1.262	2.036	0.052	0.620	0.536
isLab54	2.082	2.426	0.061	0.858	0.392
isLab17	2.142	2.477	0.063	0.865	0.388
isLab13	2.277	1.814	0.131	1.255	0.211
isLab38	4.244	2.785	0.102	1.524	0.129

APPENDIX D

RADIATION LABORATORIES MODEL RESULTS

Table D1

Radiation Laboratories Model Variation 1: Association between Independent Variables and the Number of Issues Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-32.374	9.825		-3.295	0.001
Duration	1.763	2.444	0.065	0.722	0.472
AuditorsPerMod	8.041	2.632	0.246	3.055	0.003
NumMods	5.555	1.122	0.580	4.952	0.000
Oversight	-6.292	3.236	-0.124	-1.944	0.054
YearFrac	1.854	1.268	0.101	1.463	0.146
isLab35	1.696	4.862	0.037	0.349	0.728
isLab2	2.080	5.656	0.031	0.368	0.714
isLab44	2.364	10.876	0.016	0.217	0.828
isLab19	4.525	5.339	0.098	0.848	0.398
isLab23	5.352	4.927	0.111	1.086	0.279
isLab4	5.772	5.409	0.130	1.067	0.288
isLab18	6.650	5.180	0.124	1.284	0.201
isLab30	6.768	9.867	0.045	0.686	0.494
isLab33	6.933	10.187	0.046	0.681	0.497
isLab61	8.425	5.406	0.147	1.558	0.121
isLab42	8.431	4.953	0.174	1.702	0.091
isLab43	8.679	5.214	0.171	1.665	0.098
isLab11	9.021	4.833	0.195	1.866	0.064
isLab20	9.277	9.924	0.062	0.935	0.351
isLab37	9.336	7.359	0.124	1.269	0.207
isLab5	9.460	4.976	0.213	1.901	0.059
isLab48	10.209	11.145	0.068	0.916	0.361
isLab14	10.470	5.001	0.235	2.093	0.038
isLab9	11.897	5.030	0.268	2.365	0.019
isLab21	12.381	5.490	0.200	2.255	0.026
isLab10	15.618	5.761	0.231	2.711	0.008
isLab40	16.189	5.033	0.350	3.217	0.002
isLab47	18.695	6.932	0.216	2.697	0.008
isLab38	20.155	7.462	0.190	2.701	0.008
isLab53	23.409	9.773	0.157	2.395	0.018
isLab8	25.946	5.383	0.452	4.820	0.000

Table D2

Radiation Laboratories Model Variation 2: Association between Independent Variables and the Number of Findings Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-15.731	5.652		-2.783	0.006
Duration	2.223	1.406	0.153	1.581	0.116
AuditorsPerMod	3.256	1.514	0.184	2.151	0.033
NumMods	2.062	0.645	0.398	3.195	0.002
Oversight	-0.659	1.861	-0.024	-0.354	0.724
YearFrac	2.015	0.729	0.203	2.764	0.006
islab30	-6.680	5.676	-0.083	-1.177	0.241
islab44	-5.456	6.256	-0.068	-0.872	0.385
islab35	-1.566	2.797	-0.063	-0.560	0.576
islab23	-1.468	2.834	-0.056	-0.518	0.605
islab19	-0.937	3.071	-0.037	-0.305	0.761
islab4	-0.425	3.111	-0.018	-0.137	0.891
islab2	-0.265	3.253	-0.007	-0.081	0.935
islab42	-0.006	2.849	0.000	-0.002	0.998
islab11	0.817	2.780	0.033	0.294	0.769
islab14	1.216	2.877	0.051	0.423	0.673
islab61	1.625	3.110	0.052	0.523	0.602
islab37	1.941	4.233	0.048	0.459	0.647
islab43	1.995	2.999	0.072	0.665	0.507
islab48	2.594	6.411	0.032	0.405	0.686
islab20	2.614	5.709	0.032	0.458	0.648
islab18	3.050	2.980	0.105	1.024	0.308
islab9	3.458	2.893	0.144	1.195	0.234
islab5	3.790	2.862	0.158	1.324	0.188
islab33	4.096	5.860	0.051	0.699	0.486
islab40	6.341	2.895	0.253	2.190	0.030
islab21	6.533	3.158	0.195	2.069	0.040
islab47	7.344	3.987	0.157	1.842	0.068
islab8	8.153	3.097	0.263	2.633	0.009
islab38	8.700	4.292	0.152	2.027	0.044
islab10	8.950	3.314	0.245	2.701	0.008
islab53	9.934	5.622	0.123	1.767	0.079

Table D3

Radiation Laboratories Model Variation 3: Association between Independent Variables and the Number of Technical Issues Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-18.126	6.560		-2.763	0.006
Duration	0.876	1.632	0.050	0.537	0.592
AuditorsPerMod	5.958	1.757	0.282	3.391	0.001
NumMods	3.027	0.749	0.489	4.041	0.000
Oversight	-2.609	2.160	-0.079	-1.208	0.229
YearFrac	0.562	0.846	0.047	0.664	0.507
isLab33	-1.114	6.801	-0.012	-0.164	0.870
isLab44	-0.756	7.261	-0.008	-0.104	0.917
isLab19	-0.706	3.565	-0.024	-0.198	0.843
isLab20	-0.250	6.626	-0.003	-0.038	0.970
isLab35	-0.178	3.246	-0.006	-0.055	0.956
isLab2	0.603	3.776	0.014	0.160	0.873
isLab14	0.875	3.339	0.030	0.262	0.794
isLab61	1.167	3.610	0.031	0.323	0.747
isLab4	2.702	3.611	0.094	0.748	0.456
isLab5	2.729	3.322	0.095	0.821	0.413
isLab23	3.861	3.289	0.123	1.174	0.242
isLab18	3.897	3.458	0.112	1.127	0.262
isLab40	3.948	3.360	0.132	1.175	0.242
isLab48	4.253	7.441	0.044	0.572	0.568
isLab42	4.531	3.307	0.145	1.370	0.173
isLab47	4.832	4.628	0.086	1.044	0.298
isLab11	5.167	3.227	0.173	1.601	0.111
isLab37	5.382	4.913	0.111	1.095	0.275
isLab10	5.976	3.846	0.137	1.554	0.122
isLab43	6.209	3.481	0.189	1.784	0.077
isLab21	7.011	3.666	0.175	1.913	0.058
isLab9	7.426	3.358	0.258	2.211	0.029
isLab53	7.701	6.525	0.080	1.180	0.240
isLab8	11.294	3.594	0.304	3.142	0.002
isLab30	11.789	6.588	0.122	1.790	0.076
isLab38	12.765	4.982	0.187	2.562	0.011

Table D4

Radiation Laboratories Model Variation 4: Association between Independent Variables and the Number of Technical Findings Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-9.105	3.839		-2.372	0.019
Duration	1.501	0.955	0.163	1.572	0.118
AuditorsPerMod	2.549	1.028	0.228	2.479	0.014
NumMods	1.128	0.438	0.345	2.572	0.011
Oversight	-0.087	1.264	-0.005	-0.069	0.945
YearFrac	0.886	0.495	0.141	1.788	0.076
isLab44	-5.027	4.250	-0.099	-1.183	0.239
isLab30	-3.643	3.856	-0.071	-0.945	0.346
isLab20	-3.140	3.878	-0.062	-0.810	0.419
isLab19	-2.583	2.086	-0.163	-1.238	0.218
isLab61	-1.778	2.113	-0.091	-0.841	0.401
isLab23	-1.582	1.925	-0.096	-0.822	0.413
isLab33	-1.410	3.981	-0.028	-0.354	0.724
isLab35	-1.368	1.900	-0.086	-0.720	0.473
isLab42	-1.011	1.936	-0.061	-0.523	0.602
isLab2	-0.936	2.210	-0.041	-0.423	0.673
isLab14	-0.883	1.954	-0.058	-0.452	0.652
isLab5	-0.654	1.944	-0.043	-0.336	0.737
isLab4	-0.604	2.113	-0.040	-0.286	0.775
isLab40	0.241	1.967	0.015	0.122	0.903
isLab11	0.268	1.889	0.017	0.142	0.887
isLab53	0.388	3.819	0.008	0.102	0.919
isLab37	0.508	2.876	0.020	0.177	0.860
isLab9	0.925	1.966	0.061	0.471	0.639
isLab47	0.939	2.709	0.032	0.347	0.729
isLab48	1.246	4.355	0.024	0.286	0.775
isLab43	1.527	2.037	0.088	0.749	0.455
isLab18	1.636	2.024	0.089	0.808	0.420
isLab10	2.193	2.251	0.095	0.974	0.332
isLab8	2.719	2.103	0.139	1.292	0.198
isLab21	3.068	2.145	0.145	1.430	0.155
isLab38	4.405	2.916	0.122	1.511	0.133

APPENDIX E

FULL-SERVICE LABORATORIES MODEL RESULTS

Table E1

Full-Service Laboratories Model Variation 1: Association between Independent Variables and the Number of Issues Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-36.047	14.775		-2.440	0.017
Duration	2.277	3.281	0.073	0.694	0.489
AuditorsPerMod	11.585	4.371	0.278	2.651	0.009
NumMods	5.558	1.751	0.423	3.173	0.002
Oversight	-6.090	4.491	-0.125	-1.356	0.178
YearFrac	1.184	4.675	0.021	0.253	0.801
isLab35	1.140	5.250	0.029	0.217	0.829
isLab44	1.335	12.318	0.011	0.108	0.914
isLab2	1.371	6.074	0.024	0.226	0.822
isLab4	2.779	6.512	0.073	0.427	0.670
isLab37	4.282	12.585	0.034	0.340	0.734
isLab23	4.436	5.359	0.108	0.828	0.410
isLab18	5.544	5.663	0.121	0.979	0.330
isLab19	5.982	7.236	0.094	0.827	0.410
isLab30	6.040	10.653	0.048	0.567	0.572
isLab43	7.404	6.206	0.171	1.193	0.236
isLab42	7.873	5.371	0.182	1.466	0.146
isLab20	8.013	10.735	0.064	0.747	0.457
isLab11	8.052	5.260	0.204	1.531	0.129
isLab5	8.106	5.541	0.213	1.463	0.147
isLab9	10.389	5.658	0.273	1.836	0.069
isLab21	10.589	6.297	0.186	1.682	0.096
isLab38	19.491	7.990	0.219	2.439	0.017
isLab53	22.857	10.573	0.182	2.162	0.033

Table E2

Full-Service Laboratories Model Variation 2: Association between Independent Variables and the Number of Findings Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-15.146	8.355		-1.813	0.073
Duration	2.233	1.855	0.134	1.203	0.232
AuditorsPerMod	6.596	2.471	0.296	2.669	0.009
NumMods	1.595	0.990	0.227	1.611	0.111
Oversight	-0.776	2.540	-0.030	-0.305	0.761
YearFrac	1.040	2.644	0.035	0.393	0.695
isLab30	-6.810	6.024	-0.102	-1.131	0.261
isLab44	-5.383	6.966	-0.080	-0.773	0.442
isLab37	-3.161	7.116	-0.047	-0.444	0.658
isLab4	-2.649	3.682	-0.131	-0.719	0.474
isLab23	-2.420	3.030	-0.110	-0.799	0.426
isLab35	-2.080	2.969	-0.099	-0.701	0.485
isLab2	-0.839	3.434	-0.028	-0.244	0.808
isLab19	-0.594	4.092	-0.018	-0.145	0.885
isLab42	-0.301	3.037	-0.013	-0.099	0.921
isLab11	-0.205	2.975	-0.010	-0.069	0.945
isLab43	0.026	3.509	0.001	0.007	0.994
isLab20	2.007	6.070	0.030	0.331	0.742
isLab18	2.192	3.202	0.090	0.685	0.495
isLab9	2.415	3.199	0.119	0.755	0.452
isLab5	2.861	3.133	0.141	0.913	0.363
isLab21	5.540	3.561	0.182	1.556	0.123
isLab38	8.191	4.518	0.172	1.813	0.073
isLab53	9.117	5.979	0.136	1.525	0.131

Table E3

Full-Service Laboratories Model Variation 3: Association between Independent Variables and the Number of Technical Issues Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-24.653	10.257		-2.403	0.018
Duration	1.527	2.278	0.074	0.670	0.504
AuditorsPerMod	7.561	3.034	0.276	2.492	0.014
NumMods	3.776	1.216	0.438	3.106	0.002
Oversight	-2.225	3.118	-0.070	-0.713	0.477
YearFrac	0.279	3.246	0.008	0.086	0.932
isLab44	-2.208	8.552	-0.027	-0.258	0.797
isLab20	-1.720	7.452	-0.021	-0.231	0.818
isLab35	-0.528	3.644	-0.020	-0.145	0.885
isLab2	0.133	4.216	0.004	0.031	0.975
isLab4	0.513	4.521	0.021	0.113	0.910
isLab5	1.533	3.847	0.061	0.398	0.691
isLab19	2.131	5.023	0.051	0.424	0.672
isLab37	2.137	8.737	0.026	0.245	0.807
isLab18	3.062	3.931	0.102	0.779	0.438
isLab23	3.673	3.720	0.136	0.987	0.326
isLab42	4.165	3.728	0.147	1.117	0.267
isLab11	4.853	3.652	0.187	1.329	0.187
isLab21	6.033	4.371	0.161	1.380	0.171
isLab9	6.098	3.928	0.244	1.552	0.124
isLab43	6.821	4.308	0.240	1.583	0.117
isLab53	8.045	7.340	0.098	1.096	0.276
isLab30	10.563	7.395	0.128	1.428	0.156
isLab38	12.314	5.547	0.211	2.220	0.029

Table E4

Full-Service Laboratories Model Variation 4: Association between Independent Variables and the Number of Technical Findings Identified During an Audit

Variable	B	Std. Error	Beta	t	Sig. (p)
(Constant)	-9.797	5.835		-1.679	0.096
Duration	1.506	1.296	0.139	1.162	0.248
AuditorsPerMod	4.775	1.726	0.330	2.766	0.007
NumMods	0.982	0.692	0.215	1.419	0.159
Oversight	0.227	1.774	0.013	0.128	0.898
YearFrac	0.512	1.846	0.026	0.277	0.782
isLab44	-5.007	4.865	-0.115	-1.029	0.306
isLab30	-3.921	4.207	-0.090	-0.932	0.354
isLab20	-3.759	4.239	-0.086	-0.887	0.378
isLab37	-3.263	4.970	-0.075	-0.656	0.513
isLab4	-2.278	2.572	-0.173	-0.886	0.378
isLab23	-2.205	2.116	-0.154	-1.042	0.300
isLab19	-2.107	2.858	-0.096	-0.737	0.463
isLab35	-1.759	2.073	-0.128	-0.848	0.398
isLab5	-1.385	2.188	-0.105	-0.633	0.528
isLab2	-1.352	2.399	-0.068	-0.563	0.574
isLab42	-1.103	2.121	-0.074	-0.520	0.604
isLab11	-0.360	2.078	-0.026	-0.173	0.863
isLab53	-0.087	4.176	-0.002	-0.021	0.983
isLab9	0.111	2.235	0.008	0.050	0.961
isLab43	0.435	2.451	0.029	0.178	0.859
isLab18	1.013	2.236	0.064	0.453	0.652
isLab21	2.381	2.487	0.120	0.957	0.341
isLab38	4.014	3.156	0.130	1.272	0.206

APPENDIX F

SOURCE DATA

Table F1

Source Data: DOECAP Audit Results FY2000 – FY2012.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/i	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
1	2	4	0	1	1	1	1	1	0	1	0	0	0	5	0	0	0	0	0	0	0
2	2	4	0	1	1	1	1	1	0	1	0	0	0	5	0	5	1	0	0	0	0
3	2	5	0	1	1	1	1	1	0	1	0	0	0	5	0	3	2	0	1	0	0
4	2	5	0	1	1	1	1	1	0	1	0	0	0	5	0	2	3	0	1	4	0
5	2	7	0	1	1	1	1	1	1	0	0	0	0	5	0	0	0	0	2	3	0
6	2	7	0	1	1	1	1	1	1	1	0	0	0	6	0	4	0	0	2	0	0
7	3	8	0	0	1	1	1	1	1	1	0	0	0	5	0	5	2	4	0	0	0
8	4	10	1	1	1	1	1	1	1	1	0	0	0	6	0	1	0	0	6	6	0
9	4	10	1	1	1	1	1	1	1	1	0	0	0	6	0	1	3	0	4	3	0
10	4	9	0	1	1	1	1	1	1	1	0	0	0	6	0	1	3	0	0	1	0
11	4	9	0	1	1	1	1	1	0	1	0	0	0	5	0	3	5	0	0	1	0
12	4	7	0	1	1	1	1	1	1	1	0	0	0	6	0	0	3	0	1	1	0
13	4	10	0	1	1	1	1	1	1	1	0	0	0	6	0	2	1	0	3	2	0
14	4	9	0	1	1	1	1	1	0	1	0	0	0	5	0	2	0	0	2	3	0
15	4	8	0	1	1	1	1	1	0	1	0	0	0	5	0	0	2	0	1	4	0
16	4	7	0	1	1	1	1	1	1	1	0	0	0	6	0	4	1	0	2	2	0
17	4	6	0	1	1	1	1	1	0	1	0	0	0	5	0	3	3	0	2	3	0
18	4	7	0	1	1	1	1	1	1	1	0	0	0	6	0	2	2	0	3	3	0
19	4	15	0	1	1	1	1	1	1	1	0	0	0	6	0	4	0	0	9	0	0
20	4	9	0	1	1	1	1	1	1	1	0	0	0	6	0	5	2	0	1	5	0
21	5	7	0	1	1	1	1	1	0	1	0	0	0	5	0	1	0	0	0	0	0
22	5	7	0	1	1	1	1	1	1	1	0	0	0	6	0	7	1	0	0	1	0
23	5	7	0	1	1	1	1	1	1	1	0	0	0	6	0	4	0	0	1	4	0
24	5	7	0	1	1	1	1	1	1	1	0	0	0	6	0	1	2	0	1	2	0
25	5	6	0	1	1	1	1	1	0	1	0	0	0	5	0	4	3	0	0	0	0
26	5	8	0	1	1	1	1	1	1	1	0	0	0	6	0	3	1	0	2	0	0
27	5	7	0	1	1	1	1	1	0	1	0	0	0	5	0	5	5	0	3	2	0
28	5	6	0	1	1	1	1	1	1	1	0	0	0	6	0	3	2	0	0	0	0
29	5	5	0	1	1	1	1	1	0	1	0	0	0	5	0	5	4	0	4	3	0
30	5	4	0	1	1	1	1	1	1	1	0	0	0	6	0	2	3	0	1	0	0
31	5	6	0	1	1	1	1	1	0	1	0	0	0	5	0	0	3	0	1	2	0
32	5	8	0	1	1	1	1	1	1	1	0	0	0	6	0	4	3	0	5	10	0
33	5	8	0	0	1	1	1	1	1	1	0	0	0	5	0	5	1	0	0	10	0
34	6	6	0	1	1	1	1	0	1	1	0	0	0	5	1	5	1	0	3	1	1
35	7	6	0	1	1	1	1	0	0	1	0	0	0	4	0	4	3	0	2	0	0
36	7	5	0	1	1	1	1	0	0	1	0	0	0	4	0	2	0	0	1	1	0
37	7	5	0	1	1	1	1	0	1	1	0	0	0	5	0	0	1	0	3	0	0
38	7	4	0	1	1	1	1	0	1	1	0	0	0	5	0	3	1	0	2	4	0
39	7	3	0	1	1	1	1	0	0	0	0	0	0	3	0	2	1	0	0	2	0
40	7	6	0	1	1	1	1	0	0	1	0	0	0	4	0	2	2	0	1	0	0

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	1	1	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
3	1	1	0	5	5	0	0	2	0	1	5	0	0	0	0	0	0	0	0	0	0	0
4	1	1	0	1	1	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
5	1	0	0	3	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
6	3	0	0	1	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0
7	2	2	0	7	0	0	2	0	0	7	2	0	0	0	0	0	0	0	0	0	0	0
8	1	0	1	0	4	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0
9	1	0	1	3	1	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0
11	3	2	0	2	3	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
12	1	1	0	1	1	0	1	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0
13	3	4	0	4	6	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
14	1	4	0	1	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
15	1	2	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
16	2	2	0	1	3	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
17	3	2	0	2	0	0	0	6	0	1	2	0	0	0	0	0	0	0	0	0	0	0
18	1	3	0	2	9	0	0	5	0	4	7	0	0	0	0	0	0	0	0	0	0	0
19	7	7	0	4	7	0	0	4	0	5	11	0	0	0	0	0	0	0	0	0	0	0
20	3	3	0	3	0	0	3	0	0	5	1	0	0	0	0	0	0	0	0	0	0	0
21	1	1	1	1	0	0	1	3	0	1	0	0	0	0	0	0	0	0	0	0	0	0
22	3	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
23	0	1	0	1	3	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	1	0	1	3	0	0	1	0	4	3	0	0	0	0	0	0	0	0	0	0	0
25	0	2	0	1	2	0	0	0	0	4	1	0	0	0	0	0	0	0	0	0	0	0
26	1	7	0	2	2	0	4	1	0	4	9	0	0	0	0	0	0	0	0	0	0	0
27	1	2	0	4	4	0	0	0	0	6	7	0	0	0	0	0	0	0	0	0	0	0
28	2	1	0	0	0	0	1	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0
29	1	4	0	4	1	0	0	1	0	8	3	0	0	0	0	0	0	0	0	0	0	0
30	2	3	0	2	4	0	2	1	0	2	1	0	0	0	0	0	0	0	0	0	0	0
31	0	1	0	2	5	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
32	1	3	0	10	6	0	1	4	0	3	3	0	0	0	0	0	0	0	0	0	0	0
33	0	3	0	5	1	0	1	0	0	11	2	0	0	0	0	0	0	0	0	0	0	0
34	3	0	0	0	0	0	2	0	2	8	0	0	0	0	0	0	0	0	0	0	0	0
35	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
36	4	2	0	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
37	0	0	0	0	0	0	1	1	0	7	3	0	0	0	0	0	0	0	0	0	0	0
38	1	2	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
39	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	1	1	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
1	0	0	0	0	0	0	0	0	3	0.80	1.127
2	0	10	3	8	2	0	8	2	3	0.80	1.034
3	0	26	13	11	7	0	11	15	3	1.00	1.055
4	0	17	9	6	3	0	6	11	3	1.00	1.033
5	0	11	9	7	6	0	7	4	3	1.40	1.114
6	0	18	6	18	6	0	18	0	3	1.17	
7	0	33	15	27	13	4	23	6	2	1.60	
8	0	24	18	11	8	1	10	13	3	1.67	1.034
9	0	20	13	12	9	1	11	8	3	1.67	0.940
10	0	8	1	1	0	0	1	7	3	1.50	1.016
11	0	20	11	8	5	0	8	12	3	1.80	0.959
12	0	17	6	4	3	0	4	13	3	1.17	1.034
13	0	27	22	13	10	0	13	14	3	1.67	0.959
14	0	17	11	7	4	0	7	10	4	1.80	1.151
15	0	13	9	2	2	0	2	11	3	1.60	0.904
16	0	19	12	10	5	0	10	9	4	1.17	0.880
17	0	27	12	11	7	0	11	16	4	1.20	0.934
18	0	41	21	12	6	0	12	29	3	1.17	1.003
19	0	58	34	29	20	0	29	29	4	2.50	1.357
20	0	31	15	20	7	0	20	11	3	1.50	
21	0	10	4	6	3	1	5	4	3	1.40	0.880
22	0	15	5	12	3	0	12	3	3	1.17	1.266
23	0	16	10	7	2	0	7	9	3	1.17	0.997
24	0	19	8	7	2	0	7	12	3	1.17	1.015
25	0	17	5	9	1	0	9	8	3	1.20	0.995
26	0	36	14	16	5	0	16	20	3	1.33	1.016
27	0	39	16	19	8	0	19	20	3	1.40	1.281
28	0	12	3	8	2	0	8	4	3	1.00	0.691
29	0	38	17	22	9	0	22	16	3	1.00	0.956
30	0	23	12	11	5	0	11	12	3	0.67	0.940
31	0	18	11	4	3	0	4	14	3	1.20	1.036
32	0	53	35	24	16	0	24	29	3	1.33	1.048
33	0	39	19	22	5	0	22	17	2	1.60	
34	0	27	8	25	7	4	21	2	3	1.20	
35	0	12	4	8	3	0	8	4	3	1.50	0.975
36	0	14	8	8	5	0	8	6	3	1.25	1.189
37	0	16	3	11	3	0	11	5	3	1.00	0.978
38	0	15	9	7	3	0	7	8	3	0.80	0.748
39	0	7	4	3	1	0	3	4	3	1.00	0.861
40	0	10	3	5	2	0	5	5	3	1.50	1.170

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
41	7	5	0	1	1	1	1	0	0	1	0	0	0	4	0	2	0	0	1	0	0
42	7	6	0	1	1	1	1	0	0	1	0	0	0	4	0	2	1	0	0	2	0
43	7	6	0	1	1	1	1	0	0	1	0	0	0	4	0	2	1	0	1	4	0
44	7	5	0	1	1	1	1	0	0	1	0	0	0	4	0	1	2	0	0	4	0
45	7	8	0	1	1	1	1	0	1	1	0	0	0	5	0	2	1	0	0	2	0
46	7	7	0	1	1	1	1	0	1	1	0	0	0	5	0	6	0	0	4	4	0
47	7	5	0	1	1	0	1	0	1	1	0	0	0	4	0	6	1	0	2	6	0
48	8	4	0	1	0	0	0	1	1	1	0	0	0	4	0	3	1	0	0	0	0
49	8	4	0	1	0	0	0	1	1	1	0	0	0	4	0	6	3	0	0	0	0
50	8	4	0	1	0	0	0	1	0	1	0	0	0	3	0	3	3	0	0	0	0
51	8	4	0	1	0	0	0	1	0	1	0	0	0	3	0	1	4	0	0	0	0
52	8	3	0	1	0	0	0	1	0	1	0	0	0	3	0	2	4	0	0	0	0
53	8	5	0	1	0	0	0	1	1	1	0	0	0	4	0	4	5	0	0	0	0
54	8	4	0	1	0	0	0	1	1	1	0	0	0	4	0	2	4	0	0	0	0
55	8	6	0	1	0	0	0	1	1	1	0	0	0	4	0	2	3	0	0	1	0
56	9	7	0	1	1	1	1	1	1	1	0	0	0	6	0	2	0	0	3	1	0
57	9	7	0	1	1	1	1	1	1	1	0	0	0	6	0	0	1	0	5	5	0
58	9	6	0	1	1	1	1	1	1	1	0	0	0	6	0	0	2	0	1	4	0
59	9	7	0	1	1	1	1	1	1	1	0	0	0	6	0	8	1	0	0	5	0
60	9	7	0	1	1	1	1	1	0	1	0	0	0	5	0	0	1	0	0	0	1
61	9	9	0	1	1	1	1	1	1	1	0	0	0	6	0	3	1	0	0	0	0
62	9	9	0	1	1	1	1	1	1	1	0	0	0	6	0	3	2	0	3	8	0
63	9	8	0	1	1	1	1	1	0	1	0	0	0	5	0	5	6	0	1	1	0
64	9	5	0	1	1	1	1	1	0	1	0	0	0	5	0	2	2	0	0	4	0
65	9	5	0	1	1	1	1	1	0	1	0	0	0	5	0	2	1	0	3	1	0
66	9	6	0	1	1	1	1	1	1	1	0	0	0	6	0	1	3	0	3	1	0
67	9	6	0	1	1	1	1	1	1	1	0	0	0	6	0	3	3	0	3	15	0
68	9	4	0	1	1	1	1	0	1	1	0	0	0	5	0	0	0	0	0	0	0
69	10	3	0	1	0	0	0	1	0	1	0	0	0	3	0	0	0	0	0	0	0
70	10	4	0	1	0	0	0	1	1	1	0	0	0	4	0	2	0	0	0	0	0
71	10	4	0	1	0	0	0	1	1	1	0	0	0	4	0	3	1	0	0	0	0
72	10	5	0	1	0	0	0	1	1	1	0	0	0	4	0	7	2	0	0	0	0
73	10	4	0	1	0	0	0	1	0	1	0	0	0	3	0	2	2	0	0	0	0
74	10	6	0	1	0	1	1	1	0	1	0	0	0	4	2	1	1	0	0	0	0
75	11	5	0	1	1	1	1	1	0	0	0	0	1	5	0	1	0	0	0	2	0
76	11	6	0	1	1	0	1	1	1	0	0	0	1	5	0	0	2	0	0	0	0
77	11	5	0	1	1	0	1	1	0	0	0	0	1	4	0	1	0	0	0	0	1
78	11	3	0	1	1	1	1	1	0	0	0	0	0	4	0	1	1	0	0	0	0
79	11	3	0	1	1	0	1	1	0	0	0	0	0	3	0	0	1	0	0	0	0
80	11	5	0	1	1	1	1	1	0	0	0	0	0	4	0	2	2	0	0	1	0

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
41	1	0	0	0	0	0	0	0	0	1	5	0	0	0	0	0	0	0	0	0	0	0
42	1	3	0	0	0	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0
43	3	1	0	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0
44	1	4	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
45	2	1	0	0	0	0	0	0	0	1	6	0	0	0	0	0	0	0	0	0	0	0
46	5	2	0	0	0	0	0	1	0	3	4	0	0	0	0	0	0	0	0	0	0	0
47	1	0	0	0	0	0	1	3	0	7	8	0	0	0	0	0	0	0	0	0	0	0
48	0	0	1	6	1	0	4	1	0	2	6	0	0	0	0	0	0	0	0	0	0	0
49	0	0	0	9	1	0	3	2	0	3	8	0	0	0	0	0	0	0	0	0	0	0
50	0	0	0	9	13	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
51	0	0	0	4	6	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0
52	0	0	0	5	11	0	1	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
53	0	0	0	5	17	0	0	5	0	3	4	0	0	0	0	0	0	0	0	0	0	0
54	0	0	0	5	6	0	3	1	0	2	7	0	0	0	0	0	0	0	0	0	0	0
55	0	0	0	4	1	0	3	0	0	10	0	0	0	0	0	0	0	0	0	0	0	0
56	1	0	1	1	0	0	1	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0
57	1	4	0	2	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0
58	1	1	0	0	3	0	0	2	0	1	3	0	0	0	0	0	0	0	0	0	0	0
59	1	3	0	1	1	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0
60	1	5	0	0	6	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
61	3	4	1	11	5	0	1	4	1	1	4	0	0	0	0	0	0	0	0	0	0	0
62	1	3	0	5	4	0	1	3	0	1	2	0	0	0	0	0	0	0	0	0	0	0
63	0	3	0	2	5	0	0	0	0	7	6	0	0	0	0	0	0	0	0	0	0	0
64	4	8	0	5	1	0	1	0	0	1	4	0	0	0	0	0	0	0	0	0	0	0
65	1	4	0	2	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
66	1	7	0	4	1	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
67	3	6	0	4	3	0	1	4	0	5	4	0	0	0	0	0	0	0	0	0	0	0
68	0	0	0	3	0	0	0	0	0	2	4	0	0	0	0	0	0	0	0	0	0	0
69	0	0	0	3	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
70	0	0	0	4	2	0	0	2	0	2	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0	0	8	2	0	1	5	0	3	2	0	0	0	0	0	0	0	0	0	0	0
72	0	0	0	8	6	0	4	2	0	5	0	0	0	0	0	0	0	0	0	0	0	0
73	0	0	2	2	0	1	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0
74	0	0	3	2	3	0	9	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
75	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	12	1	0	0
76	1	2	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	2	5	0	0
77	0	0	0	6	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0
78	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0
79	1	1	0	5	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
80	0	0	0	6	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
41	0	10	2	5	2	0	5	5	3	1.25	1.016
42	0	14	6	5	1	0	5	9	3	1.50	1.034
43	0	16	9	9	4	0	9	7	3	1.50	0.861
44	0	14	9	3	1	0	3	11	3	1.25	0.825
45	0	15	5	5	2	0	5	10	3	1.60	0.997
46	0	29	15	18	9	0	18	11	3	1.40	1.283
47	0	35	9	17	3	0	17	18	3	1.25	
48	0	25	8	16	7	1	15	9	3	1.00	1.074
49	0	35	10	21	9	0	21	14	3	1.00	3.853
50	0	31	22	12	9	0	12	19	3	1.33	1.015
51	0	23	10	9	4	0	9	14	3	1.33	0.915
52	0	26	16	9	5	0	9	17	3	1.00	1.019
53	0	43	22	12	5	0	12	31	3	1.25	1.074
54	0	30	11	12	5	0	12	18	3	1.00	0.995
55	0	24	6	19	4	0	19	5	3	1.50	
56	0	14	7	12	6	1	11	2	3	1.17	0.995
57	0	21	17	9	8	0	9	12	3	1.17	0.863
58	0	18	10	3	2	0	3	15	3	1.00	1.151
59	0	24	11	14	2	0	14	10	3	1.17	0.901
60	0	17	13	3	2	1	2	14	3	1.40	1.034
61	0	39	24	21	15	2	19	18	3	1.50	1.014
62	0	36	24	14	9	0	14	22	3	1.50	0.942
63	0	36	12	15	3	0	15	21	3	1.60	1.073
64	0	32	22	13	9	0	13	19	3	1.00	0.861
65	0	18	11	10	6	0	10	8	3	1.00	0.975
66	0	25	17	11	8	0	11	14	3	1.00	1.038
67	0	54	34	19	10	0	19	35	3	1.00	0.975
68	0	9	3	5	3	0	5	4	3	0.80	
69	0	9	9	3	3	0	3	6	3	1.00	0.838
70	0	12	6	8	4	0	8	4	3	1.00	0.943
71	0	25	10	15	8	0	15	10	3	1.00	1.016
72	0	34	14	24	8	0	24	10	3	1.25	1.282
73	0	17	4	15	4	3	12	2	3	1.33	1.015
74	0	22	8	17	5	5	12	5	3	1.50	
75	0	19	5	15	2	0	15	4	3	1.00	0.959
76	0	16	7	5	3	0	5	11	3	1.20	1.036
77	0	20	12	8	7	1	7	12	3	1.25	0.921
78	0	11	2	2	1	0	2	9	3	0.75	0.956
79	0	10	9	6	6	0	6	4	3	1.00	0.959
80	0	13	9	8	6	0	8	5	3	1.25	1.151

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
81	11	5	0	1	1	1	1	1	0	1	0	0	0	5	0	0	4	0	0	2	0
82	11	4	0	0	1	1	1	1	0	1	0	0	0	4	0	2	1	0	0	0	0
83	11	5	0	1	1	1	1	1	0	1	0	0	0	5	0	0	4	0	2	1	0
84	11	6	0	1	1	1	1	1	1	1	0	0	0	6	0	0	7	0	2	3	0
85	11	7	0	1	1	1	1	1	1	1	0	0	0	6	0	1	3	0	1	5	0
86	11	5	0	1	1	1	1	1	1	1	0	0	0	6	0	2	2	0	4	9	0
87	12	7	0	1	1	1	1	0	1	1	0	0	0	5	1	4	5	1	3	1	0
88	12	7	0	1	1	1	1	0	1	1	0	0	0	5	0	6	4	0	1	1	0
89	12	7	0	1	1	1	1	0	1	1	0	0	0	5	0	6	4	0	1	0	0
90	12	7	0	1	1	1	1	0	1	1	0	0	0	5	0	0	2	0	2	1	0
91	12	7	0	1	1	1	1	0	1	1	0	0	0	5	0	2	0	0	2	1	0
92	12	6	0	1	1	1	1	0	1	1	0	0	0	5	0	6	5	0	2	9	0
93	12	5	0	1	1	1	1	0	1	1	0	0	0	5	0	3	0	0	2	5	0
94	12	5	0	1	1	1	1	0	1	0	0	0	0	4	0	10	3	0	9	14	0
95	13	5	1	1	1	1	1	0	1	1	0	0	0	5	0	3	2	0	6	0	0
96	13	5	0	1	1	1	1	0	1	1	0	0	0	5	0	2	1	0	4	1	3
97	13	6	0	1	1	1	1	0	1	1	0	0	0	5	0	1	1	0	1	1	0
98	13	6	0	1	1	1	1	0	1	1	0	0	0	5	0	1	1	0	6	1	0
99	13	5	0	1	1	1	1	0	1	1	0	0	0	5	0	5	0	1	3	1	0
100	13	5	0	1	1	1	1	0	1	1	0	0	0	5	0	0	3	0	2	2	0
101	13	5	0	1	1	1	1	0	1	1	0	0	0	5	0	1	4	0	1	1	0
102	13	5	0	1	1	1	1	0	1	1	0	0	0	5	0	1	4	0	2	3	0
103	13	6	0	1	1	1	1	0	1	1	0	0	0	5	0	0	3	0	1	1	0
104	13	7	0	1	1	1	1	0	1	1	0	0	0	5	0	1	3	0	2	4	0
105	13	7	0	1	1	1	1	0	1	1	0	0	0	5	0	3	4	0	3	5	0
106	13	6	0	1	1	1	1	0	1	1	0	0	0	5	0	6	3	0	9	5	0
107	13	5	0	1	1	1	1	1	1	0	0	0	0	5	0	12	3	0	6	8	0
108	14	6	1	1	0	0	0	1	1	1	0	0	0	4	0	1	0	0	0	0	0
109	14	4	0	1	0	0	0	1	0	1	0	0	0	3	0	1	1	0	0	0	0
110	14	4	0	1	0	0	0	1	0	1	0	0	0	3	0	4	4	0	0	0	0
111	14	5	0	1	0	0	0	1	1	1	0	0	0	4	0	1	2	0	0	0	0
112	14	4	0	1	0	0	0	1	0	1	0	0	0	3	0	0	5	0	0	0	0
113	14	5	0	1	0	0	0	1	0	1	0	0	0	3	0	0	1	0	0	0	0
114	14	6	0	1	0	0	0	1	1	1	0	0	0	4	0	0	3	0	0	0	0
115	14	4	0	1	0	0	0	1	0	1	0	0	0	3	0	1	1	0	0	0	0
116	14	3	0	1	0	0	0	1	0	1	0	0	0	3	0	1	3	0	0	0	0
117	14	5	0	1	0	0	0	1	1	1	0	0	0	4	0	0	4	0	0	0	0
118	14	5	0	1	0	0	0	1	1	1	0	0	0	4	0	0	0	0	0	0	0
119	14	5	0	1	0	0	0	1	1	1	0	0	0	4	0	0	11	0	0	0	0
120	14	4	0	1	0	0	0	1	1	1	0	0	0	4	0	1	7	0	0	1	0

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
81	0	1	0	5	3	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
82	0	1	0	4	2	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
83	0	8	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
84	0	6	0	3	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
85	2	2	0	5	11	0	0	2	0	1	3	0	0	0	0	0	0	0	0	0	0	0
86	3	4	0	6	7	0	1	0	0	6	2	0	0	0	0	0	0	0	0	0	0	0
87	7	1	0	0	0	0	6	2	0	6	1	0	0	0	0	0	0	0	0	0	0	0
88	2	6	0	0	0	0	0	3	0	2	5	0	0	0	0	0	0	0	0	0	0	0
89	9	3	0	0	0	0	2	1	0	4	3	0	0	0	0	0	0	0	0	0	0	0
90	1	4	0	0	0	0	2	3	0	0	2	0	0	0	0	0	0	0	0	0	0	0
91	1	0	0	0	0	0	0	2	0	3	0	0	0	0	0	0	0	0	0	0	0	0
92	3	1	0	0	0	0	3	2	0	1	6	0	0	0	0	0	0	0	0	0	0	0
93	4	8	0	0	0	0	3	1	0	1	3	0	0	0	0	0	0	0	0	0	0	0
94	9	0	1	0	1	0	1	0	1	6	1	0	0	0	0	0	0	0	0	0	0	0
95	0	0	0	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
96	0	2	0	0	0	0	0	1	0	0	4	0	0	1	0	0	0	0	0	0	0	0
97	5	0	0	0	0	0	1	1	0	1	4	0	0	0	0	0	0	0	0	0	0	0
98	5	2	0	0	0	0	1	1	0	2	1	0	0	0	0	0	0	0	0	0	0	0
99	4	3	0	0	0	0	1	4	0	1	3	0	0	0	0	0	0	0	0	0	0	0
100	4	2	0	0	0	0	1	3	0	3	1	0	0	0	0	0	0	0	0	0	0	0
101	5	2	0	0	0	0	0	2	0	1	5	0	0	0	0	0	0	0	0	0	0	0
102	5	5	0	0	0	0	3	3	0	3	2	0	0	0	0	0	0	0	0	0	0	0
103	2	3	0	0	0	0	2	1	0	3	7	0	0	0	0	0	0	0	0	0	0	0
104	2	1	0	0	0	0	0	0	0	4	1	0	0	0	0	0	0	0	0	0	0	0
105	7	8	0	0	0	0	2	1	0	1	5	0	0	0	0	0	0	0	0	0	0	0
106	6	5	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0
107	5	1	0	0	0	0	2	1	0	4	0	0	0	0	0	0	0	0	0	0	0	0
108	0	0	0	4	1	0	0	4	0	3	2	0	0	0	0	0	0	0	0	0	0	0
109	0	0	0	2	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0
110	0	0	0	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
111	0	0	0	6	1	0	7	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
112	0	0	0	10	1	0	0	0	0	1	5	0	0	0	0	0	0	0	0	0	0	0
113	0	0	0	5	2	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
114	0	0	0	1	2	0	1	3	0	0	3	0	0	0	0	0	0	0	0	0	0	0
115	0	0	0	1	2	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0
116	0	0	0	2	2	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
117	0	0	0	0	2	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
118	0	0	0	0	2	0	1	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0
119	0	0	0	0	4	0	1	7	0	3	14	0	0	0	0	0	0	0	0	0	0	0
120	0	0	0	2	1	0	1	2	0	3	7	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
81	0	19	11	7	5	0	7	12	3	1.00	0.844
82	0	12	7	6	4	0	6	6	3	1.00	1.015
83	0	18	12	2	2	0	2	16	3	1.00	0.940
84	0	24	16	5	5	0	5	19	3	1.00	1.016
85	0	36	26	10	8	0	10	26	3	1.17	0.981
86	0	46	33	22	13	0	22	24	3	0.83	
87	0	38	13	28	11	2	26	10	3	1.40	1.214
88	0	30	10	11	3	0	11	19	3	1.40	0.767
89	0	33	13	22	10	0	22	11	3	1.40	0.825
90	0	17	8	5	3	0	5	12	3	1.40	1.015
91	0	11	4	8	3	0	8	3	2	1.40	0.841
92	0	38	15	15	5	0	15	23	3	1.20	1.132
93	0	30	19	13	6	0	13	17	2	1.00	1.037
94	0	56	34	37	19	2	35	19	3	1.25	
95	0	15	6	12	6	0	12	3	3	1.00	0.995
96	0	19	10	9	7	3	6	10	3	1.00	1.016
97	0	16	7	9	6	0	9	7	3	1.20	0.959
98	0	21	14	15	11	0	15	6	3	1.20	0.997
99	0	26	12	15	8	1	14	11	3	1.00	1.034
100	0	21	10	10	6	0	10	11	3	1.00	0.940
101	0	22	9	8	6	0	8	14	3	1.00	1.052
102	0	31	15	14	7	0	14	17	3	1.00	0.764
103	0	23	7	8	3	0	8	15	2	1.20	1.018
104	0	18	9	9	4	0	9	9	3	1.40	0.997
105	0	39	23	16	10	0	16	23	3	1.40	0.975
106	0	40	25	24	15	0	24	16	2	1.20	1.034
107	0	42	20	29	11	0	29	13	2	1.00	
108	0	15	5	8	4	0	8	7	3	1.50	1.015
109	0	7	2	4	2	0	4	3	3	1.33	1.074
110	0	12	0	7	0	0	7	5	3	1.33	0.940
111	0	19	7	15	6	0	15	4	3	1.25	0.959
112	0	22	11	11	10	0	11	11	3	1.33	1.034
113	0	10	7	5	5	0	5	5	3	1.67	1.036
114	0	13	3	2	1	0	2	11	3	1.50	0.844
115	0	10	3	4	1	0	4	6	3	1.33	0.901
116	0	12	4	4	2	0	4	8	3	1.00	0.956
117	0	9	2	0	0	0	0	9	3	1.25	0.904
118	0	7	2	1	0	0	1	6	2	1.25	0.995
119	0	40	4	4	0	0	4	36	3	1.25	0.923
120	0	25	4	7	2	0	7	18	2	1.00	

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
121	16	5	0	1	1	1	1	0	1	1	0	0	0	5	0	1	1	0	2	0	0
122	16	7	1	1	1	1	1	0	1	1	0	0	0	5	0	0	1	0	0	2	0
123	16	4	1	1	1	1	1	0	1	1	0	0	0	5	0	3	4	0	2	0	0
124	16	4	0	1	1	1	1	0	1	1	0	0	0	5	0	2	3	0	1	1	0
125	16	6	0	1	1	1	1	0	1	1	0	0	0	5	0	2	1	0	3	3	0
126	16	5	0	1	1	1	1	0	1	1	0	0	0	5	0	1	0	0	1	0	0
127	16	5	0	1	1	1	1	0	1	1	0	0	0	5	0	2	6	0	1	0	0
128	16	4	0	0	1	1	1	0	1	1	0	0	0	4	0	3	3	0	1	1	0
129	16	4	0	1	1	1	1	0	1	1	0	0	0	5	0	2	4	0	0	1	0
130	16	5	0	1	1	1	1	0	0	1	0	0	0	4	0	1	3	0	0	4	0
131	16	5	0	1	1	1	1	0	1	1	0	0	0	5	1	10	5	0	2	4	0
132	16	6	0	1	1	1	1	0	1	1	0	0	0	5	0	5	3	0	1	3	0
133	16	5	0	1	1	1	1	0	1	1	0	0	0	5	0	9	8	0	10	9	0
134	17	5	0	1	1	1	1	0	0	1	0	0	0	4	0	5	3	0	0	5	0
135	17	6	0	1	1	1	1	0	1	1	0	0	0	5	0	6	4	0	5	1	0
136	17	5	0	1	1	1	1	0	0	1	0	0	0	4	0	1	4	0	1	1	0
137	17	7	0	1	1	1	1	1	1	1	0	0	0	6	0	2	2	0	2	3	0
138	18	5	0	1	1	1	1	1	0	1	0	0	0	5	0	7	3	0	1	0	0
139	18	7	0	1	1	1	1	1	1	1	0	0	0	6	0	3	2	0	1	1	0
140	18	7	0	1	1	1	1	1	0	1	0	0	0	5	0	3	2	0	0	0	0
141	18	6	0	1	1	1	1	1	1	0	0	0	0	5	0	0	2	0	0	0	0
142	18	5	0	1	1	1	1	1	0	1	0	0	0	5	0	1	1	0	2	1	0
143	18	5	0	1	1	1	1	1	0	1	0	0	0	5	0	1	0	0	1	3	0
144	18	5	0	1	1	1	1	1	0	1	0	0	0	5	0	2	1	0	5	4	0
145	18	6	0	1	1	1	1	1	1	1	0	0	0	6	0	0	2	0	1	1	0
146	18	4	0	1	1	0	1	0	1	1	0	0	0	4	0	2	3	0	2	3	0
147	18	3	0	1	1	0	1	0	1	0	0	0	0	3	0	2	2	0	3	3	0
148	18	6	0	1	1	1	1	0	1	1	0	0	0	5	0	1	0	0	0	3	0
149	18	5	0	1	1	1	1	0	0	1	0	0	0	4	0	3	1	0	0	4	0
150	18	7	0	1	1	1	1	1	1	1	0	0	0	6	0	4	3	0	0	4	0
151	19	5	1	1	0	1	1	1	0	1	0	0	0	4	0	0	0	0	0	0	0
152	19	4	1	1	0	1	1	1	0	0	0	0	0	3	0	1	3	0	0	0	0
153	19	5	0	1	0	1	1	1	0	1	0	0	0	4	0	6	2	0	0	0	0
154	19	5	0	1	0	1	1	1	0	1	0	0	0	4	0	3	1	0	0	0	0
155	19	3	0	1	0	0	0	1	1	0	0	0	0	3	0	1	1	0	0	0	0
156	19	3	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
157	19	6	0	1	0	0	0	1	0	1	0	0	0	3	0	5	3	0	0	0	0
158	19	6	0	1	0	0	0	1	0	1	0	0	0	3	0	0	8	0	0	0	0
159	19	5	0	1	0	0	0	1	0	1	0	0	0	3	0	0	1	0	0	0	0
160	19	4	0	1	0	0	0	0	1	1	0	0	0	3	0	0	2	0	0	0	0

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
121	3	2	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
122	0	1	0	0	0	0	0	2	0	3	5	0	0	0	0	0	0	0	0	0	0	0
123	4	0	0	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0
124	3	1	0	0	0	0	2	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
125	2	2	0	0	0	0	2	3	0	4	2	0	0	0	0	0	0	0	0	0	0	0
126	2	3	0	0	0	0	0	1	0	5	6	0	0	0	0	0	0	0	0	0	0	0
127	4	8	0	0	0	0	1	2	0	3	4	0	0	0	0	0	0	0	0	0	0	0
128	3	5	0	0	0	0	2	5	0	3	3	0	0	0	0	0	0	0	0	0	0	0
129	3	2	0	0	0	0	3	3	0	0	6	0	0	0	0	0	0	0	0	0	0	0
130	1	2	0	0	0	0	0	0	0	2	4	0	0	0	0	0	0	0	0	0	0	0
131	5	5	0	0	0	0	1	0	0	5	0	0	0	0	0	0	0	0	0	0	0	0
132	7	3	0	0	0	0	0	3	0	1	7	0	0	0	0	0	0	0	0	0	0	0
133	2	1	0	0	1	0	0	0	0	5	9	0	0	0	0	0	0	0	0	0	0	0
134	1	0	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0
135	3	2	1	10	3	0	1	3	0	2	9	0	0	0	0	0	0	0	0	0	0	0
136	1	0	0	0	0	0	0	0	0	5	4	0	0	0	0	0	0	0	0	0	0	0
137	6	0	0	6	6	0	4	5	0	5	2	0	0	0	0	0	0	0	0	0	0	0
138	1	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
139	1	1	0	6	0	0	0	2	0	2	1	0	0	0	0	0	0	0	0	0	0	0
140	0	0	1	1	2	0	0	0	0	1	4	0	0	0	0	0	0	0	0	0	0	0
141	0	1	0	0	2	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
142	0	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
143	1	2	0	5	1	0	0	0	0	2	4	0	0	0	0	0	0	0	0	0	0	0
144	3	2	0	2	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
145	5	6	0	12	10	0	1	0	0	5	4	0	0	0	0	0	0	0	0	0	0	0
146	2	5	0	0	0	0	1	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
147	1	2	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0
148	2	6	0	0	0	0	0	1	0	6	2	0	0	0	0	0	0	0	0	0	0	0
149	2	0	0	0	0	0	0	0	0	6	3	0	0	0	0	0	0	0	0	0	0	0
150	8	0	1	0	1	0	3	0	0	3	4	0	0	0	0	0	0	0	0	0	0	0
151	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
152	3	0	0	2	1	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
153	0	5	0	3	1	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
154	4	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
155	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
156	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
157	0	0	0	2	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
158	0	0	0	0	2	0	0	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0
159	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0
160	0	0	0	1	3	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
121	0	12	7	9	5	0	9	3	3	1.00	1.015
122	0	14	3	3	0	0	3	11	3	1.40	0.805
123	0	17	6	12	6	0	12	5	3	0.80	1.112
124	0	17	6	10	4	0	10	7	3	0.80	0.981
125	0	24	10	13	5	0	13	11	3	1.20	1.051
126	0	19	6	9	3	0	9	10	3	1.00	0.997
127	0	31	13	11	5	0	11	20	3	1.00	0.997
128	0	29	10	12	4	0	12	17	3	1.00	0.805
129	0	24	6	8	3	0	8	16	3	0.80	1.034
130	0	17	7	4	1	0	4	13	3	1.25	1.014
131	0	38	16	24	7	1	23	14	3	1.00	0.926
132	0	33	14	14	8	0	14	19	3	1.20	1.045
133	0	54	23	26	12	0	26	28	2	1.00	
134	0	20	6	9	1	0	9	11	3	1.25	0.652
135	0	50	25	28	19	1	27	22	3	1.20	0.844
136	0	17	3	8	2	0	8	9	3	1.25	1.149
137	0	43	23	25	14	0	25	18	2	1.17	
138	0	15	3	10	3	0	10	5	3	1.00	1.015
139	0	20	10	13	8	0	13	7	3	1.17	1.016
140	0	14	4	6	2	1	5	8	3	1.40	0.904
141	0	8	3	1	0	0	1	7	3	1.20	1.031
142	0	9	7	6	5	0	6	3	3	1.00	1.111
143	0	20	13	10	7	0	10	10	3	1.00	1.055
144	0	22	16	13	10	0	13	9	3	1.00	0.825
145	0	47	35	24	18	0	24	23	3	1.00	0.959
146	0	21	12	9	4	0	9	12	3	1.00	0.915
147	0	16	9	7	4	0	7	9	3	1.00	0.978
148	0	21	11	9	2	0	9	12	3	1.20	0.518
149	0	19	6	11	2	0	11	8	3	1.25	1.130
150	0	31	14	19	9	1	18	12	3	1.17	
151	0	0	0	0	0	0	0	0	3	1.25	1.127
152	0	12	6	7	5	0	7	5	3	1.33	0.981
153	0	20	9	10	3	0	10	10	3	1.25	1.033
154	0	10	5	7	4	0	7	3	3	1.25	0.959
155	0	3	1	1	0	0	1	2	3	1.00	1.015
156	0	2	2	0	0	0	0	2	3	3.00	1.074
157	0	13	2	8	2	0	8	5	3	2.00	0.866
158	0	18	2	4	0	0	4	14	3	2.00	0.937
159	0	7	0	0	0	0	0	7	3	1.67	0.975
160	0	11	4	3	1	0	3	8	3	1.33	0.901

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
161	19	8	0	1	0	0	0	1	1	1	0	0	0	4	0	0	2	0	0	0	0
162	19	6	0	1	0	0	0	1	1	1	0	0	0	4	0	3	2	0	0	0	0
163	19	2	0	1	0	0	0	0	0	1	0	0	0	2	0	1	3	0	0	0	0
164	19	4	0	1	0	0	0	1	0	0	0	0	0	2	0	2	0	0	0	0	0
165	20	7	0	1	1	1	1	1	1	1	0	0	0	6	1	4	4	0	2	5	0
166	20	7	0	1	1	1	1	1	1	1	0	0	0	6	0	6	4	0	8	11	0
167	21	6	0	1	1	1	1	0	1	1	0	0	0	5	0	0	0	0	0	0	0
168	21	6	1	1	1	1	1	0	1	1	0	0	0	5	0	2	1	0	3	0	0
169	21	6	0	1	1	1	1	0	1	1	0	0	0	5	0	0	2	0	3	0	0
170	21	4	0	1	1	1	1	0	0	1	0	0	0	4	0	1	1	0	1	1	0
171	21	4	0	1	1	1	1	0	1	1	0	0	0	5	0	1	1	0	1	4	0
172	21	6	0	1	1	1	1	0	0	1	0	0	0	4	0	4	0	0	5	2	0
173	21	6	0	1	1	1	1	1	0	1	0	0	0	5	0	1	1	0	2	2	0
174	21	6	0	1	1	1	1	1	0	1	0	0	0	5	0	1	2	0	1	1	0
175	21	1	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
176	21	5	0	1	1	1	1	1	0	1	0	0	0	5	0	6	1	0	2	1	0
177	21	5	0	1	1	1	1	1	0	1	0	0	0	5	0	1	1	0	0	0	0
178	21	6	0	1	1	1	1	1	1	1	0	0	0	6	0	1	1	0	1	0	0
179	21	6	0	1	1	1	1	0	1	1	0	0	0	5	0	6	0	0	3	6	0
180	22	3	0	1	1	0	1	0	0	1	0	0	0	3	0	3	3	0	0	0	0
181	23	4	1	1	1	1	1	1	0	0	0	0	0	4	0	1	0	0	0	0	0
182	23	5	0	1	1	1	1	1	0	0	0	0	0	4	0	2	1	0	0	2	0
183	23	4	0	1	1	1	1	1	0	0	0	0	0	4	0	3	1	0	2	0	0
184	23	4	0	1	1	1	1	1	0	0	0	0	0	4	0	2	2	0	0	0	0
185	23	4	0	1	1	1	1	1	0	0	0	0	0	4	0	0	0	0	0	0	0
186	23	5	0	1	1	1	1	1	0	1	0	0	0	5	0	1	5	0	0	0	0
187	23	5	0	1	1	1	1	1	0	1	0	0	0	5	0	4	3	0	0	5	0
188	23	4	0	0	1	1	1	1	0	1	0	0	0	4	0	2	2	0	1	2	0
189	23	5	0	0	1	1	1	1	0	1	0	0	0	4	0	0	2	0	2	4	0
190	23	6	0	1	1	1	1	1	1	1	0	0	0	6	0	2	0	0	0	4	0
191	23	6	0	1	1	1	1	1	1	1	0	0	0	6	0	3	3	0	1	4	0
192	24	2	1	1	0	1	1	0	0	1	0	0	0	3	0	0	0	0	0	0	0
193	24	2	0	1	0	1	1	0	0	1	0	0	0	3	0	0	0	0	0	0	0
194	24	1	1	1	0	1	1	0	0	1	0	0	0	3	0	2	0	0	0	0	0
195	24	1	0	1	0	0	0	0	0	0	0	0	0	1	0	2	1	0	0	0	0
196	24	1	0	1	0	1	1	0	0	0	0	0	0	2	0	0	4	0	0	0	0
197	24	1	0	1	0	1	1	0	0	0	0	0	0	2	0	1	0	0	0	0	0
198	24	2	0	1	0	1	1	0	0	1	0	0	0	3	0	0	0	0	0	0	0
199	24	2	0	1	0	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	0
200	24	2	0	1	0	0	0	0	0	1	0	0	0	2	0	1	0	0	0	0	0

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
161	0	0	0	1	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
162	0	0	0	2	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
163	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
164	0	0	0	3	1	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
165	0	2	0	1	0	0	1	1	0	3	3	0	0	0	0	0	0	0	0	0	0	0
166	5	0	0	8	2	0	1	0	0	9	4	0	0	0	0	0	0	0	0	0	0	0
167	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
168	1	1	0	0	0	0	0	0	0	5	1	0	0	0	0	0	0	0	0	0	0	0
169	2	0	0	0	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
170	1	1	0	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
171	1	2	0	0	0	0	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0
172	6	2	0	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0
173	3	0	0	6	4	0	0	0	0	3	4	0	0	0	0	0	0	0	0	0	0	0
174	1	3	0	11	2	0	0	0	0	6	2	0	0	0	0	0	0	0	0	0	0	0
175	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
176	1	0	0	9	6	0	1	0	0	8	4	0	0	0	0	0	0	0	0	0	0	0
177	0	3	0	2	2	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
178	0	3	0	0	4	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0
179	5	0	0	0	0	0	3	2	0	11	2	0	0	0	0	0	0	0	0	0	0	0
180	0	0	0	0	0	0	0	2	0	0	0	0	0	2	0	0	0	0	0	0	0	0
181	1	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
182	1	5	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
183	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
184	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
185	3	1	0	5	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
186	0	0	0	5	5	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
187	0	1	0	3	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
188	0	2	0	0	2	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0
189	0	6	0	0	1	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0
190	0	4	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
191	0	3	0	1	4	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
192	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
193	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
194	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
195	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
196	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
197	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
198	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
199	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
200	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
161	0	8	6	1	1	0	1	7	3	2.00	0.901
162	0	12	7	5	2	0	5	7	3	1.50	0.386
163	0	4	0	1	0	0	1	3	2	1.00	0.690
164	0	8	4	7	3	0	7	1	3	2.00	
165	0	27	10	12	3	1	11	15	3	1.17	1.130
166	0	58	34	37	21	0	37	21	3	1.17	
167	0	0	0	0	0	0	0	0	3	1.20	1.111
168	0	14	5	11	4	0	11	3	3	1.20	0.940
169	0	11	5	7	5	0	7	4	3	1.20	0.978
170	0	10	4	4	2	0	4	6	3	1.00	1.053
171	0	14	8	5	2	0	5	9	3	0.80	0.896
172	0	23	15	18	11	0	18	5	3	1.50	1.633
173	0	26	17	15	11	0	15	11	3	1.20	0.633
174	0	30	19	20	13	0	20	10	3	1.20	0.512
175	0	0	0	0	0	0	0	0	1	1.00	0.735
176	0	39	19	27	12	0	27	12	3	1.00	0.956
177	0	10	7	3	2	0	3	7	4	1.00	1.049
178	0	14	8	2	1	0	2	12	2	1.00	1.130
179	0	38	14	28	8	0	28	10	2	1.20	
180	0	10	0	3	0	0	3	7	3	1.00	
181	0	4	3	3	2	0	3	1	4	1.00	1.204
182	0	13	10	4	2	0	4	9	3	1.25	1.016
183	0	8	4	5	2	0	5	3	3	1.00	2.108
184	0	7	3	3	1	0	3	4	3	1.00	1.038
185	0	13	13	8	8	0	8	5	3	1.00	1.036
186	0	17	10	7	5	0	7	10	3	1.00	0.921
187	0	19	12	7	3	0	7	12	3	1.00	1.086
188	0	15	7	3	1	0	3	12	3	1.00	0.984
189	0	19	13	2	2	0	2	17	3	1.25	0.959
190	0	13	9	2	0	0	2	11	3	1.00	0.978
191	0	22	13	6	2	0	6	16	2	1.00	
192	0	0	0	0	0	0	0	0	1	0.67	1.111
193	0	3	0	3	0	0	3	0	1	0.67	0.997
194	0	4	1	3	0	0	3	1	1	0.33	1.016
195	0	3	0	2	0	0	2	1	1	1.00	0.959
196	0	4	0	0	0	0	0	4	1	0.50	1.015
197	0	1	0	1	0	0	1	0	1	0.50	1.074
198	0	1	1	1	1	0	1	0	1	0.67	0.866
199	0	0	0	0	0	0	0	0	1	1.00	0.937
200	0	1	0	1	0	0	1	0	1	1.00	0.975

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
201	24	2	0	0	0	0	0	0	0	1	0	0	0	1	0	2	1	0	0	0	0
202	24	1	0	1	0	0	0	0	0	0	0	0	0	1	0	2	3	0	0	0	0
203	24	2	0	1	1	0	1	0	0	0	0	0	0	2	0	0	16	0	0	0	0
204	25	2	0	1	0	1	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0
205	25	3	0	1	0	1	1	0	0	0	0	0	0	2	0	0	3	0	0	0	0
206	26	2	0	1	0	1	1	0	0	1	0	0	0	3	0	0	0	0	0	0	0
207	26	2	0	1	0	1	1	0	0	1	0	0	0	3	0	0	0	0	0	0	0
208	26	4	0	1	0	0	0	0	0	1	0	0	0	2	0	3	1	0	0	0	0
209	26	2	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
210	26	3	0	1	0	0	0	0	1	1	0	0	0	3	0	0	1	0	0	0	0
211	26	2	0	1	0	1	1	0	0	0	0	0	0	2	0	2	2	0	0	0	0
212	27	4	0	0	1	1	1	0	1	1	0	0	0	4	0	2	3	0	1	7	0
213	27	3	0	0	1	1	1	0	0	1	0	0	0	3	0	2	4	0	1	10	0
214	28	3	0	1	1	1	1	0	1	1	0	0	0	5	0	1	1	0	0	1	0
215	28	4	0	1	1	1	1	0	0	1	0	0	0	4	0	6	3	0	0	3	0
216	28	5	0	1	1	1	1	0	0	1	0	0	0	4	0	3	2	0	1	5	0
217	28	8	0	1	1	1	1	0	1	1	0	0	0	5	0	1	7	0	0	2	0
218	28	7	0	1	1	1	1	0	0	1	0	0	0	4	0	3	0	0	1	6	0
219	28	4	0	1	1	1	1	0	0	1	0	0	0	4	0	2	6	0	1	5	0
220	28	5	0	1	1	1	1	0	1	1	0	0	0	5	0	2	4	0	1	1	0
221	28	6	0	1	1	1	1	0	1	1	0	0	0	5	0	3	3	0	0	0	0
222	28	5	0	1	1	1	1	0	1	1	0	0	0	5	0	2	2	0	0	3	0
223	29	6	0	1	1	1	1	1	1	1	0	0	0	6	0	4	3	0	9	7	0
224	30	6	0	1	1	1	1	1	1	1	0	0	0	6	0	0	2	0	0	5	0
225	30	6	0	1	0	1	1	1	1	1	0	0	0	5	0	2	2	0	0	0	0
226	31	2	0	1	1	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0
227	32	2	0	1	0	0	0	0	0	1	1	0	0	3	0	0	0	0	0	0	0
228	32	2	0	1	0	0	0	0	0	1	1	0	0	3	0	1	0	0	0	0	0
229	32	2	0	1	0	0	0	0	0	1	1	0	0	3	0	0	0	0	0	0	0
230	32	2	0	1	0	0	0	0	0	1	1	0	0	3	0	0	0	0	0	0	0
231	32	2	0	1	0	0	0	0	0	1	1	0	0	3	0	0	2	0	0	0	0
232	32	3	0	1	0	0	0	0	0	1	1	0	0	3	0	1	2	0	0	0	0
233	32	3	0	1	0	0	0	0	0	1	0	0	0	2	0	1	0	0	0	0	0
234	32	3	0	1	0	0	0	0	0	1	0	0	0	2	0	3	2	0	0	0	0
235	32	2	0	1	0	0	0	0	0	0	0	0	0	1	0	2	3	0	0	0	0
236	33	5	0	1	1	1	1	0	1	1	0	0	0	5	0	4	2	0	0	0	0
237	33	4	0	0	1	1	1	0	1	1	0	0	0	4	0	3	3	0	4	0	0
238	33	4	0	1	0	0	0	1	0	1	0	0	0	3	0	0	0	0	0	0	0
239	33	3	0	1	1	1	1	0	0	1	0	0	0	4	0	0	0	0	0	0	0
240	33	5	0	1	1	1	1	0	1	1	0	0	0	5	0	8	1	0	1	2	0

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
201	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
202	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0
203	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
204	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
205	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
206	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
207	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
208	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
209	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0
210	0	3	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0
211	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0	0	0	0	0	0	0	0
212	2	5	0	0	0	0	0	1	0	3	8	0	0	0	0	0	0	0	0	0	0	0
213	1	3	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0
214	0	1	0	0	0	0	4	3	0	0	3	0	0	0	0	0	0	0	0	0	0	0
215	2	1	0	0	0	0	0	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0
216	1	3	0	0	0	0	0	0	0	2	7	0	0	0	0	0	0	0	0	0	0	0
217	5	5	0	0	0	0	0	2	0	3	3	0	0	0	0	0	0	0	0	0	0	0
218	1	4	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
219	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
220	1	2	0	0	0	0	1	1	0	1	3	0	0	0	0	0	0	0	0	0	0	0
221	3	8	0	0	0	0	2	1	0	2	4	0	0	0	0	0	0	0	0	0	0	0
222	1	6	0	0	0	0	5	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0
223	2	6	0	9	8	0	0	3	0	6	4	0	0	0	0	0	0	0	0	0	0	0
224	2	5	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
225	3	11	0	2	5	0	0	0	0	1	6	0	0	0	0	0	0	0	0	0	0	0
226	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
227	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
228	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
229	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
230	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
231	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
232	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
233	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
234	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
235	0	0	0	0	0	0	0	1	0	1	4	0	2	2	0	0	0	0	0	0	0	0
236	1	1	0	0	0	0	2	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
237	1	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
238	0	0	0	0	0	0	3	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
239	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
240	3	1	0	0	0	0	2	1	0	1	2	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
201	0	6	0	2	0	0	2	4	1	2.00	0.912
202	0	9	0	2	0	0	2	7	1	1.00	1.085
203	0	16	0	0	0	0	0	16	1	1.00	
204	0	1	0	1	0	0	1	0	1	1.00	1.036
205	0	4	0	1	0	0	1	3	1	1.50	
206	0	0	0	0	0	0	0	0	3	0.67	6.877
207	0	3	3	2	2	0	2	1	1	0.67	1.001
208	0	7	0	6	0	0	6	1	2	2.00	1.015
209	0	6	0	0	0	0	0	6	1	2.00	1.142
210	0	8	3	4	0	0	4	4	1	1.00	0.984
211	0	9	0	2	0	0	2	7	2	1.00	
212	0	32	15	8	3	0	8	24	3	1.00	0.956
213	0	24	15	5	2	0	5	19	2	1.00	
214	0	14	2	5	0	0	5	9	3	0.60	1.108
215	0	21	6	11	2	0	11	10	4	1.00	0.997
216	0	24	10	7	2	0	7	17	3	1.25	1.241
217	0	28	12	9	5	0	9	19	3	1.60	0.767
218	0	18	12	6	2	0	6	12	3	1.75	0.825
219	0	17	7	4	1	0	4	13	3	1.00	1.015
220	0	17	5	6	2	0	6	11	3	1.00	0.984
221	0	26	11	10	3	0	10	16	2	1.20	0.959
222	0	23	10	8	1	0	8	15	2	1.00	
223	0	61	41	30	20	0	30	31	3	1.00	
224	0	23	21	2	2	0	2	21	3	1.00	1.049
225	0	32	21	8	5	0	8	24	3	1.20	
226	0	0	0	0	0	0	0	0	1	1.00	
227	0	0	0	0	0	0	0	0	1	0.67	0.959
228	0	1	0	1	0	0	1	0	1	0.67	0.995
229	0	1	0	1	0	0	1	0	1	0.67	0.992
230	0	2	0	1	0	0	1	1	1	0.67	0.866
231	0	5	0	2	0	0	2	3	1	0.67	1.398
232	0	5	0	2	0	0	2	3	1	1.00	0.951
233	0	1	0	1	0	0	1	0	1	1.50	0.984
234	0	8	0	4	0	0	4	4	1	1.50	1.016
235	0	15	0	5	0	0	5	10	1	2.00	
236	0	14	2	9	1	0	9	5	2	1.00	0.852
237	0	13	5	10	5	0	10	3	2	1.00	0.967
238	0	7	0	5	0	0	5	2	2	1.33	0.825
239	0	0	0	0	0	0	0	0	2	0.75	1.186
240	0	22	7	15	4	0	15	7	2	1.00	

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
241	34	5	0	1	1	1	1	1	1	0	0	0	0	5	0	4	0	0	3	1	0
242	35	4	1	1	1	1	1	1	0	1	0	0	0	5	0	2	1	0	0	0	0
243	35	5	0	1	1	1	1	1	0	1	0	0	0	5	0	1	2	0	0	0	0
244	35	5	0	1	1	1	1	1	0	1	0	0	0	5	0	0	1	0	3	1	0
245	35	6	0	1	1	1	1	1	0	1	0	0	0	5	0	1	2	0	3	0	0
246	35	4	0	1	1	1	1	1	0	1	0	0	0	5	0	0	0	0	0	0	0
247	35	5	0	1	1	1	1	1	0	1	0	0	0	5	0	0	1	0	0	0	0
248	35	4	0	1	1	1	1	1	0	1	0	0	0	5	0	1	1	0	0	1	0
249	35	5	0	1	1	1	1	1	0	1	0	0	0	5	0	0	4	0	1	0	0
250	35	5	0	1	1	1	1	1	0	1	0	0	0	5	0	1	0	0	1	1	0
251	35	5	0	1	1	1	1	1	0	1	0	0	0	5	0	1	2	0	2	6	0
252	35	5	0	1	1	1	1	1	0	1	0	0	0	5	0	4	4	0	0	0	0
253	35	6	0	1	1	1	1	1	1	1	0	0	0	6	0	0	1	0	2	1	0
254	36	4	0	1	1	1	1	0	0	1	0	0	0	4	0	5	4	0	5	0	0
255	36	5	0	1	1	1	1	0	1	1	0	0	0	5	0	4	2	0	1	2	0
256	36	5	0	1	1	1	1	0	1	1	0	0	0	5	0	3	5	0	2	9	0
257	37	4	1	1	0	1	1	1	0	0	0	0	0	3	0	0	0	0	0	0	0
258	37	2	0	1	0	0	0	1	0	0	0	0	0	2	0	1	0	0	0	0	0
259	37	2	0	1	0	0	0	1	0	0	0	0	0	2	0	1	0	0	0	0	0
260	37	2	0	1	0	0	0	1	0	0	0	0	0	2	0	6	0	0	0	0	0
261	37	3	0	1	1	1	1	1	1	1	0	0	0	6	0	3	0	0	0	0	0
262	38	5	0	1	1	1	1	1	0	1	0	0	0	5	0	2	1	0	4	2	0
263	38	5	0	1	1	1	1	1	0	1	0	0	0	5	0	2	3	0	1	3	0
264	38	6	0	1	1	1	1	1	1	1	0	0	0	6	0	5	5	0	5	12	0
265	39	5	1	1	1	1	1	0	1	1	0	0	0	5	0	1	0	0	0	0	0
266	39	6	0	1	1	1	1	0	0	1	0	0	0	4	0	2	3	0	0	1	0
267	39	4	0	1	1	1	1	0	0	1	0	0	0	4	0	0	0	0	0	0	0
268	39	5	0	1	1	1	1	0	1	1	0	0	0	5	0	2	1	0	0	1	0
269	39	3	0	1	1	1	1	0	0	0	0	0	0	3	0	0	1	0	0	0	0
270	39	4	0	1	1	1	1	0	0	1	0	0	0	4	0	2	0	0	0	0	0
271	39	4	0	1	1	1	1	0	0	1	0	0	0	4	0	4	1	0	0	1	0
272	39	4	0	1	1	1	1	0	0	1	0	0	0	4	0	1	0	0	0	0	0
273	39	4	0	1	1	1	1	0	0	1	0	0	0	4	0	0	2	0	0	0	0
274	39	4	0	1	1	1	1	0	0	1	0	0	0	4	0	0	1	0	0	2	0
275	39	5	0	1	1	1	1	0	1	1	0	0	0	5	0	0	1	0	0	5	0
276	39	4	0	1	1	1	1	0	1	1	0	0	0	5	0	2	2	0	0	5	0
277	40	4	1	1	0	0	0	1	1	1	0	0	0	4	0	2	2	0	0	0	0
278	40	5	0	1	0	0	0	1	1	1	0	0	0	4	0	4	0	0	0	0	0
279	40	4	0	1	0	0	0	1	1	1	0	0	0	4	0	4	1	0	0	0	0
280	40	4	0	1	0	0	0	1	1	1	0	0	0	4	0	3	0	0	0	0	0

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
241	2	2	0	2	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
242	0	0	0	2	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
243	1	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
244	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
245	3	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
246	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
247	0	0	0	2	1	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0
248	0	2	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0
249	1	2	0	3	3	0	0	0	0	2	7	0	0	0	0	0	0	0	0	0	0	0
250	1	4	0	1	3	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0
251	2	1	0	1	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
252	0	0	0	1	1	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
253	3	0	0	0	2	0	0	1	0	3	3	0	0	0	0	0	0	0	0	0	0	0
254	3	2	0	0	0	0	3	0	0	3	7	0	0	0	0	0	0	0	0	0	0	0
255	2	4	0	0	0	0	6	6	0	3	6	0	0	0	0	0	0	0	0	0	0	0
256	0	5	0	0	0	0	1	0	0	10	4	0	0	0	0	0	0	0	0	0	0	0
257	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
258	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
259	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
260	0	0	0	6	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
261	0	0	0	6	3	0	0	1	0	0	3	0	0	0	0	0	0	0	0	0	0	0
262	1	1	1	11	7	0	0	0	0	7	1	0	0	0	0	0	0	0	0	0	0	0
263	0	3	0	0	4	0	2	1	0	0	5	0	0	0	0	0	0	0	0	0	0	0
264	6	4	0	5	2	0	5	2	0	8	5	0	0	0	0	0	0	0	0	0	0	0
265	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
266	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
267	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
268	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
269	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
270	0	0	0	0	0	0	0	0	0	5	4	0	0	0	0	0	0	0	0	0	0	0
271	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
272	0	0	0	0	0	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
273	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
274	0	2	0	0	0	0	1	2	0	0	4	0	0	0	0	0	0	0	0	0	0	0
275	0	0	0	0	0	0	0	2	0	2	5	0	0	0	0	0	0	0	0	0	0	0
276	0	5	0	0	0	0	0	0	0	5	3	0	0	0	0	0	0	0	0	0	0	0
277	0	0	0	0	0	0	1	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0
278	0	0	0	1	3	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
279	0	1	0	2	3	0	1	1	0	4	3	0	0	0	0	0	0	0	0	0	0	0
280	0	0	0	2	8	0	0	4	0	1	4	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
241	0	16	11	11	7	0	11	5	3	1.00	
242	0	6	2	5	2	0	5	1	3	0.80	0.997
243	0	6	2	3	1	0	3	3	3	1.00	0.981
244	0	7	6	4	4	0	4	3	3	1.00	1.016
245	0	10	7	7	6	0	7	3	3	1.20	1.012
246	0	2	1	1	1	0	1	1	3	0.80	0.770
247	0	9	3	4	2	0	4	5	3	1.00	1.052
248	0	9	3	1	0	0	1	8	3	0.80	1.225
249	0	23	10	7	5	0	7	16	3	1.00	0.978
250	0	19	11	4	3	0	4	15	3	1.00	0.973
251	0	18	12	7	5	0	7	11	2	1.00	0.962
252	0	13	2	5	1	0	5	8	2	1.00	1.000
253	0	16	8	8	5	0	8	8	2	1.00	
254	0	32	10	19	8	0	19	13	3	1.00	0.901
255	0	36	9	16	3	0	16	20	3	1.00	0.915
256	0	39	16	16	2	0	16	23	3	1.00	
257	0	0	0	0	0	0	0	0	2	1.33	0.997
258	0	4	3	2	1	0	2	2	2	1.00	0.975
259	0	4	3	3	2	0	3	1	2	1.00	1.425
260	0	14	7	13	6	0	13	1	2	1.00	8.199
261	0	16	9	9	6	0	9	7	3	0.50	
262	0	38	27	26	17	1	25	12	3	1.00	1.227
263	0	24	11	5	1	0	5	19	3	1.00	1.052
264	0	64	34	34	16	0	34	30	3	1.00	
265	0	3	0	3	0	0	3	0	3	1.00	1.016
266	0	7	2	2	0	0	2	5	3	1.50	0.904
267	0	2	0	2	0	0	2	0	3	1.00	1.070
268	0	6	2	4	1	0	4	2	3	1.00	0.921
269	0	1	0	0	0	0	0	1	3	1.00	1.016
270	0	11	0	7	0	0	7	4	3	1.00	0.997
271	0	8	1	6	0	0	6	2	3	1.00	1.064
272	0	4	0	3	0	0	3	1	2	1.00	0.847
273	0	4	0	0	0	0	0	4	3	1.00	0.975
274	0	12	4	1	0	0	1	11	3	1.00	1.099
275	0	15	5	2	0	0	2	13	3	1.00	0.997
276	0	22	10	7	0	0	7	15	2	0.80	
277	0	9	0	7	0	0	7	2	3	1.00	1.000
278	0	12	4	6	1	0	6	6	3	1.25	0.918
279	0	20	6	11	2	0	11	9	3	1.00	0.959
280	0	22	10	6	2	0	6	16	3	1.00	1.150

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
281	40	3	0	1	0	0	0	1	0	1	0	0	0	3	0	4	3	0	0	0	0
282	40	5	0	1	0	0	0	1	1	1	0	0	0	4	0	1	4	0	0	0	0
283	40	5	0	1	0	0	0	1	0	1	0	0	0	3	0	8	1	0	0	0	0
284	40	5	0	1	0	0	0	1	0	1	0	0	0	3	0	2	1	0	0	0	0
285	40	4	0	1	0	0	0	1	0	1	0	0	0	3	0	4	7	0	0	0	0
286	40	3	0	1	0	0	0	1	0	1	0	0	0	3	0	6	0	0	0	0	0
287	40	4	0	1	0	0	0	1	0	1	0	0	0	3	0	1	5	0	0	0	0
288	40	5	0	1	0	0	0	1	1	1	0	0	0	4	0	2	1	0	0	0	0
289	41	4	0	1	1	1	1	0	1	1	0	0	0	5	0	0	0	0	0	0	0
290	41	5	0	1	1	1	1	0	0	1	0	0	0	4	0	2	1	0	0	2	0
291	41	5	0	1	1	1	1	0	0	1	0	1	0	5	0	3	1	0	0	0	0
292	41	4	0	1	1	1	1	0	0	1	0	1	0	5	0	1	2	0	0	0	0
293	41	5	0	1	1	1	1	0	1	1	0	1	0	6	0	7	2	0	0	2	0
294	41	5	0	1	1	1	1	0	0	1	0	0	0	4	0	15	1	0	1	1	0
295	41	3	0	1	1	1	1	0	0	1	0	0	0	4	0	0	3	0	1	1	0
296	41	4	0	1	1	1	1	0	0	1	0	0	0	4	0	1	3	0	2	1	0
297	41	2	0	1	1	1	1	0	0	0	0	0	0	3	0	1	3	0	2	2	0
298	41	2	0	1	1	1	1	0	0	1	0	0	0	4	0	5	5	0	5	2	0
299	42	6	0	1	1	1	1	1	0	0	0	0	1	5	0	1	0	0	1	0	0
300	42	5	0	1	1	1	1	1	0	0	0	0	1	5	0	0	2	0	0	0	0
301	42	4	0	1	1	1	1	1	0	0	0	0	1	5	0	3	2	0	1	0	0
302	42	1	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
303	42	4	0	1	1	1	1	1	0	0	0	0	0	4	0	1	2	0	0	0	1
304	42	3	0	1	1	1	1	1	0	0	0	0	0	4	0	0	1	0	1	1	0
305	42	4	0	1	1	1	1	1	0	0	0	0	0	4	0	1	1	0	0	2	0
306	42	5	0	1	1	1	1	1	0	1	0	0	0	5	0	0	4	0	1	1	0
307	42	5	0	1	1	1	1	1	0	1	0	0	0	5	0	7	1	0	3	3	0
308	42	5	0	1	1	1	1	1	0	1	0	0	0	5	0	3	3	0	0	4	0
309	42	4	0	1	1	1	1	0	1	1	0	0	0	5	0	0	1	0	0	3	0
310	42	3	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
311	42	7	0	1	1	1	1	1	1	1	0	0	0	6	0	2	3	0	0	10	0
312	43	3	0	1	0	1	1	1	0	0	0	0	0	3	0	0	1	0	0	0	0
313	43	4	0	1	0	1	1	1	0	0	0	0	0	3	0	1	4	0	0	0	0
314	43	6	0	1	0	1	1	1	0	0	0	0	0	3	0	4	1	0	0	0	1
315	43	4	0	1	0	1	1	1	0	0	0	0	0	3	0	1	3	0	0	0	0
316	43	3	0	1	0	1	1	1	0	0	0	0	0	3	0	0	1	0	0	0	0
317	43	3	0	1	0	1	1	1	0	0	0	0	0	3	0	3	0	0	0	0	0
318	43	3	0	1	0	1	1	1	0	0	0	0	0	3	0	0	0	0	0	0	0
319	43	4	0	1	0	1	1	1	0	1	0	0	0	4	0	0	0	0	0	0	0
320	43	6	0	1	1	1	1	1	0	1	0	0	0	5	0	1	3	0	0	3	0

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
281	0	0	0	0	0	0	0	0	0	4	1	0	0	0	0	0	0	0	0	0	0	0
282	0	0	0	12	2	0	4	1	0	1	10	0	0	0	0	0	0	0	0	0	0	0
283	0	0	0	11	8	0	0	0	0	3	2	0	0	0	0	0	0	0	0	0	0	0
284	0	0	0	1	1	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0
285	0	0	0	7	0	0	0	0	0	3	4	0	0	0	0	0	0	0	0	0	0	0
286	0	0	0	3	0	0	0	0	0	1	4	0	0	0	0	0	0	0	0	0	0	0
287	0	0	0	0	7	0	0	0	0	6	3	0	0	0	0	0	0	0	0	0	0	0
288	0	0	0	12	1	0	3	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
289	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
290	4	3	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
291	3	5	0	0	0	0	0	0	0	1	2	0	0	0	0	2	1	0	0	0	0	0
292	0	0	0	0	0	0	0	0	0	1	5	0	0	0	0	0	1	0	0	0	0	0
293	0	2	0	0	0	0	2	3	0	1	3	0	0	0	0	0	3	0	0	0	0	0
294	7	3	0	0	0	0	0	0	0	6	1	0	0	0	0	0	0	0	0	0	0	0
295	1	3	0	0	0	0	0	0	0	4	1	0	0	0	0	0	0	0	0	0	0	0
296	2	1	0	0	0	0	0	0	0	1	6	0	0	0	0	0	0	0	0	0	0	0
297	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
298	4	3	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
299	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	0	0
300	1	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	3	0	0
301	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	3	11	0	0
302	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
303	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
304	1	4	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
305	1	2	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
306	1	3	0	3	4	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
307	2	6	0	1	2	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
308	1	8	0	5	4	0	0	3	0	1	4	0	0	0	0	0	0	0	0	0	0	0
309	2	9	0	0	0	0	0	1	0	1	2	0	0	0	0	0	0	0	0	0	0	0
310	0	0	0	1	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
311	1	9	0	0	1	0	4	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
312	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
313	1	3	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
314	0	0	1	4	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
315	4	1	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
316	1	0	0	4	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
317	0	1	0	13	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
318	1	3	0	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
319	1	2	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
320	0	4	0	5	3	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
281	0	12	0	8	0	0	8	4	3	1.00	0.981
282	0	35	14	18	12	0	18	17	3	1.25	1.014
283	0	33	19	22	11	0	22	11	3	1.67	1.037
284	0	10	2	5	1	0	5	5	3	1.67	0.995
285	0	25	7	14	7	0	14	11	3	1.33	0.844
286	0	14	3	10	3	0	10	4	3	1.00	1.126
287	0	22	7	7	0	0	7	15	3	1.33	1.034
288	0	21	13	19	12	0	19	2	7	1.25	
289	0	0	0	0	0	0	0	0	3	0.80	1.166
290	0	14	9	8	4	0	8	6	3	1.25	0.978
291	0	18	8	9	3	0	9	9	3	1.00	0.825
292	0	10	0	2	0	0	2	8	3	0.80	1.015
293	0	25	4	10	0	0	10	15	3	0.83	1.037
294	0	35	12	29	8	0	29	6	3	1.25	2.068
295	0	14	6	6	2	0	6	8	3	0.75	0.863
296	0	17	6	6	4	0	6	11	3	1.00	1.651
297	0	11	7	4	3	0	4	7	2	0.67	1.337
298	0	27	14	15	9	0	15	12	3	0.50	
299	0	8	3	6	2	0	6	2	3	1.20	1.208
300	0	11	5	4	3	0	4	7	3	1.00	0.978
301	0	23	4	8	2	0	8	15	3	0.80	0.634
302	0	0	0	0	0	0	0	0	1	1.00	0.227
303	0	6	3	3	2	1	2	3	3	1.00	0.978
304	0	11	10	2	2	0	2	9	3	0.75	0.997
305	0	9	7	3	2	0	3	6	3	1.00	0.748
306	0	20	13	5	5	0	5	15	3	1.00	1.168
307	0	29	17	14	6	0	14	15	3	1.00	0.995
308	0	36	22	10	6	0	10	26	3	1.00	0.978
309	0	19	14	3	2	0	3	16	2	0.80	0.137
310	0	12	12	1	1	0	1	11	3	3.00	1.125
311	0	32	21	8	1	0	8	24	3	1.17	
312	0	2	1	1	1	0	1	1	3	1.00	1.016
313	0	11	6	2	1	0	2	9	3	1.33	0.959
314	0	14	9	10	6	2	8	4	3	2.00	1.015
315	0	12	8	6	5	0	6	6	3	1.33	0.962
316	0	10	9	5	5	0	5	5	3	1.00	0.614
317	0	20	17	16	13	0	16	4	3	1.00	1.697
318	0	7	7	3	3	0	3	4	2	1.00	0.956
319	0	6	4	1	1	0	1	5	2	1.00	0.962
320	0	22	15	6	5	0	6	16	3	1.20	2.146

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
322	44	4	0	1	1	1	1	1	0	1	0	0	0	5	0	1	3	0	0	2	0
323	44	6	0	1	1	1	1	1	1	1	0	0	0	6	0	3	2	0	0	1	0
324	45	4	0	1	0	0	0	1	1	1	0	0	0	4	0	1	6	0	0	0	0
325	46	4	0	1	1	1	1	0	0	1	0	0	0	4	0	1	0	0	0	0	0
326	46	4	0	1	1	1	1	0	0	1	0	0	0	4	0	0	0	0	0	0	0
327	46	7	0	1	1	1	1	0	1	1	0	0	0	5	0	3	1	0	1	2	0
328	46	3	0	1	1	1	1	0	0	0	0	0	0	3	0	2	1	0	1	0	0
329	46	3	0	1	1	1	1	0	0	0	0	0	0	3	0	0	0	0	2	0	0
330	46	4	0	1	1	1	1	0	0	0	0	0	0	3	0	1	0	0	1	1	0
331	46	5	0	1	1	1	1	0	0	1	0	0	0	4	0	2	2	0	0	0	0
332	46	6	0	1	1	1	1	0	0	1	0	0	0	4	0	3	1	0	4	3	0
333	46	4	0	1	1	1	1	0	1	1	0	0	0	5	0	3	0	0	0	0	0
334	46	2	0	1	0	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	0
335	46	3	0	1	0	0	0	0	1	1	0	0	0	3	0	0	0	0	0	0	0
336	47	4	0	1	0	0	0	1	0	1	0	0	0	3	0	2	0	0	0	0	0
337	47	4	0	1	0	0	0	1	0	1	0	0	0	3	0	2	4	0	0	0	0
338	47	4	0	1	0	0	0	1	0	1	0	0	0	3	0	5	1	0	0	0	0
339	47	6	0	1	0	0	0	1	1	1	0	0	0	4	0	3	2	0	0	0	0
340	48	2	0	1	0	0	0	1	0	0	0	0	0	2	0	0	2	0	0	0	0
341	48	2	0	1	0	0	0	1	0	0	0	0	0	2	0	0	0	0	0	0	0
342	49	4	0	1	1	1	1	0	0	1	0	0	0	4	0	4	4	0	1	1	2
343	49	4	0	1	1	1	1	0	0	1	0	0	0	4	0	6	3	0	2	0	0
344	49	4	0	1	1	1	1	0	0	1	0	0	0	4	0	2	2	0	0	0	0
345	49	5	0	1	1	1	1	0	0	1	0	0	0	4	0	3	3	0	8	2	0
346	49	4	0	1	0	1	1	0	1	1	0	0	0	4	0	7	1	0	5	0	0
347	49	5	0	1	1	1	1	0	1	1	0	0	0	5	0	5	1	0	2	0	0
348	49	3	0	1	1	1	1	0	0	1	0	0	0	4	0	6	8	0	4	7	0
349	52	2	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0
350	53	3	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
351	53	4	0	1	0	1	1	1	0	1	0	0	0	4	0	4	2	0	0	0	0
352	53	4	0	0	1	1	1	1	0	1	0	0	0	4	0	8	3	0	3	5	0
353	54	5	0	1	1	1	1	0	1	1	0	0	0	5	0	3	2	0	1	0	1
354	54	5	0	1	1	1	1	0	1	1	0	0	0	5	0	3	2	0	4	1	0
355	54	3	0	1	0	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	0
356	54	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0
357	54	3	0	1	1	1	1	0	1	1	0	0	0	5	0	3	3	0	1	2	0
358	54	5	0	1	1	0	1	0	0	1	0	0	0	3	0	6	13	0	6	3	0
359	57	1	0	0	0	1	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0
360	57	5	0	1	1	1	1	0	1	1	0	0	0	5	0	1	3	0	2	4	1

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
322	0	1	0	2	1	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0
323	1	2	0	9	2	0	2	1	0	2	3	0	0	0	0	0	0	0	0	0	0	0
324	0	0	0	3	1	0	4	1	0	2	0	0	0	0	0	0	0	0	0	0	0	0
325	2	2	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0
326	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
327	1	2	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
328	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
329	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
330	3	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
331	2	5	0	0	0	0	0	0	0	2	4	0	0	0	0	0	0	0	0	0	0	0
332	5	4	0	0	0	0	0	0	0	4	16	0	0	0	0	0	0	0	0	0	0	0
333	0	0	0	0	0	0	2	0	0	8	1	0	0	0	0	0	0	0	0	0	0	0
334	0	0	0	0	0	0	3	0	0	4	2	0	0	0	0	0	0	0	0	0	0	0
335	1	0	0	0	0	0	2	0	0	4	5	0	0	0	0	0	0	0	0	0	0	0
336	0	0	0	1	0	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
337	0	0	0	1	0	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0
338	0	0	0	7	10	0	5	4	0	1	7	0	0	0	0	0	0	0	0	0	0	0
339	0	0	0	15	4	0	1	1	0	6	8	0	0	0	0	0	0	0	0	0	0	0
340	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
341	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
342	2	2	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
343	3	1	0	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
344	1	3	0	0	0	0	0	0	0	2	3	0	0	0	0	0	0	0	0	0	0	0
345	4	2	0	0	0	0	0	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0
346	4	2	0	0	0	0	5	0	0	3	3	0	0	0	0	0	0	0	0	0	0	0
347	0	2	0	0	0	0	3	5	0	3	1	0	0	0	0	0	0	0	0	0	0	0
348	6	3	0	0	0	0	5	5	0	8	2	0	0	0	0	0	0	0	0	0	0	0
349	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
350	0	0	0	0	0	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
351	1	4	0	3	3	0	2	0	1	4	5	0	0	0	0	0	0	0	0	0	0	0
352	2	6	0	3	7	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
353	3	2	0	0	0	0	1	0	0	1	7	0	0	0	0	0	0	0	0	0	0	0
354	4	6	0	0	0	0	6	0	0	6	9	0	0	0	0	0	0	0	0	0	0	0
355	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
356	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
357	5	7	0	0	0	0	0	0	1	10	5	0	0	0	0	0	0	0	0	0	0	0
358	3	5	0	0	0	0	0	0	0	9	4	0	0	0	0	0	0	0	0	0	0	0
359	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
360	0	5	0	0	0	0	2	5	0	1	2	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
322	0	15	6	5	2	0	5	10	5	0.80	1.071
323	0	28	15	17	10	0	17	11	3	1.00	
324	0	18	4	10	3	0	10	8	2	1.00	
325	0	7	4	4	2	0	4	3	2	1.00	0.975
326	0	2	1	1	1	0	1	1	2	1.00	1.016
327	0	12	6	7	2	0	7	5	2	1.40	0.997
328	0	6	3	4	2	0	4	2	2	1.00	0.997
329	0	3	3	3	3	0	3	0	3	1.00	0.956
330	0	8	7	5	4	0	5	3	2	1.33	1.093
331	0	17	7	6	2	0	6	11	2	1.25	1.153
332	0	40	16	16	9	0	16	24	2	1.50	1.220
333	0	14	0	13	0	0	13	1	3	0.80	1.166
334	0	9	0	7	0	0	7	2	2	1.00	0.641
335	0	12	1	7	1	0	7	5	2	1.00	
336	0	7	1	5	1	0	5	2	2	1.33	0.995
337	0	12	1	5	1	0	5	7	3	1.33	0.896
338	0	40	17	18	7	0	18	22	2	1.33	1.096
339	0	40	19	25	15	0	25	15	4	1.50	
340	0	2	0	0	0	0	0	2	1	1.00	1.753
341	0	0	0	0	0	0	0	0	2	1.00	
342	0	19	8	9	5	2	7	10	3	1.00	0.975
343	0	19	6	12	5	0	12	7	3	1.00	0.978
344	0	13	4	5	1	0	5	8	3	1.00	1.436
345	0	26	16	18	12	0	18	8	3	1.25	0.849
346	0	30	11	24	9	0	24	6	3	1.00	0.932
347	0	22	4	13	2	0	13	9	3	1.00	1.137
348	0	54	20	29	10	0	29	25	3	0.75	
349	0	3	3	3	3	0	3	0	3	2.00	
350	0	4	0	1	0	0	1	3	2	3.00	0.195
351	0	29	11	15	4	1	14	14	3	1.00	1.302
352	0	41	26	17	8	0	17	24	3	1.00	
353	0	21	7	10	5	1	9	11	3	1.00	1.073
354	0	41	15	23	8	0	23	18	3	1.00	1.518
355	0	3	0	0	0	0	0	3	2	1.50	0.548
356	0	0	0	0	0	0	0	0	2	1.00	0.178
357	0	37	15	20	6	1	19	17	3	0.60	1.034
358	0	49	17	24	9	0	24	25	3	1.67	
359	0	2	2	2	2	0	2	0	2	1.00	0.499
360	0	26	12	7	3	1	6	19	4	1.00	0.822

Table F1 continued.

Record #	LABID#	TeamNumber	Oversight	Mod1_QA	Mod2_Organic	Mod3_Inorg	isChemLab	Mod4_Rad/isRadLab	Mod5_LIMS	Mod6_HRMM	Mod7_Geo	Mod8_AQT	Mod9_NDA	NumMods	@1QAI	@1QAII	@1QAO	@2ORGI	@2ORGII	@2ORGO	@3INI
361	57	5	0	1	1	1	1	0	1	1	0	0	0	5	0	1	1	0	0	0	0
362	57	6	0	1	1	1	1	0	1	1	0	0	0	5	0	2	0	0	2	4	0
363	59	4	0	1	1	1	1	0	0	1	0	0	0	4	0	2	0	0	2	0	0
364	59	4	0	1	1	1	1	0	0	1	0	0	0	4	0	3	2	0	1	1	0
365	59	4	0	1	1	1	1	0	0	1	0	0	0	4	0	1	1	0	1	3	0
366	59	3	0	1	1	1	1	0	1	1	0	0	0	5	0	1	1	1	1	0	0
367	59	3	0	1	1	1	1	0	0	0	0	0	0	3	0	6	4	0	2	3	0
368	59	4	0	1	1	1	1	0	1	1	0	0	0	5	0	5	2	0	2	2	0
369	60	4	0	1	1	1	1	0	0	1	0	0	0	4	0	2	4	0	0	2	0
370	60	4	0	1	1	1	1	0	0	1	0	0	0	4	0	10	4	0	8	2	0
371	61	3	0	1	0	0	0	1	1	1	0	0	0	4	0	4	1	0	0	0	0
372	61	3	0	1	0	0	0	1	0	1	0	0	0	3	0	3	0	0	0	0	0
373	61	5	0	1	0	0	0	1	0	1	0	0	0	3	0	1	1	0	0	0	0
374	61	5	0	1	0	0	0	1	1	1	0	0	0	4	0	1	2	0	0	0	0
375	61	4	0	1	0	0	0	1	0	1	0	0	0	3	0	2	2	0	0	0	0
376	61	4	0	1	0	0	0	1	1	1	0	0	0	4	0	3	3	0	0	0	0
377	61	4	0	1	0	0	0	1	0	1	0	0	0	3	0	1	4	0	0	0	0
378	61	4	0	1	0	0	0	1	1	1	0	0	0	4	0	9	3	0	0	0	0
379	62	2	0	1	1	1	1	1	0	1	0	0	0	5	0	1	0	0	0	0	0
380	62	4	0	1	1	1	1	1	0	1	0	0	0	5	0	0	0	0	1	0	0
381	62	5	0	1	1	1	1	1	0	1	0	0	0	5	0	1	2	0	0	0	1
382	62	4	0	1	1	1	1	1	0	0	0	0	0	4	0	2	1	0	0	0	0
383	62	4	0	1	1	1	1	1	0	1	0	0	0	5	0	1	1	0	0	0	0
384	62	3	0	1	0	0	0	1	0	1	0	0	0	3	0	3	2	0	0	0	0
385	65	4	0	1	1	1	1	0	1	1	0	0	0	5	0	3	2	0	1	1	0
386	65	3	0	1	1	1	1	0	0	1	0	0	0	4	0	1	0	0	3	2	0
387	65	4	0	1	1	1	1	0	0	1	0	0	0	4	0	12	2	0	1	3	0
388	66	1	0	1	0	0	0	0	0	0	0	1	0	2	0	2	4	0	0	0	0
389	66	1	0	1	0	0	0	0	0	0	0	0	0	1	0	2	4	0	0	0	0
390	66	1	0	1	0	0	0	0	0	0	0	0	0	1	0	3	2	0	0	0	0
391	68	1	0	1	0	0	0	0	0	0	0	1	0	2	0	2	2	0	0	0	0
392	69	3	0	1	0	0	0	0	1	1	0	1	0	4	0	0	1	0	0	0	0
393	69	2	0	1	0	0	0	0	0	1	0	1	0	3	0	0	0	0	0	0	0
394	69	2	0	1	0	0	0	0	0	1	0	1	0	3	0	3	2	0	0	0	0
395	69	1	0	1	0	0	0	0	0	1	0	1	0	3	0	7	2	0	0	0	0
396	70	2	0	1	0	0	0	0	0	1	0	0	0	2	0	0	0	0	0	0	0
397	70	2	0	1	0	0	0	0	0	1	0	0	0	2	0	1	1	0	0	0	0
398	72	3	1	1	1	0	1	0	1	1	0	0	0	4	0	5	3	0	0	4	0

Table F1 continued.

Record #	@3INII	@3INO	@4RADI	@4RADII	@4RADO	@5LIMSI	@5LIMSII	@5LIMSO	@6HRI	@6HRII	@6HRO	@7GEI	@7GEII	@7GEO	@8AQTI	@8AQTII	@8AQTO	@9NDAI	@9NDAII	@9NDAO	OvsI	OvsII
361	3	6	0	0	0	0	2	0	0	3	5	0	0	0	0	0	0	0	0	0	0	0
362	9	1	0	0	0	0	14	5	0	6	5	0	0	0	0	0	0	0	0	0	0	0
363	0	4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
364	0	1	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
365	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
366	1	2	0	0	0	0	0	1	0	2	1	0	0	0	0	0	0	0	0	0	0	0
367	5	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
368	2	4	0	0	0	0	0	0	0	2	4	0	0	0	0	0	0	0	0	0	0	0
369	0	0	0	0	0	0	0	0	0	4	5	0	0	0	0	0	0	0	0	0	0	0
370	4	2	0	0	0	0	0	0	0	6	3	0	0	0	0	0	0	0	0	0	0	0
371	0	0	0	0	3	0	0	0	0	2	1	0	0	0	0	0	0	0	0	0	0	0
372	0	0	0	2	2	0	0	0	0	1	3	0	0	0	0	0	0	0	0	0	0	0
373	0	0	1	1	1	0	0	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0
374	0	0	0	2	1	0	1	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0
375	0	0	0	1	1	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0
376	0	0	0	1	4	0	4	0	0	3	1	0	0	0	0	0	0	0	0	0	0	0
377	0	0	0	2	4	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
378	0	0	0	11	16	0	1	0	0	2	5	0	0	0	0	0	0	0	0	0	0	0
379	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
380	2	0	1	2	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
381	3	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
382	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
383	0	0	0	6	1	0	0	0	0	2	5	0	0	0	0	0	0	0	0	0	0	0
384	0	0	0	5	5	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0
385	0	1	0	0	0	0	6	1	0	4	1	0	0	0	0	0	0	0	0	0	0	0
386	0	2	0	0	0	0	0	0	0	4	3	0	0	0	0	0	0	0	0	0	0	0
387	8	4	0	0	0	0	0	0	0	4	7	0	0	0	0	0	0	0	0	0	0	0
388	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
389	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
390	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
391	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0
392	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
393	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
394	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0
395	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	2	0	0	0	0	0	0
396	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0
397	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
398	0	0	0	0	0	0	1	0	0	2	2	0	0	0	0	0	0	0	0	0	0	0

Table F1 continued.

Record #	OvsO	Issues	TechnicalIssues	Findings	TechnicalFindings	PI	PII	Observations	Duration	AuditorsPerMod	YearFrac
361	0	21	9	9	3	0	9	12	3	1.00	0.729
362	0	48	16	33	11	0	33	15	3	1.20	
363	0	9	6	5	2	0	5	4	3	1.00	1.093
364	0	10	3	6	1	0	6	4	3	1.00	0.901
365	0	9	6	4	2	0	4	5	3	1.00	0.959
366	0	11	5	6	3	1	5	5	3	0.60	0.995
367	0	24	14	13	7	0	13	11	3	1.00	2.493
368	0	23	10	11	4	0	11	12	3	0.80	
369	0	17	2	6	0	0	6	11	3	1.00	0.882
370	0	39	16	28	12	0	28	11	3	1.00	
371	0	11	3	6	0	0	6	5	3	0.75	0.995
372	0	11	4	6	2	0	6	5	3	1.00	0.978
373	0	9	3	5	2	1	4	4	3	1.67	0.978
374	0	11	3	4	2	0	4	7	3	1.25	1.015
375	0	9	2	4	1	0	4	5	3	1.33	0.956
376	0	19	5	11	1	0	11	8	3	1.00	1.153
377	0	13	6	3	2	0	3	10	3	1.33	1.090
378	0	47	27	23	11	0	23	24	3	1.00	
379	0	3	2	2	1	0	2	1	3	0.40	0.921
380	0	8	6	8	6	2	6	0	3	0.80	1.016
381	0	9	6	6	5	2	4	3	3	1.00	0.995
382	0	4	1	3	1	0	3	1	3	1.00	1.073
383	0	16	7	9	6	0	9	7	3	0.80	1.356
384	0	18	10	8	5	0	8	10	2	1.00	
385	0	20	3	14	1	0	14	6	3	0.80	0.995
386	0	15	7	8	3	0	8	7	3	0.75	1.074
387	0	41	16	25	9	0	25	16	3	1.00	
388	0	6	0	2	0	0	2	4	2	0.50	0.970
389	0	6	0	2	0	0	2	4	2	1.00	1.003
390	0	5	0	3	0	0	3	2	2	1.00	
391	0	6	0	2	0	0	2	4	2	0.50	
392	0	2	0	1	0	0	1	1	2	0.75	0.978
393	0	2	0	2	0	0	2	0	1	0.67	0.879
394	0	7	0	4	0	0	4	3	1	0.67	1.033
395	0	15	0	9	0	0	9	6	2	0.33	
396	0	3	0	3	0	0	3	0	1	1.00	1.166
397	0	4	0	3	0	0	3	1	1	1.00	
398	0	17	4	8	0	0	8	9	2	0.75	

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CHEM-793, "Chemistry Special Topics: Quality Assurance," (2008).
Graduate-level course in research quality assurance.

Publications:

Peer Reviewed Journals

Marawar, R. W., Cowles, D. C., Keeler, R. E., White, A. P., and Farley, J. W. (1994). "Diode laser autodetachment spectroscopy," *Rev. Sci. Instrum.*, Vol. 65, No. 9.

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Jones, P., Keeler, R. E., Keith, D., Knop, M., (1999). *Submittal and Incorporation of Data to the Technical Data Management System*. U. S. Department of Energy, Office of Civilian Radioactive Waste Management.

Poster Presentations

Keeler, R. E., Smiecinski, A. J., Marks, S., Bertoia, J. A. (2008). "NSHE Nuclear Waste Cooperative Agreement: July 1998 – September 2008." 2008 UNLV Renewable Energy Symposium.

Research & Professional Experience:

2010 – pres. Quality Assurance Manager. Navarro-Intera, LLC, Las Vegas, Nevada. Environmental and engineering support services contractor for the United States Department of Energy National Nuclear Security Administration.

2009 – pres. Senior Quality Assurance Specialist. S.M. Stoller Corporation, Las Vegas, Nevada. Environmental and engineering support services contract with Navarro-Intera and the United States Department of Energy National Nuclear Security Administration.

2008 – 2009 Principal Investigator: "Chemical Analyses in Support of Natural Gradient Cross-Hole Tracer Tests," University of Nevada, Las Vegas, Harry Reid Center for Environmental Studies. Contract with Nye County, Nevada, Nuclear Waste Repository Projects Office, $70,000.

2008	Principal Investigator: “Groundwater Level Monitoring and Analytical Chemistry Investigations,” University of Nevada, Las Vegas, Harry Reid Center for Environmental Studies. Contract with Sandía National Laboratory, $400,000.
2004 – 2009	Project Director, “Scientific and engineering studies of the high-level waste repository at Yucca Mountain.” University of Nevada, Las Vegas, Harry Reid Center for Environmental Studies. Cooperative Agreement between the Nevada System of Higher Education and the Department of Energy Office of Civilian Radioactive Waste Management, $27,669,000.
2004 – 2009	Principal Investigator: “NSHE Co-op Administration,” University of Nevada, Las Vegas, Harry Reid Center for Environmental Studies. Financial assistance award from the Department of Energy Office of Civilian Radioactive Waste Management, $1,243,000.
2002 – 2009	Nevada System of Higher Education Licensing Support Network Point of Contact: Cooperative Agreements DE-FC28-04RW12237, DE-FC28-98NV12081 and DE-FC28-04RW12232.
2001 – 2009	Technical Liaison, “Scientific and Engineering Studies of the high-level waste repository at Yucca Mountain,” Nevada System of Higher Education. Cooperative Agreements DE-FC28-98NV12081 and DE-FC28-04RW12232.
2000 – 2009	Technical and Electronic Data Quality Assurance Specialist – Harry Reid Center for Environmental Studies, University of Nevada, Las Vegas.
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Certifications:

2010 – pres.	Certified Auditor, United States Department of Energy Consolidated Audit Program (DOECAP)
2009 – pres.	Certified Hazardous Waste Worker, U. S. Occupational Safety and Health Administration
2009 – pres.	Certified Radiation Worker I and II, United States Department of Energy
2009 – pres.	Certified Lead Assessor, Navarro-Intera, LLC
2007 – pres.	Adult AED/CPR, American Heart Association, American Red Cross
2000 – 2010	Certified Nuclear Quality Assurance Auditor (ASME-NQA-1), Nevada System of Higher Education. Certified Lead Auditor 2002 – 2010

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Certificate of Merit, TRW Environmental Safety Systems

Back Pat Award, TRW Environmental Safety Systems

Award for Superior Job Performance, U.S. Department of Energy

Award of Excellence, U.S. Department of Energy

Doer of Deeds Award for White House and Congressional briefings, U.S. Dept. of Energy

Best Presentation Award, University of Nevada, Las Vegas

Professional Association Membership:

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Professional Development Courses Taught:

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Data Submittal
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University of Nevada, Reno (2001 - 2009)
Quality Assurance Indoctrination
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University of California, San Diego (2002 - 2007)
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Denver Free University/Learning Unlimited (1986)
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