# THE UTILIZATION AND EFFECT OF INFORMATION TRANSFER IN AUDITING: AMONG AUDIT ENGAGEMENT TEAMS, AUDIT CLIENTS, AND SUPPLY CHAIN PARTNERS

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A dissertation submitted to the

Graduate School – Newark

Rutgers, The state University of New Jersey

In partial fulfillment of requirements

For the degree of

Doctor of Philosophy

Graduate Program in Management

Written under the direction of

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Newark, New Jersey

May 2018

## ABSTRACT OF THE DISSERTATION


**THE UTILIZATION AND EFFECT OF INFORMATION TRANSFER IN AUDITING: AMONG AUDIT ENGAGEMENT TEAMS, AUDIT CLIENTS, AND SUPPLY CHAIN PARTNERS**

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This dissertation consists of three essays that examine the utilization and effect of information transfer in auditing practice. Specially, I investigate two types of information transfer: information sharing and information diffusion. In information sharing, the information is transferred purposefully to target agents or spread within pre-selected groups. Unlike information sharing, information diffusion occurs when information is created, delivered and propagated by any active nodes within certain groups without purposeful directions.

In the first essay, I explore the possibilities of information sharing between audit engagement teams and demonstrate the benefits of doing this, under the assumption that the same audit firm serves multiple clients competing in the same industry. I introduce a number of sharing schemes for utilizing contemporaneous accounting information from peer companies without violating clients' confidentiality. To satisfy different levels of privacy protection, I propose different sharing schemes by utilizing auditors' self-generated expectations, and find that auditors can achieve comparable levels of benefits

from only sharing self-generated estimation residuals (errors) with that from sharing predicted or actual accounting numbers, both in estimation accuracy and in error detection performance. To satisfy stricter privacy concerns, I also propose a scheme based on sharing categorical information derived from prediction errors. Finally, I use Borda counts to analyze how the choice of the best model changes depending on the cost of errors within different experimental settings.

The second essay examines the effect on audit quality of “horizontal” information diffusion among audit clients within geographic industry clusters. I define the geographic industry clusters as the agglomerations of firms from the same industry, located in the same metropolitan statistical area (MSA). Based on a significant negative effect of geographic industry clusters on audit quality, I also investigate the reasons that foster such quality gap. As predicted, the quality difference is more pronounced for firms with stronger local connection measured by the number of local industry competitors sharing the same auditor. In addition, I also find that the geographic industry clusters have a positive effect on audit pricing and the existence of local connection intensifies such impact. Overall, the evidence suggests that due to the lower communication cost in the geographic industry clusters, clients are more likely to learn questionable accounting practices and form alliances to negotiate with auditors and convince them to accept questionable accounting practices. For fear of losing clients, auditors charge clients within the clusters higher audit fees to compensate the raising litigation risks, especially those clients with local connections.

The third essay investigates the effect of “vertical” information diffusion between supply chain partners and emphasizes the role of auditors in reducing information

asymmetry and sustaining business relationships. I examine the association between auditor reputation of suppliers and the duration of supply chain relationships and find empirical evidence that a poor reputation for the supplier's auditor increases the likelihood of customer-supplier relationship termination. However, that effect will be mitigated if customers and suppliers are located close to each other or if they share common auditors. Furthermore, suppliers who remediate the problem by switching from low reputation auditors to high reputation auditors will send positive signals to customers, which will decrease the likelihood of a relationship breakdown in the following year.

## ACKNOWLEDGMENTS

This dissertation would not have been accomplished without the help and support of my committee members, my colleagues, and my family. I appreciate this great opportunity to convey my gratitude to them with all my sincerity.

First of all, I would love to express my respect and appreciation to my advisor Dr. Alexander Kogan for his rigorous training, unlimited patience and pertinent suggestions. The weekly meetings that we spent together, provided me with great experiences. I am very grateful to Dr. Miklos A. Vasarhelyi for his generous support and constant care. I am deeply thankful to Dr. Helen Brown-Liburd for her valuable feedback in auditing research and Dr. Rajendra Srivastava for serving on the committee and providing precious insight for my future career. Also, I would like to express my gratitude to Dr. Dan Palmon for his trust, recognition, protection and encouragement. Without his help, I would not know where to go. Last but not least, I would like to thank Dr. Bikki Jaggi for his extraordinary guidance in accounting studies.

I was lucky to have friends and colleagues with warm heart and love. My special thanks go to my treasured friends and colleagues: Xin Cheng, Yinan Yang, Feiqi Huang, Yulin Sun, Lingyi Zheng, Xuan Peng, Yifei Chen, Fujun Tang, Xianjue Wang, He Li, Ting Sun, Qiao Li, Zhaokai Yan, Yue Liu, Tiffany Chiu, and Yunsen Wang.

Finally, I express my greatest thanks to my family members for their support and love.

## TABLE OF CONTENTS

## LIST OF TABLES

# CHAPTER 1: INTRODUCTION

In the realm of accounting, an “information transfer” occurs when a value-relevant information (e.g. earnings announcement) for one firm affects the expectations (e.g. stock prices) for other firms, whose economic prospects are interrelated (e.g. production process, customer group) with each other (Foster 1981; Ettredge and Richardson 2003) For example, if one firm announces bad news (e.g. usually lower than expected earnings), that firm is likely to experience negative CAR (cumulative abnormal returns). Further, similar firms (e.g. competitors within the same industry or supply chain partners) are likely to experience simultaneous abnormal returns. Such simultaneous abnormal returns can be negative due to industry commonalities or be positive because of competitive shifts between rival firms (Kim, Lacina and Park 2008). Prior studies provide evidence on information transfers from earnings announcements (Firth 1976; Foster 1981; Clinch and Sinclair 1987; Han and Wild 1990; Freenab and Tse 1992; Ramnath 2002; Thomas and Zhang 2008), management forecasts (Baginski, 1987; Han, Wild and Ramesh, 1989; Pyo and Lustgarten, 1990; Kim, Lacina and Park 2008), accounting standards harmonization (Wang 2014) and even the case of hacker attacks (Ettredge and Richardson 2003).

However, there are fewer studies that investigate the utilization and effect of information transfer in auditing practice for two possible reasons. First, in current regimes (Rule 1.700.001.01, AICPA), auditors are forbidden to directly utilize “transferred” information (e.g. contemporaneous accounting information from other clients audited by other engagement teams) from other engagement teams under the requirements of client confidentiality.  Second, prior studies focus on the role of auditors as accounting assurance providers rather than as information transfer repositories/ intermediators (Bae et al. 2017; Fiolleau et al. 2013). Therefore, to bridge such research gaps, this dissertation is going to investigate the utilization and effect of information transfer in auditing practice, among audit engagement teams, audit clients, and supply chain partners. Specially, in the following three chapters, I am planning to discuss two types of information transfer: information sharing and information diffusion.

In information sharing, the information is transferred purposefully to target receivers or spread among pre-selected group members. This procedure may include mediators, usually unrealted third parties, to guarantee the independence of interventions. Studies of information transfer usually seek to identify two prime factors: the firms with interrelated economic prospects and the information events that are value-relevant for firms directly affected (Ettredge and Richardson 2003). According to the above two criteria, the firms with interrelated economic prospects were identified as peer firms. An illustrative value-relevant information event can be the account estimation during analytical procedures, since prior studies show that peer companies data can be utilized to improve auditing effectiveness through analytical procedures (Hoitash et al. 2006). However, these studies assume the availability of a database repository used to enable data sharing among auditors. The feasibility of creating such a repository is in question due to audit clients' privacy concerns. Hence, my second chapter (first essay) is trying to answer the question of how to set up a practical privacy-preserving framework for sharing information among auditors without violations of clients' confidentiality. I introduce a number of sharing schemes for utilizing contemporaneous accounting information from peer companies without violating clients' confidentiality and observe significant improvements associated with sharing contemporaneous information from peer companies, both in estimation accuracy and error detection performance. To satisfy different levels of privacy protection, I propose different sharing schemes by utilizing auditors' self-generated expectations, and find that auditors can achieve comparable levels of benefits from only sharing self-generated estimation residuals (errors) with that from sharing predicted or actual accounting numbers, both in estimation accuracy and in error detection performance. To satisfy stricter privacy concerns, I also propose a scheme based on sharing categorical information derived from prediction errors. Finally, I use Borda counts to analyze how the choice of the best model changes depending on the cost of errors within different experimental settings.

After investigating the utilization of information sharing among audit engagement teams, I explore the effect of information diffusion among audit clients within the same industry. Unlike information sharing, information diffusion is the process where information is created, delivered, and propagated among any active nodes (agents) with no purposeful directions. At the beginning, information diffuses sequentially from some particular information source, such as a group of nodes (agents) outside the group or other information intermediators such as mass media or thorough "word of mouth". For example, investors often spend lots of time discussing investment strategies with other investors (Liu et al. 1997). With the development of online social networks, investors may create, discuss and spread information through social media, such as Facebook and Twitter (Guille et al. 2013). This kind of social activity tends to become a form of group pressure, which has influence on investors' original expectations. Prior literature documents various research questions such as how to identify influential spreaders (Li et al. 20142014), how to infer the underlying spreading cascade (Gomez et al. 2010), how to predict specific diffusion process by learning past diffusion traces (Galuba et al. 2010), and how to detect the popular topics (Kempe et al. 2003).

In this dissertation, I focus on the information diffusion among audit clients especially clients from the same industry and MSA[1] (industry clusters) and believe the diffusion effects are more prevalent within geographic industry clusters due to both closer industrial and geographic distances. As suggested by Kewei Hou (2007), firms within an industry compete in the same product market and their operating decisions reflect strategic interaction between them. As the industry experiences expansions and contractions, these firms' growth opportunities and investing and financing decisions are highly interrelated. Additionally, the engagements and negotiations with auditors can be treated as one of value-relevant information events. Thus, it is worthy to investigate the effect of information diffusion among audit clients on audit quality and audit pricing.

The third chapter (second essay) of the dissertation examines whether there is a difference in audit quality between firms within "geographic industry clusters" and those firms outside clusters, using a large sample of audit client firms from 2000 to 2015. Consistent with prior literature, I define the geographic industry clusters as the agglomerations of firms from the same industry located in the same metropolitan statistical area (MSA) (Almazan et al. 2010). Further, based on a significant negative effect of

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[1] A geographic entity defined by the federal Office of Management and Budget for use by federal statistical agencies, based on the concept of a core area with a large population nucleus, plus adjacent communities having a high degree of economic and social integration with that core. https://factfinder.census.gov/help/en/metropolitan_statistical_area_msa.htm

geographic industry clusters on audit quality, I also investigate the reasons that foster such quality gap. As predicted, the quality difference is more pronounced for firms with stronger local connection measured by the number of local industry competitors sharing the same auditor. In addition, I also find that the geographic industry clusters have a positive effect on audit pricing and the existence of local connection intensifies such impact. Overall, the empirical evidence suggests that due to the lower communication cost in the geographic industry clusters, clients are more likely to learn questionable accounting practices and form alliances to negotiate with auditors and convince them to accept questionable accounting practices. For fear of losing clients, auditors charge clients within the clusters higher audit fees to compensate the rising litigation risks, especially those clients with local connections.

Most studies investigate the information transfer within the same industry, named "horizontal" information transfer, but Olsen et al. (1985) find "vertical" information transfer occurs among supply chain partners as well. The information diffusion over supply chains may occur when either suppliers or customers (un) obtain value-relevant information about their collaborators. This information may change their expectations on future prospects and business cooperation of their supply chain partners. Following this research stream, I extend my research scope to investigate the effect of "vertical" information diffusion over supply chains and emphasize the importance of auditors in aiding management decision making and sustaining business relationships. The fourth chapter discusses the importance of auditors in reducing information asymmetries and sustaining supply chain relationships and studies the association between auditor reputation and the duration of customer-supplier relationships. I argue that the reliability of auditors' opinions influences customers' confidence in suppliers' financial reporting and operating performance, which affects the level of information asymmetry and the quality of information sharing between these supply chain partners.

The auditor's reputation, measured by the number of announcements of restatements, is a publicly available proxy for customers' perceived level of trust in their collaborations with their suppliers (Swanquist and Whited 2015). Investigating the hypothesis that customers and suppliers may view transaction conditions more favorably and sustain longer relationships if the customers are assured of the quality of information that was audited by trusted auditors (Kinney 2000), we provide empirical evidence that a poor reputation for the supplier's auditor increases the likelihood of customer-supplier relationship termination. However, that effect will be mitigated if customers and suppliers are located close to each other or if they share common auditors. Furthermore, suppliers who remediate the problem by switching from low reputation auditors to high reputation auditors will send positive signals to customers, which will decrease the likelihood of a relationship breakdown in the following year. The empirical findings emphasize the significant role of auditors and the importance of auditor reputation in maintaining supply chain relationships.

To summarize, the structure of this dissertation is as follows: in Chapter 2, I propose several information sharing schemes that explore the benefits and possibilities of utilizing information transfer (sharing) in auditing practice. Chapter 3 studies the effect of "horizontal" information diffusion among audit clients by investigating the influence of geographic industry clusters on audit quality. Chapter 4 discusses the effect of "vertical" information diffusion among supply chain partners and emphasizes the important role of auditors in reducing information asymmetries and sustaining supply chain relationships. The last chapter provides some concluding remarks.

# CHAPTER 2: PRIVACY-PRESERVING INFORMATION SHARING WITHIN AN AUDIT FIRM

## 2.1 Introduction

The well-publicized audit failures of Enron, WorldCom and others have brought to the forefront the issue of audit effectiveness. The emergence of data-driven technologies and methodologies, and the big data context, put more emphasis on developing and refining innovative audit data analysis techniques. A promising family of such techniques utilizes information sharing in the auditing process, especially information from similar companies subjected to the common financial environment (macro-economic cycle, market conditions, etc.). Such peer companies also experience similar non-financial shocks. Therefore, comparisons of their results can provide valuable information for auditors. Prior studies show that peer companies data can be utilized to improve auditing effectiveness through analytical procedures. Specially, Hoitash, Kogan and Vasarhelyi (2006) introduce an approach for selecting peers and perform tests to examine the contribution of peers' information to the performance of analytical procedures. However, this study assumes the availability of a database repository used to enable data sharing among auditors. The feasibility of creating such a repository is in question due to audit clients' privacy concerns. Hence, an important question left unanswered is how to design a practical privacy-preserving artifact for sharing information among auditors without violations of clients' confidentiality.

This chapter fills this research gap and follows the paradigm of design science[1] to create effective analytical procedures that enable auditors to share client information within an audit firm in a privacy-preserving manner, under the assumption that the same audit firm serves multiple clients competing in the same industry. The rationale for this assumption is based on the theory of audit firm industry specialization[2] (Mayhew et al. 2003, Chan et al. 2004). In particular, our approach is more instructive for those audit firms which follow a cost minimization strategy and gain market share by providing service to a large portion of companies within the same industry (Cahan, Debra and Vic 2011).

The design of artifacts is not exempt from natural laws or behavioral theories but relies on existing kernel theories (Walls et al. 1992; Markus et al. 2002). The foundation for our design is based on the usefulness of peer firm data. To be specific, many previous studies (Healy and Palepu 2007; Stickney et al. 2007; Damodaran 2007) have showed the advantages of using peer firms as a benchmark[3] and the methodologies of choosing peers (Hoitash et al. 2006; Minutti-Meza, M. 2013; De Franco et al. 2015). In more relevant studies, prior literature has extensively examined the importance of information transfer

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[1] The design-science paradigm is fundamentally a problem-solving paradigm and has its roots in engineering and the sciences of the artificial (Simon 1996).

[2] This theory asserts that audit firms differentiate themselves from other competitors to maximize profitability. Developing industry specific knowledge can allow auditors to satisfy clients' demands and earn profits due to economies of scale. Therefore, audit firms make costly investments to train specialists in specific industries and differentiate themselves from others in terms of assurance services (Hogan and Jeter 1999, Dunn and Mayhew 2000).

[3] For instance, financial analysts use peer firms to support their valuation multiples, earnings forecasts and overall stock recommendations (De Franco et al. 2011). Investment managers use peer firms in structuring their portfolios (Chan et al. 2007). Peer firms are used by compensation committees in setting executive compensation (Albuquerque 2009; Albuquerque et al. 2013), in determining valuation multiples (Bhojraj and Lee 2002), as well as by auditors in conducting analytical procedures (Hoitash et al. 2006; Minutti-Meza 2013).

and industry expertise in providing high-quality audits[4]. With the development of data-driven methodologies in analytical procedures since 1980s, researchers have proposed numerous ways[5] to boost the performance of analytical procedures. The extant literature has provided sufficient evidence to believe that incorporating peer-based industrial contemporaneous data could improve the performance of analytical procedures.

Since peer companies typically have the same fiscal years, and audit opinions have to be formulated before the disclosure of financial statements, contemporaneous data from peer companies are not publicly available. The data availability problem becomes a hurdle in the way of obtaining the benefits from incorporating contemporaneous information. Thus, many previous studies only used company specific current data plus publicly available data but did not use contemporaneous data from peer companies[6]. A reasonable solution to this problem would be sharing contemporaneous data from peer companies audited by the same audit firm. The current regime (Rule 1.700.001.01) requires auditors to protect clients' data confidentiality but does not forbid auditors from using clients' data to improve their audit quality, as stated in Rule 1.700.001.02.). Moreover, in circumstances

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[4] For instance, they suggest that knowledge of the industry may increase audit quality (Balsam et al. 2003; Krishnan 2003; Reichelt and Wang 2010), improve the accuracy of error detection (Solomon et al. 1999; Owhoso et al. 2002), enhance the quality of auditors' risk assessment (Taylor 2000; Low 2004), and optimize the allocation of audit resources and audit efforts (Low 2004).

[5] They start to use higher data frequency (Wild 1987; Dzeng 1994), apply more sophisticated statistical models (Dugan et al. 1985; Pany 1990; Leitch and Chen 2003), and consider multiple companies in similar industries (Lev 1980; AICPA 1988; Wheeler and Pany 1990; Allen 1992) as well as multi-location data (Allen et al. 1999).

[6] In Hoitash et al. (2006), they find that the inclusion of contemporaneous data from peer companies does not always outperform benchmark model when other contemporaneous variables are included. This finding implies that the inclusion of contemporaneous data could always improve the estimation accuracy, and thus sharing the prediction that contains contemporaneous data could provide more information than sharing the historical public available data alone. Therefore, this is the reason why we explore the possibilities of obtaining the benefits from sharing contemporaneous data instead of from utilizing public available data.

where the auditor specializes in a specific industry, the auditor may use clients' data to develop plausible expectations[7] (Guy and Carmichael 2002). As Gal (2008) suggested, auditors have responsibilities to determine the precise definition of sensitive data, the timeliness of information released and the appropriateness of technologies used for information protection. Therefore, we believe that if the auditor can guarantee no disclosure or leakage of confidential information during the sharing process, it is valuable to study a possible implementation of a privacy-preserving information sharing scheme among the auditors in the same audit firm.

To address the client privacy preservation needs articulated above, we first theoretically develop a so-called "generic sharing scheme" by introducing a third party (e.g., the central office / headquarters of accounting firms) as a control unit responsible for generating, assigning and passing aggregated/modified information derived from clients' private data in an anonymous setting.

Next, to alleviate the concerns related to the impairment of third parties' independence, we propose a modified generic sharing scheme that avoids the involvement of third parties. The modified generic sharing scheme trades off some efficiency of the generic sharing scheme to enable participants to exchange information between each other following a pre-defined path.

Further, to mitigate the concerns of raw data exposure and enable different levels of privacy protection, we offer a number of information sharing schemes as alternatives

[7] For example, gross margin percentage, other income statement ratios, and receivable and inventory turnover ratios.

that utilize auditors' self-generated accounting expectations of numerical and categorical nature. Specifically, we first propose a prediction-based expectation sharing scheme in which the auditors share the standardized self-generated predicted values instead of clients' raw data. A residual-based expectation sharing scheme is proposed to satisfy even more stringent privacy requirements. It allows the auditors to share the standardized self-generated prediction errors (residuals) instead of prediction values to further reduce the possibilities of raw data exposure. Additionally, as an extension of the residual-based sharing scheme, we develop a categorical sharing scheme based on the information derived from prediction residuals. In this sharing scheme, the auditors convert the numerical prediction residuals into two pieces of categorical information: the sign of prediction errors and the level of deviations and share either one of these two variables or both of them.

Based on how similar the shared information is to the raw data, we categorize the proposed levels of sharing from high to low: the high-level sharing scheme (sharing the actual clients' data by utilizing the generic/modified generic sharing scheme), the medium-level sharing scheme (the prediction-based expectation sharing scheme), the low-level sharing scheme (the residual-based expectation sharing scheme), the categorical sharing scheme with both categorical variables, and the categorical sharing scheme with only one categorical variable.

Design science is well recognized in the IS (Information Systems) literature and addresses research through the building and evaluation of artifacts that are developed to meet the identified business needs (Von et al. 2004). Unlike behavioral and empirical paradigms that are commonly accepted in accounting research, design science aims to determine how a new developed artifact works instead of why the artifact works. In other words, it puts more emphasis on the utility not the truth of the artifacts. As argued by prior literature (Simon 1996 and Von et al. 2004), the research paradigms are inseparable and the contribution of a certain research should be evaluated by its practical implications not methodologies. Thanks to the mathematical basis, design science allows many types of quantitative evaluation methodologies, such as optimization proofs, analytical simulation, and quantitative comparisons with alternative/ previous designs. In this chapter, we use commonly accepted designs and metrics to evaluate our sharing schemes not only in terms of estimation accuracy but also in error detection performance in comparison with competing artifacts. For simplicity, we test the case of "overestimating revenue" and the case of "underestimating cost of goods sold" as illustrations[8].

In the evaluation phase, we use ten representative industries that contained the largest number of firms from 1991-2015 using 4-digit SIC codes. Since the disaggregated monthly data performed better in analytical procedures than did the quarterly data, we interpolate our quarterly data to monthly data. Adapting from Hoitash et al. (2006), we use the simple auto-regression model that contains both last year public available information and current year contemporaneous data as the benchmark model. In order to rigorously simulate the real practice, we impose a constraint that peer firms need to be audited by the

[8] In practice, auditors provide assurance on management assertions in the financial statements and verify the occurrence of transactions related to assets, revenues, liabilities, and expenses. Usually, managers may have incentives to overestimate their assets and revenues and underestimate their liabilities and expenses to report inflated profits. However, accounting literature (e.g. Kross et al. 2011, Ma et al. 2017) also provides extensive evidence that managers have strong incentives to meet earnings expectations and manage earnings downward to 0 in order to obtain benefits from discretionary accruals.

same auditor in the current year, resulting in a large reduction in our sample[9]. Later, to investigate the applicability and generalizability of our proposed sharing schemes, we remove such strict peer selection criteria and increase the number of industries from ten to twenty, as presented in the Supplementary Appendix A.

First, we compare the MAPEs (mean absolute percentage errors) of all competing prediction models: the original model, the actual-sharing model, the prediction-sharing model, and the error-sharing model and categorical-sharing models. We expect the MAPE will significantly decrease from the original model to other sharing models. If, at the same time the MAPE is at a comparable level among sharing models, it will show that the improvement of prediction accuracy by incorporating peer companies' information can be attained by sharing auditors' self-generated information during the estimation process. In this manner, the clients' confidentiality can be protected completely by only sharing auditors' estimation adjustment errors without utilizing any clients' accounting numbers. Moreover, if the MAPE generated by fine-tuned categorical sharing models, is at a comparable level with higher level sharing models, it provides auditors a more conservative option to gain the benefits of sharing without violating confidentiality. To verify that our results are not affected by extreme outliers, we not only tabulate the mean of the MAPE, but also provide the median of the MAPE. Additionally, because of the loss of information, the validation performance of the categorical sharing model with only one categorical variable may suffer, compared to other peer models.

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[9] The sample shrinkage is consistent with prior literature that investigates the effect of sharing common auditors between suppliers and customers on audit quality (Johnstone, Li and Luo 2014).

Next, we discuss the error detection performance by comparing the original model and the sharing models. Specially, we compare the error detection performance between the original model, the three sharing models with different privacy levels and the four categorical models with separately tuned parameters. A simulation approach known as "error seeding" is used to compare the anomaly detection capabilities of different models. In our experiment, we added artificial errors[10] to the original values and checked whether the model could detect the data had been polluted. In the context of our research, the error detection capability of models is measured as the cost of errors[11]. In addition, taking the randomness of choosing contaminated observations into account, we test the impact of the magnitude of contaminated errors ranging from 5% to 1%, repeat the error seeding procedure ten times and use the average level as the evaluation to generalize our results, reduce the selection bias and achieve the robustness of results.

In order to investigate how the choice of the best model changes depending on different experimental settings, we compare the total cost of errors for different models varying five different cost ratios, three magnitudes of errors, and five different prediction intervals. We adapt the Borda count voting method to determine the most suitable model for each company based on preference ballots with different parameter pairs.

Our analysis shows a new way of increasing prediction accuracy through sharing self-generated estimations/ residuals among auditors serving the same industry within an audit firm. In this way, the auditors can benefit without sharing any client raw information, and

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[10] The magnitude of errors is determined by the magnitude of original values, e.g., 2% of account receivables.
[11] The cost of errors can be calculated using three metrics: the numbers of false negative and false positive errors and the magnitude of the cost ratio between the two types of errors.

naturally not violate confidentiality constraints. In addition, we also show that the peer-based sharing models have superior error detection over the original model and more interestingly, the low-level sharing scheme in which the auditors only share the estimation residuals (errors), turns out comparable performance with the medium-level and high-level sharing schemes in which auditors will share their estimations and actual data respectively. Moreover, the evaluation results show that the so-called categorical sharing scheme can achieve a comparable improvement in audit analytical procedures with fine-tuned thresholds. Finally, in the comparison of the model performances of error detection, we observe that the best model is usually the mixed categorical information-sharing model that shares both the sign and the level of deviations of prediction errors. The best model selection remains relatively stable when we put enough weight on the occurrence of false negatives.

This study adds to the literature in the following four ways. First, to our best knowledge, this research is the first to explicitly utilize a design science paradigm in auditing literature to solve the problem of information sharing among auditors within an audit firm. We extend and transform Hotaish et al. (2006) theoretical design into a practical implementation by showing that the self-generated expectation sharing schemes with properly tuned parameters can achieve similar prediction performance as the actual data sharing schemes, and under these settings, the auditors can easily realize the benefits of sharing peer information without violating client confidentiality. Second, our evaluation evidence supports the conclusion that these improvements are not limited to more accurate predictions but also result in more effective error detections. Thus, when auditors within an audit firm have peer clients, utilizing self-generated expectation sharing schemes will result in achieving better audit quality through suitably parameterized audit analytical procedures in a privacy-preserving manner. Finally, our design of the peer-based analytical procedures enables auditors to achieve better prediction performance and error detection without violating clients' confidentiality, demonstrates the possibility of sharing data among auditors, and encourages the regulators to reconsider the interaction between auditors to achieve better auditing results while still preserving clients' information security. Finally, our proposed artifacts well satisfy auditors' different demands of privacy with extremely low cost by sharing their self-generated aggregated information. It is to be expected that the adoption of these methods across different industries will reduces the cost of adoption, implementation, as well as the learning curve.

The remainder of this chapter is organized as follows. Section 2 provides the background on information sharing during the audit process and describes different sharing schemes based on different data privacy demands. Section 3 describes the evaluation of proposed designs including the research questions, the data, the model specifications, and the methodologies used in our validation tests. The validation tests themselves are summarized in Section 4. A discussion of the results and some concluding remarks are presented in Section 5.

## 2.2 Background and Sharing Schemes

### *2.2.1 Background*

During the auditing process, the auditors can request nearly any information about their clients. Under the standard confidentiality contract clauses, the auditor must guarantee that disaggregated information of the client cannot be exchanged, leaked or sold to other individuals or institutions, even to the auditors working in the same audit firm but assigned to different engagements. We consider hypothetical scenarios designed to model the practical problems occurring in public accounting firms related to the challenge of privacy-preserving information sharing between the auditors within the same firm.

The current legal regime requires the auditors to protect clients' data but does not prevent the auditors from using these proprietary data for their own analyses. Specifically, Rule 700.001.01 (previously Rule 301) of the American Institute of Certified Public Accountants (AICPA) Code of Professional Conduct (2015) states that "a member in a public practice shall not disclose any confidential client information without specific consent of the client". However, current rules do not restrict auditors from using clients' data to improve their audits, as stated in Rule 700.001.02. In fact, AU section 329.05 states that, "Analytical procedures involve comparisons of recorded amounts, or ratios developed from recorded amounts, to expectations developed by the auditor. The auditor develops such expectations by identifying and using plausible relationships that are reasonably expected to exist based on the auditor's understanding of the client and of the industry in which the client operates." Additionally, there is anecdotal evidence suggesting that national offices of large public accounting firms use data from a pool of companies in the same industry as a benchmark for other companies (Hoitash et al. 2006). Moreover, auditors need to make sure that clients' confidential information is not disclosed in the work papers of another client because such information may be subpoenaed in the future. As noted in Rule 1.700.100, the member's disclosure of confidential client information in compliance with a validly issued and enforceable subpoena or summons would not violate Rule 1.700.001. However, the disclosure of another company's private information (such as name, sales and purchases) may potentially violate Rule 1.700.090 [12] and Rule 1.700.010[13].

Recently, a stream of literature investigated the impact of sharing common auditors on corporate decisions (e.g. Johnstone, Li and Luo 2014; Cai et al. 2016; Dhaliwal et al. 2016; Bae, Gil Soo, et al. 2017). For example, Cai et al. (2016) take a purely empirical approach to investigate how sharing auditors can reduce deal uncertainty between participants and bypass the ethical question of sharing clients' information within an audit firm. Further, Dhaliwal, et al. (2016) point out a flow of information between bidders and targets and argue that in order to maintain the relationship between a client and large acquisition clients, auditors may intend to connect target firms with acquirers and bias the information to acquiring firms. These studies imply the existence of sharing information between auditors within the same audit firm and put spotlight on the ethical issues of protecting clients' confidential information in auditing practice. Thus, it is urgent and necessary to emphasize the importance of data privacy while utilizing clients' information to improve audit quality.

The cryptology technologies such as public or secret-key encryption (e.g. Bellare et al. 2001; Boneh et al. 2004) and zero knowledge authentication (e.g. Blum, Feldman and Micali 1988) were well documented in the IS (Information Security) literature. However,

[12] Rule 1.700.090: The member's disclosure of a client's name would not violate the "Confidential Client Information Rule" [1.700.001] if disclosure of the client's name does not constitute the release of confidential client information

[13] Rule 1.700.010: When a member provides professional services to clients that are competitors, threats to compliance with the "Confidential Client Information Rule" [1.700.001] may exist because the member may have access to confidential client information, such as sales, purchases, and gross profit percentages of the respective competitors.

these technologies do not help auditors to share peer data without leaking clients' information, simply because once the auditors use their private (or shared secret) key to decrypt the encrypted data, the client's data is revealed. Another stream of privacy preserving data mining technologies which can blindly pool and analyze data (e.g. Vaidya and Clifton 2002, 2003), seems to be a potential solution. However, in audit analytical procedures, the goal is to improve the estimation power of a specified model for a certain audit client not an improved industry model by pooling all peer data together.

It is reasonable to consider the possibility of utilizing contemporaneous peer information by subject matter experts working in the national offices of auditing firms who can run analytical procedures at the request of the engagement teams and communicate the results to the engagement team without disclosing the actual data of peer clients competing in the same industry and thus conceivably avoiding privacy rules violations. However, based on our personal communications with some Big Four partners, this solution is not feasible. In fact, if audit engagement teams consult with national office specialists and obtain their help in analyzing their clients' data, those specialists are considered to be temporary members of the engagement team for the duration of the consultation. Therefore, the same privacy rules apply to these specialists and prevent them from utilizing yet undisclosed peer competitors' data in their work for the engagement team.

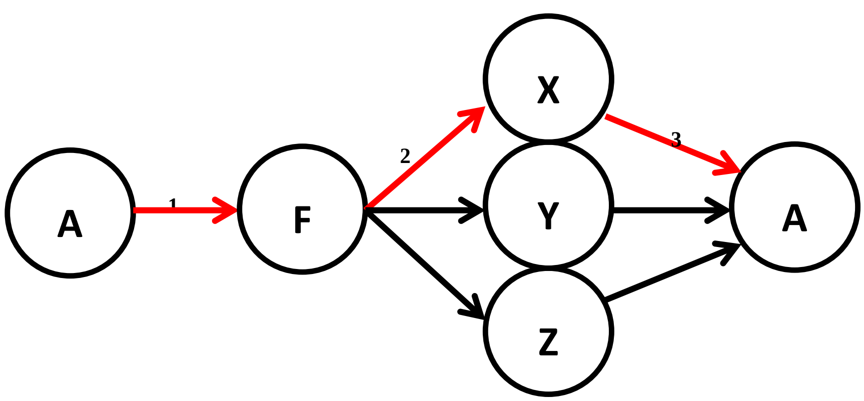
### *2.2.2 Sharing Schemes*

#### **A generic sharing scheme**

As discussed above, auditors are strictly forbidden from leaking any client-owned data outside the engagement team without explicit consent of their clients. A potential way to deal with the barriers of confidentiality is to share aggregated / modified information derived from clients' private data. Thus, the main challenge of sharing information among engagement teams is to aggregate/ modify the information from clients' data and transfer from one engagement team to another without any sensitive disclosures. The function of disguising, aggregating, and passing data can be controlled by a reliable third party.

The objective of developing a generic sharing scheme is to provide the auditors with a privacy-preserving data aggregation technique. The basic idea can be described in the following four steps: add noise to self-owned raw data (e.g., actual accounting numbers, predictions or residuals produced by regression models), share thus contaminated data with other engagement teams auditing peer companies, sum up the contaminated data received from others, and reduce the pre-announced total noise (announced and assigned before sharing). To be more specific, we provide a simple example below.

**Figure 1. The Generic Sharing Scheme: An Example**




In this example, A represents an auditor (engagement team) engaged with a client C, F represents the national office of the audit firm of A, and X, Y and Z are peer companies (and their audit engagement teams) selected in the current year for client C (engagement team A). In step 1, A passes its last year's revenue multiplied by a large number to F. In step 2, F passes a random split of the large number received from A to X, Y and Z separately. In step 3, A receives the sum of private contaminated information from X, Y and Z and subtracts the known self-generated large number to get the aggregation of private information from X, Y and Z.

An engagement team of client "A", whose peers are companies X, Y and Z in the current year, sends its last year revenue $R_{t-1}$ multiplied with a large number M to the national office of its audit firm "F" that acts as a trusted third party, and requests F to split the product randomly into the number of parts equal to the number of peers. In this case, since there are three peer companies for client A, the number of parts equals to three. To accomplish that, F generates three random parameters $(\alpha_X, \alpha_Y, \alpha_Z)$ and calculates the ratio of each parameter to their total sum, to guarantee that the resulting ratios add up to 1. Specifically, F passes $R_{t-1} * M * \frac{\alpha_X}{\alpha_X+\alpha_Y+\alpha_Z}$ , $R_{t-1} * M * \frac{\alpha_Y}{\alpha_X+\alpha_Y+\alpha_Z}$ and $R_{t-1} * M * \frac{\alpha_Z}{\alpha_X+\alpha_Y+\alpha_Z}$ to the engagement teams of peer companies X, Y and Z respectively. Next, the engagement teams of X, Y and Z add the numbers received from F to their self-owned data (e.g., current year's revenue $R_t$). After the engagement teams of X, Y and Z pass thus contaminated information back to the engagement team of A, it calculates the aggregated information (the sum of revenues of peer companies) by deducting the known amount $R_{t-1} * M$ from $R_t^X + R_t^Y + R_t^Z + R_{t-1} * M * (\frac{\alpha_X}{\alpha_X+\alpha_Y+\alpha_Z} + \frac{\alpha_Y}{\alpha_X+\alpha_Y+\alpha_Z} + \frac{\alpha_Z}{\alpha_X+\alpha_Y+\alpha_Z})$.

In this sharing scheme, the privacy of information from X, Y and Z is guaranteed by adding untraceable noise to the sensitive data. The term "untraceable" requires that the proposed noise (e.g., last year revenue) should be multiplied by a very large number (M). If the account balance of revenue is a small number, then adding noise of the same magnitude may be too weak to protect a larger account balance of peer companies[14]. Further, the split ratios are randomly chosen from a uniform distribution between 0 and 1 so that one (or more) ratios could be much smaller than the others. In this case, the protection will not work either since the added noise becomes too small to provide significant contamination to the original number. Therefore, the proposed scheme uses a very large number (say, 1,000,000) to multiply the revenue account by, and the privacy of peer companies is preserved.

The generic sharing scheme has at least three possible weaknesses. First, this scheme can only provide privacy protection in the probabilistic sense. In some extremely rare circumstances, some of the generated random numbers can be so small, that the contamination will be insufficient to protect the original data. Second, the scheme works only if the client has more than one peer in the current year. In fact, there are existing examples of companies having only one peer in a certain year, thus invalidating this assumption of the information protection scheme. Third, the involvement of third parties may pose ethical issues that can potentially compromise their reliability. Additionally, in this generic sharing scheme, it is hard to vary the levels of privacy needed according to a dynamic (data-driven) demand for privacy protection in audit practice. Therefore, to satisfy stricter privacy concerns, one has to respond to the challenge of how to eliminate the involvement of third parties, to reduce the exposure of actual data and to provide multiple selections of the levels of privacy.

[14] For example, assume A's last year revenue is 0.2 million dollars but the revenues of peer companies X, Y and Z are more than 10 million dollars. In this scenario, the protection fails because the actual revenues of peer companies can be extracted by simply ignoring the digits after the decimal point.

**A modified generic sharing scheme**

As we discussed above, the generic sharing scheme utilizes a third party. Since the involvement of third parties may cause ethical/operating concerns[15], we propose a modified generic sharing scheme that relies on the participation of auditors themselves rather than the centralized information collection mechanism held by third parties. The basic idea can be presented as follows.

For company X, with its peer companies Y and Z, they first agree on a pre-defined information exchange path that starts from X, passes through Y and Z and goes back to X. To protect X's actual data, auditor A of company X randomly selects a large enough amount $\varepsilon_x$ as the noise, adds it to X's original account number $N_x$, and then passes the sum $(\varepsilon_x + N_x)$ to auditor B who is engaged with company Y. Because $\varepsilon_x$ is large enough to hide the relatively small actual number, auditor B has no need to add an additional amount but to add client Y's original number $N_Y$ to the amount received from A. Then B passes the new amount $(\varepsilon_x + N_x + N_Y)$ to the participant C, who is the auditor of company Z. Similarly, for C, it is impossible to infer the actual numbers of companies X and Y from the received amount. Next, C adds client Z's actual number $N_z$ and sends the total back to A. Auditor A finally receives the total $(\varepsilon_x + N_x + N_Y + N_z)$, reduces the known amount $\varepsilon_x$, divides it by 3 and gets the mean of the numbers from companies X, Y and Z. In the last step, the privacy of client Y and Z is guaranteed because auditor A only knows the sum of

[15] The involvement of third parties may lead to some concerns, such as the independence of execution, the authentication of assignment and the potential concurrent conflict.

$N_Y + N_z$ by reducing the known amount $\varepsilon_x + N_x$ but has no idea how to split this amount and get the individual numbers of companies Y and Z respectively.

The choice of the large number $\varepsilon_x$ would be critical in this sharing scheme. For example, if we choose 10003 as the noise and the actual number of X is only 56.27, the addition of the noise and the actual number will be 10059.27. Then, company Y can easily reduce 10000 and get a very close estimate of 59.27. In this case, the "effective" noise amount is actually 3, which is definitely not a large enough number to provide reasonable protection for company X's sensitive information. A better way is to estimate the reasonable interval of the sensitive data, for instance, [20,100], then randomly choose a number from the interval and add this number to the sensitive data. For example, we choose 39.12 from this interval and add to 56.27. It becomes impossible for company Y to guess the actual number of company X from the received number 95.39. Similarly, in the final step, the privacy of company Y and Z can be protected since the actual number from company Y is a proper noise for the actual data from company Z and vice versa, assuming that company Y and Z are peer companies.

The modified sharing scheme enables auditors to share information without the third parties, trading off the efficiency of the generic sharing scheme. In the generic sharing scheme, clients X, Y and Z just need to upload their own encrypted data directly to the third party without any inter-connections. However, in the modified generic sharing scheme, the process of information sharing relies on the inter-connections between participants X, Y and Z. In particular, the "single round" data exchange in the generic sharing scheme is replaced by the "multiple rounds" in the modified generic sharing scheme. Consequently, the "multiple rounds" of exchange may lead to a higher probability of data breach. Especially, when the chosen noises in the multiple rounds are extremely similar, the sensitive data are likely to be decoded. For instance, the auditor of company Z has access to the addition $\varepsilon_1 + N_x$, $\varepsilon_2 + N_y$, and $\varepsilon_3 + N_x + N_y$ after several rounds of exchanging. If the noises satisfy the relationship like $2\,\varepsilon_3 = \varepsilon_1 + \varepsilon_2$, then company Z can easily infer the noise $\varepsilon_3$ by adding $\varepsilon_1 + N_x$ and $\varepsilon_2 + N_y$ together and reducing $\varepsilon_3 + N_x + N_y$. This potentially causes serious data leaking problems. Thus, to reduce the likelihood of such failures, the participants need to change the way of selecting errors in each round by applying different distributions, utilizing multiple discontinuous intervals without overlaps, and utilizing other ways of reinforcing the otherness/ complexities of noise.

In summary, in the generic or modified generic sharing scheme, auditors can gather the aggregated actual contemporaneous firm-specific information from their peer companies with privacy controls[16]. In order to eliminate the size effects on firm-specific information, auditors can standardize the sharing information themselves in advance. For example, for company X, after engagement team A receives the standardized aggregated mean of actual value $(\mathrm{z}_{t\_B} + \mathrm{z}_{t\_C})$ / 2[17] from its peer companies Y and Z, the auditor A can add it as an independent variable in an actual sharing model $\mathrm{M}^{a}$, an auto regression model: $\mathrm{Y}_t = \alpha + \beta_1 Y_{t-12} + \beta_2 X_t + \beta_3 \mathrm{IND\_ACTUAL}_t + \varepsilon_t$, where $\mathrm{Y}_t$ is the estimation account of interest and $\mathrm{IND\_ACTUAL}_t$ equals $(\mathrm{z}_{t\_B} + \mathrm{z}_{t\_C})$ / 2 .

[16] The privacy control may collapse when participants collude with each other.
[17] The value z is the standardized score for clients' real data.

### Expectation sharing schemes

Since the generic/modified generic sharing scheme only provides privacy protection in the probabilistic sense, it is still risky to exchange clients' actual data. Therefore, we propose to share auditors' self-generated expectations instead of clients' raw data to attenuate clients' privacy concerns about raw data exposure.

The auditors' self-generated expectations, based on both historical data as well as non-public contemporaneous data, contain the firm-specific information that may improve analytical procedures for all peer companies. The type of the expectations can vary from numerical numbers to categorical judgements or from predicted account values to unexplained residuals. The aggregated auditors' self-generated expectation is an informative proxy that captures the contemporaneous industrial information in the current year.

The logic of the expectation sharing scheme is that, by sharing the self-generated expectations, auditors may both benefit from information advantages of non-public contemporaneous data as well as avoid violating clients' confidentiality, simply because in this sharing scheme, there is no raw clients' data exchanged.

First, we introduce a prediction-based expectation sharing scheme as follows. Assume company X, Y and Z are assigned to different engagement teams A, B and C respectively in the current year T. Based on prior years' (T-1) sales and growth numbers, Y and Z were selected as X's peer companies. Engagement teams A, B and C estimate the account of interest first, based on their clients' provided contemporaneous data combined with the historical audited data, independently. Since A, B and C are serving as auditors in the same audit firm, it is possible that they choose the same estimation model, for example, an auto regression model $\mathrm{M}^{o}$ (original model): $\mathrm{Y}_t = \alpha + \beta_1 Y_{t-12} + \beta_2 X_t + \varepsilon_t$. In this scheme, the auditors use previous three years (T-3, T-2, and T-1) data to estimate the original prediction model $\mathrm{M}^{o}$, based on the rolling window approach. Then they plug in the fourth year (the current year T) data to predict the fourth year's account number $\widehat{\mathrm{Y}_t}$ . To avoid the impact of company size on the peer average, a standard score is calculated for each participants X, Y and Z by their assigned auditors A, B and C, as follows: $z = \frac{\mathrm{y}-\mu(\mathrm{y})}{\sigma(\mathrm{y})}$ , where *y* represents a monthly number[18] generated by account balance, and the mean and the standard deviation of the monthly numbers calculated over the previous twelve months. Next, auditor A collects standardized prediction values $\widehat{\mathrm{z}_{t\_B}}$ and $\widehat{\mathrm{z}_{t\_C}}$ from B and C and adds the average of standardized value $\mathrm{IND\_PREDICT}_t = (\widehat{\mathrm{z}_{t\_B}} + \widehat{\mathrm{z}_{t\_C}})/2$ as an independent variable in the prediction sharing model $\mathrm{M}^{p}$: $\mathrm{Y}_t = \alpha + \beta_1 Y_{t-12} + \beta_2 X_t + \beta_3 \mathrm{IND\_PREDICT}_t + \varepsilon_t$.

Being more conservative, auditors may still feel risky to share the prediction values. To eliminate such concerns, we propose a residual-based expectation sharing scheme, which shares the prediction residuals (actual value minus predicted value) among auditors. The residuals are likely to contain useful abnormal information that is not captured in the original estimation model, such as the direction or the magnitude of the errors between the actual value and the auditors' prediction value. In the accounting literature, there are

[18] In previous studies, disaggregated monthly data performed better in analytical procedures than did quarterly data (Wild 1987; Chen and Leitch 1998; Cogger 1981; Knechel 1988; Dzeng 1994). Therefore, we use monthly observations instead of yearly/quarterly data in our experiment.

numerous studies utilizing abnormal accruals (discretionary accruals) based on Jones model (1991). The abnormal accrual is a regression residual usually used as a proxy for disclosure quality and a signal of earnings management (Klein et al. 2002, Kothari et al. 2005). Similarly, in the auditing literature, there are a number of papers (Eshleman et al. 2013, Blankley et al. 2012, Choi et al. 2010) discussing the informativeness of "abnormal audit fees", the regression residuals produced by audit fee models. Therefore, utilizing the residuals as supplementary contemporaneous information is a reasonable choice.

To be specific, consistent with the prediction-based expectation sharing scheme, instead of collecting the standardized prediction values, auditor A collects the standardized mean of errors $\mathrm{IND\_ERROR}_t = (\varepsilon_{t\_B} + \varepsilon_{t\_C})\ /\ 2$ from B and C, where the errors $\varepsilon_t$ are calculated by using the holdout data $\mathrm{Y}_t$ (the fourth year data) minus predicted value of the fourth year $\widehat{\mathrm{Y}}_t$. Then auditor A adds the mean of errors $\mathrm{IND\_ERROR}_t$ as an independent variable in the error sharing model $\mathrm{M}^e\text{: }\mathrm{Y}_t = \alpha + \beta_1 Y_{t-12} + \beta_2 X_t + \beta_3 \mathrm{IND\_ERROR}_t + \varepsilon_t$.

The design of the prediction/ residual-based expectation sharing scheme allows for different levels of privacy. The level of privacy is the opposite to the level of sharing. For example, sharing the actual data under the generic/modified generic sharing scheme provides the highest level of sharing but the lowest level of privacy, since the actual number can be breached due to improper sharing. However, in the prediction/ residual-based expectation sharing scheme, the auditors only have access to the average of aggregated predictions/ prediction errors, which can be considered as far less risky exposure compared to the actual data. Based on how similar the shared information is to the raw numbers, we categorize the proposed levels of sharing from high to low: the high-level sharing scheme (sharing the actual clients' data by utilizing the generic/modified generic sharing scheme), the medium-level sharing scheme (the prediction-based expectation sharing scheme), and the low-level sharing scheme (the residual-based expectation sharing scheme). Again, as we mentioned before, the auditors can only utilize one of the medium-level and low-level sharing schemes, since utilizing both of them is equal to utilizing the high-level sharing scheme with no privacy protections. The three levels of sharing schemes are summarized as follows:

**Table 1. The Summary of Sharing Schemes with Three Levels of Privacy**

| Privacy Levels | **Peer Sharing Model** |
|---|---|
| Low Level | $\overline{\varepsilon_{i \neq j}}$ |
| Medium Level | $\overline{\hat{y}_p}$ |
| High Level | $\overline{y_i, i \neq j}$ |

For the low-level sharing scheme, auditors will add standardized estimation residuals $\overline{\boldsymbol{\varepsilon}_{i \neq j}}$ from peer companies as an independent variable; For medium-level sharing scheme, auditors will add standardized prediction $\overline{\hat{\boldsymbol{y}}_{\boldsymbol{p}}}$ from peer companies as an independent variable; For high-level sharing scheme, auditors will add standardized real accounting numbers $\overline{\boldsymbol{y}_i, \boldsymbol{i} \neq \boldsymbol{j}}$ as an independent variable.

Since dummy (categorical) variables are relativey less informative than numerical (continuous) variables, utilizing such variables will further reduce potential exposure. Thus, to enhance privacy protection, the low-level sharing scheme can be modified to protect privacy even better through sharing only categorical information derived from residuals instead of sharing the residuals themselves. More specifically, the shared "expectation" information consists of two dummy variables: the sign of prediction errors and the level of deviations.

The sign of prediction errors provides an indication of overestimation or underestimation based on peer firms' contemporaneous experience and helps to modify prediction models in the right direction. If the sign of prediction errors is positive (negative), it implies auditors have overestimated (underestimated) the account balance. The level of deviation is a measure of how much the actual number deviates from the prediction. It is categorized based on a certain threshold: if the deviation (absolute value of prediction errors) is less than the standard error of prediction times a predefined parameter, the level of deviation equals zero, but if the deviation is larger than the threshold, the level of deviation is one. Intuitively, the value of the threshold may significantly affect the effectiveness of the level of deviation. Specifically, if the value of the threshold is too large, most observations will have the level of deviation equal to zero, adding no value to improving the performance of the prediction model. On the contrary, if the value of the threshold is too small, most observations will have the level of deviation equal to one, also resulting in minimal effect on the performance of the sharing model. Thus, the threshold has to be properly chosen to improve the performance of the sharing models.

Extending the illustrations presented above, consider companies X, Y and Z as the participants in the sharing scheme. In the categorical sharing scheme, the auditors use both historical and contemporaneous data to estimate the prediction model $\mathrm{M}^{o}$ using the method discussed above. Rather than collecting the standardized mean of errors from peer companies, auditor A of company X collects the sign of prediction errors and the level of deviations from other auditors B and C (within the same audit firm), who are engaged with peer companies Y, and Z, respectively. The sign of prediction errors and the level of deviations are both dummy variables. For instance, if auditor B overestimates the revenue with a large deviation, the data shared will be (1, 1). On the contrary, if auditor C underestimates the revenue with a small deviation, the sharing will be (0, 0). Then auditor A calculates the aggregated information (average) based on the collected information from companies Y and Z and adds it as an independent variable that captures the auditors' prediction adjustments, to improve the performance of analytical procedures. In such manner, the categorical sharing model will be either $\mathrm{M}^{s}\colon \mathrm{Y}_t = \alpha + \beta_1 Y_{t-12} + \beta_2 X_t + \beta_3 \mathrm{IND\_SIGN}_t + \varepsilon_t$ (sharing the sign of prediction errors) or $\mathrm{M}^{l}\colon \mathrm{Y}_t = \alpha + \beta_1 Y_{t-12} + \beta_2 X_t + \beta_3 \mathrm{IND\_DEVIATION}_t + \varepsilon_t$ (sharing the level of deviation). Additionally, it is reasonable to expect that sharing both the sign of prediction errors and the level of deviations from peer companies will provide more information than sharing only one of them. Thus, the model with two categorical variables is expected to outperform the other two categorical information sharing models. Specifically, the auditors add both $\mathrm{IND\_SIGN}_t$ and $\mathrm{IND\_DEVIATION}_t$ in the sharing model, creating a "mixed" categorical information sharing model $\mathrm{M}^{m}\colon \mathrm{Y}_t = \alpha + \beta_1 Y_{t-12} + \beta_2 X_t + \beta_3 \mathrm{IND\_SIGN}_t + \beta_4 \mathrm{IND\_DEVIATION}_t + \varepsilon_t$.

The categorical expectation sharing schemes preserve more privacy than those sharing schemes based on numerical data, but these sharing scheme has disadvantages as well. For a particular firm that has only one peer in the current year, the sharing model will be reduced to the original model when the peer firm underestimates the account balance with a small deviation within a certain threshold. Thus, the performance of this sharing scheme will be downward biased (worse than expected). In addition, a Boolean variable only contains relatively small amount of information derived from residuals thus resulting in significant reduction in estimation accuracy. The more the loss of information, the poorer the performance will be. However, as discussed above, sharing both categorical variables derived from residuals with a fine-tuned threshold may provide a comparable good result to the other sharing models.

## 2.3 Evaluation of Proposed Designs

### *2.3.1 Data*

#### Data preparation

For the purposes of evaluation, twenty industries that contained the largest number of firms and experienced varying sales growth rates from 1991–2015 were initially selected using 4-digit SIC codes. The way of choosing industries ensures a good representativeness of the various economic sectors. For example, the selected industries include the Steel Works & Blast Furnaces industry (Standard Industrial Classification [SIC] 4911) that experienced on average 4.86 percent annual growth during the sample period, and the Pharmaceutical Preparations industry (SIC 2834) that experienced an average annual growth of 23.22 percent. Quarterly data for the total revenue, cost of revenue, accounts receivable, and accounts payable were downloaded from the Compustat Fundamentals quarterly database for the period 1991 – 2015. These accounts were chosen because the revenue and the purchasing processes are two major business processes that occur in nearly every companies. Other account, such as inventory, may present additional data constraints and limit our pool of peers for each audit client. For example, service companies do not have the inventory account at all. Thus, we did not use inventory as a variable in our sample. To remain in the sample, firms had to satisfy the following requirements:

1. Firms should have complete data without missing and zero values.
2. Firms should have uninterrupted quarterly data for five years for each estimation because we plan to use uninterrupted three years of data as training data to estimate prediction models to predict the fourth year data and compare the predicted value with the actual value in the fourth year. In order to improve the prediction accuracy, we also use interpolation techniques to convert our quarterly data into monthly data, so there will be boundary missing data in the first year. In this way, we need at least five years of uninterrupted quarterly data for our research.
3. Firms should have year-to-year sales growth of no more than 500 percent.
4. Firms should be eliminated from our sample if there is an acquisition or merger. (In our case, we find duplicate records with similar company name, the same SIC within the same year. e.g. gvkey: 123754, 028004, and 062290).

Our final sample includes 7,516 quarterly observations. The selected industries are presented together with their average sales growth in Table 2.

**Table 2. Descriptive Statistics - Sample from 1991–2015**

| SIC Code | **Number of Firms** | **Account Payable** | **Cost of Goods Sold** | **Account Receivable** | **Revenue** | **Growth Rate** |
|---|---|---|---|---|---|---|
| 7372 | 316 | 31.16 | 12.89 | 118.36 | 60.87 | 0.12 |
| 6798 | 234 | 72.16 | 21.38 | 209.03 | 35.43 | 0.09 |
| 1311 | 212 | 224.03 | 112.11 | 220.13 | 160.43 | 0.22 |
| 7370 | 180 | 223.22 | 88.20 | 502.00 | 167.50 | 0.16 |
| 2834 | 150 | 172.64 | 56.02 | 436.77 | 216.18 | 0.23 |
| 3674 | 140 | 88.91 | 42.01 | 149.02 | 102.97 | 0.12 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 4911 | 126 | 279.73 | 167.14 | 351.59 | 237.03 | 0.05 |
| 5812 | 121 | 51.40 | 73.60 | 40.33 | 101.50 | 0.08 |
| 7373 | 120 | 42.11 | 26.90 | 113.02 | 44.83 | 0.13 |
| 2836 | 111 | 69.31 | 17.05 | 115.81 | 57.50 | 0.24 |
| 3845 | 100 | 15.42 | 7.71 | 51.81 | 22.08 | 0.15 |
| 4813 | 98 | 360.40 | 146.35 | 665.33 | 291.09 | 0.13 |
| 3663 | 82 | 198.08 | 103.79 | 282.76 | 163.89 | 0.10 |
| 4931 | 73 | 301.35 | 208.00 | 364.52 | 275.78 | 0.07 |
| 3841 | 68 | 37.25 | 13.61 | 69.27 | 32.86 | 0.15 |
| 9995 | 67 | 104.88 | 16.18 | 167.91 | 21.38 | 0.06 |
| 7990 | 65 | 28.37 | 34.96 | 43.55 | 59.81 | 0.13 |
| 3714 | 63 | 250.25 | 137.77 | 345.54 | 169.77 | 0.09 |
| 6331 | 62 | 1894.05 | 339.76 | 3821.02 | 398.74 | 0.10 |
| 6211 | 59 | 7949.69 | 119.42 | 11451.87 | 234.24 | 0.12 |
| 3576 | 58 | 38.14 | 34.71 | 163.70 | 97.68 | 0.06 |

This table presents descriptive statistics for 20 industries between the years 1991–2015. The mean account value for the total revenues, cost of sales, total assets, accounts receivable and accounts payable are presented for different four-digit SIC code. The mean sales growth for each four-digit SIC code is presented together with the number of firms that met the data availability criteria.

### Peer selection

Companies from the same industry are likely to share a number of common characteristics ranging from macro-economic factors to accounting policies. Therefore, information collected from client X that is audited by auditor i can potentially be used to perform analytical procedures for client Y that is audited by another auditor j who joins in the sharing scheme. Since the current industry classification coding system is too general to pick up suitable peer companies for a certain primary company, we adapt the dynamic peer selection method from Hoitash et al. (2006) to further partition the four-digit SIC coding system. Theoretically speaking, there are many ways to do the partitions, such as unsupervised clustering or supervised classification (labeling some companies manually according to research preferences). In our research, the process of identifying peer companies is done as follows. In each four-digit SIC code, firms are ranked based on their revenue (size proxy) and their growth rate (change proxy). This ranking is done based on the public available last year audited sample. Peers are selected for each company based on their size and growth proximity to that company at a given time. The iterative process of assigning peer companies for each audit client within an industry continues until peers are selected or no appropriate peers are found. Using this approach, the peer selection process results in a relatively homogeneous but not symmetric group of peers for each audit client.

An illustration of the peer selection process is presented in Table 3, in which we demonstrate the process of assigning peers for each company in an industry of seven companies for a specific audit year. A company is assigned specific peers only if their size and growth rate rankings both fall into the ranking intervals. This process may result in companies with no peers, and subsequently those companies are dropped from the sample if they do not have any peers after the first three years, because the initial three years of data are used to estimate the models and at that time we cannot calculate the prediction error (actual value – predicted value) at all. Thus, peer relationship must exist only starting with the fourth year of each firm. If the firm cannot find any peers starting in the fourth year to the end, this firm will be removed from our dataset.  In reality, auditors can do a better job in finding proper peer companies based on both public and private information. Thus, the evaluation results in our study are relatively underestimated based on a crude peer selection method.

**Table 3. An illustration of the Peer Selection Criteria**

(Example: 1996, SIC=2821, 7 firms, S: n/5, G: n/4)

| Year | Company ID | rank_r(revenue) | rank_g (growth rate) | Selected Peers |
|---|---|---|---|---|
| 1996 | A | 6 | 4 | / |
| 1996 | B | 1 | 5 | G |
| 1996 | C | 5 | 1 | / |
| 1996 | D | 3 | 3 | / |
| 1996 | E | 7 | 2 | / |
| 1996 | F | 4 | 7 | / |
| 1996 | G | 2 | 6 | B |

Within each four-digit SIC code, companies are ranked by their total revenues (rank_r) and revenue growth (rank_g). The total size of the SIC (n) represents the number of companies within each SIC code for a particular fiscal year. As an illustration, for SIC 2821 in 1996, n equals 7. The allowable proximity for each year is determined as follows: sales have to be within Integer (n /5) of each peer and the sales growth rank is set to be within Integer (n /4) allowing for more variation in the growth in comparison to the size proxy. The decimal of the factor will round to 1 if it is larger than 0.5: in this case, 7/5 will round to 1 and 7/4 will round to 2. Therefore, potential peers for client B will have sales growth rank between 3 and 7. Both criteria—size and growth have to be met for each audit client in order to be considered as peers. Thus for client B, client G should be his peer company.

In order to rigorously evaluate our proposed artifacts in a realistic audit scenario, we only keep peer companies who actually share common auditors with audit client in the current year. Consistent with prior literature (. Johnstone, Li and Luo 2014; Dhaliwal et al. 2015), this constraint largely reduce our sample size, leaving us a quarter ( approximately 25%) of original sample size. In order to make sure the feasibility of our evaluation, we only keep ten industries that contain enough number of companies (>10). Later, with respect to the applicability and generalizability of our designs, we remove such strict peer selection criteria and increase the number industries from ten to twenty. The evaluation results of the expansions can be found in the Supplementary Appendix A.

**Interpolation**

Prior literature argues that the high frequency data performs better in analytical procedures than does quarterly data (Wild 1987; Chen and Leitch 1998; Cogger 1981; Knechel 1988; Dzeng 1994). However, there is always a tradeoff in the time series analysis between the sample size and the model's stability over long periods of time. In fact, in auditing practice, auditors value recent data more than historical data in a rapidly growing economy. Therefore, the time window we are going to utilize is not long enough to significantly influence the stability of the model. In order to enhance the estimation power of the model, we take advices to expand our sample size by using monthly observations instead of quarterly data. Given that monthly data are not readily available for a large number of companies, a data interpolation technique was used in this study. We follow the cubic splines interpolation introduced within the auditing literature by Chen and Leitch (1998) and Leitch and Chen (1999), and implemented by Hoitash et al. (2006). In the current study, cubic splines are used to convert publicly available quarterly observations into monthly observations. From each of the four quarterly observations, 12 monthly points are generated and later used as monthly data points.

In the process of interpolating accounting data, it is essential to distinguish between the "stocks" that are measured at points in time and the "flows" that represent the totals or averages over a time window. For example, in the process of interpolating income statement accounts, the algorithm must guarantee that the interpolated values sum up to the original value (e.g. the sum of the first three months should be equal to the first quarterly number). Basically, we use a third degree polynomial equation ($S_i(X) = a_i(X - X_i)^3 + b_i(X - X_i)^2 + c_i(X - X_i) + d_i$ (1)) to interpolate the data and estimates the coefficients of the cubic polynomials. The coefficients define the curve so that it passes through each of the data points in a smooth way.[19]

We can use the basic form of the Eq. (1) above to interpolate accounts that are stocks (balance sheet accounts). However, it needs to be slightly modified for the purpose of interpolating flows (income statement accounts). This is done by simply constraining the three monthly observations in the income statement accounts to sum up to the quarterly value.

Altogether, we have 1097808 observations (firm-month) in our dataset.

### *2.3.3 Model*

**Model specification**

We present our predictive models in Table 4 where models 1 and 2 are the original models with no information sharing while Models 3 through 14 are peer models. *SALES*, *COGS*, *AR*, *and AP* represent total revenue, cost of goods sold, accounts receivable and accounts payable balances for month *t*. The *IND_* term in the peer models represents the

[19] If there is a huge jump between the peak and the trough of the wave, the interpolated number can possibly be negative, which cannot happen in the real life accounting setting (e.g. sales cannot be negative). Therefore, we check the cases where we have the negative numbers, and drop those companies from our sample to ensure the correctness of our empirical data.

average standard score for a group of peers and is calculated as $z = \frac{y - \mu(y)}{\sigma(y)}$, where $y$ represents a monthly number generated by account balance, and the mean and the standard deviation of the monthly numbers are calculated over the previous twelve months. In all the models, we use a 12-month lag term as an independent variable in the auto regression model.

**Table 4. Specification of Models**

$$\mathrm{IND_t} = \frac{\sum_1^i Z_i}{i}$$

$$\mathrm{SALE}_t = \alpha + \beta_1 SALE_{t-12} + \beta_2 AR_t + \varepsilon_t \text{ (1)}$$

$$\mathrm{COGS}_t = \alpha + \beta_1 COGS_{t-12} + \beta_2 AP_t + \varepsilon_t \text{ (2)}$$

$$\mathrm{SALE}_t = \alpha + \beta_1 SALE_{t-12} + \beta_2 AR_t + IND\_ERROR_t + \varepsilon_t \text{ (3)}$$

$$\mathrm{COGS}_t = \alpha + \beta_1 COGS_{t-12} + \beta_2 AP_t + IND\_ERROR_t + \varepsilon_t \text{ (4)}$$

$$\mathrm{SALE}_t = \alpha + \beta_1 SALE_{t-12} + \beta_2 AR_t + IND\_PREDICT_t + \varepsilon_t \text{ (5)}$$

$$\mathrm{COGS}_t = \alpha + \beta_1 COGS_{t-12} + \beta_2 AP_t + IND\_PREDICT_t + \varepsilon_t \text{ (6)}$$

$$\mathrm{SALE}_t = \alpha + \beta_1 SALE_{t-12} + \beta_2 AR_t + IND\_ACTUAL_t + \varepsilon_t \text{ (7)}$$

$$\mathrm{COGS}_t = \alpha + \beta_1 COGS_{t-12} + \beta_2 AP_t + IND\_ACTUAL_t + \varepsilon_t \text{ (8)}$$

$$\mathrm{SALE}_t = \alpha + \beta_1 SALE_{t-12} + \beta_2 AR_t + IND\_SIGN_t + \varepsilon_t \text{ (9)}$$

$$\mathrm{COGS}_t = \alpha + \beta_1 COGS_{t-12} + \beta_2 AP_t + IND\_\mathrm{SIGN}_t + \varepsilon_t \text{ (10)}$$

$$\mathrm{SALE}_t = \alpha + \beta_1 SALE_{t-12} + \beta_2 AR_t + IND\_DEVIATION_t + \varepsilon_t \text{ (11)}$$

$$\mathrm{COGS}_t = \alpha + \beta_1 COGS_{t-12} + \beta_2 AP_t + IND\_DEVIATION_t + \varepsilon_t \text{ (12)}$$

$$\mathrm{SALE}_t = \alpha + \beta_1 SALE_{t-12} + \beta_2 AR_t + IND\_SIGN_t + IND\_DEVIATION_t + \varepsilon_t \text{ (13)}$$

$$\mathrm{COGS}_t = \alpha + \beta_1 COGS_{t-12} + \beta_2 AP_t + IND\_SIGN_t + IND\_DEVIATION_t + \varepsilon_t \text{ (14)}$$

*SALES*, *COGS*, *AR*, *and AP* represent total revenue, cost of goods sold, accounts receivable and accounts payable balances for month *t*. The *IND* term in the peer models represents the average standard score ($Z_i$) for a group of peers and is calculated as presented in this chapter. ERROR indicates the estimation error, PREDICT – the prediction, and ACTUAL means the actual accounting numbers. Additionally, the SIGN is the sign of prediction errors and the DEVIATION (third order central moment) is the level of deviation indicating how much the prediction deviates from the actual number.

**Model validation**

There are a number of issues related to the proposed residual-based sharing scheme, which need to be discussed. First, in this chapter we use a simple auto regression time series prediction model as an illustration. Design-science research often simplifies a problem. Such simplifications may not be realistic enough to have a significant impact on practice but may represent a starting point (Von et al. 2004). In reality, auditors can use more sophisticated analytics to estimate specific account numbers to obtain audit evidence. Second, the residuals generated from regression models are generally regarded as white noise following Gaussian distribution, if the “Best, Linear, Unbiased, Estimation (BLUE)” assumption holds. However, in this chapter, we find that the information derived from residuals may improve not only the estimation accuracy but also the error detection performance. This finding can be interpreted as a violation of “BLUE” assumptions (e.g., due to omitted variables). In this scenario, the coefficients may not have any economic meaning and become unreliable. Nevertheless, in the case of predictive modeling, omitted variables would not be a big issue, because the objective of using a predictive model is to utilize any combination of possible/reasonable observed independent variables to get an optimal prediction, not a reliable coefficient. In the accounting literature, there are numerous studies (Klein et al. 2002, Kothari et al. 2005) utilizing abnormal accruals (discretionary accruals) based on Jones model (1991). Similarly, in the auditing literature, there are a number of papers discussing the usefulness of “abnormal audit fee”, the regression residuals produced by audit fee models. The existence of abnormal audit fee can be explained in two reasonable ways: extra audit efforts and impairments of audit independence (Eshleman et al. 2013, Blankley et al. 2012, Choi et al. 2010). Therefore, utilizing the residuals as supplementary contemporaneous information is reasonable. Third, during the evaluation phase, we utilize a cross-validation method based on the measures of MAPE, the percentage of False Negatives and False Positives. To be specific, we use prior 3 years of historical data as the training sample to predict the fourth year data and then use the following year data as the test sample to evaluate the prediction performance. Unlike other empirical research using regression models, our design science research emphasizes the utility (the accuracy of prediction) of our proposed sharing schemes instead of the fittingness of the model (VIF and $R^2$ ).

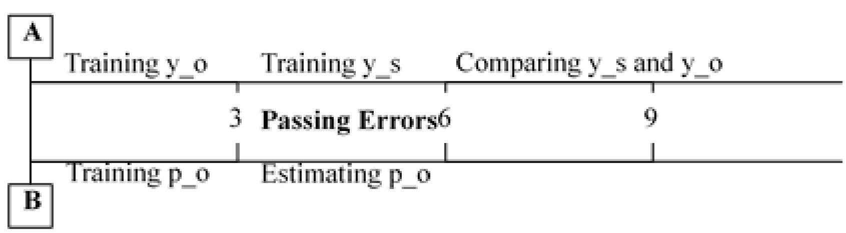
### *2.2.4 Methodologies*

#### **Estimation accuracy**

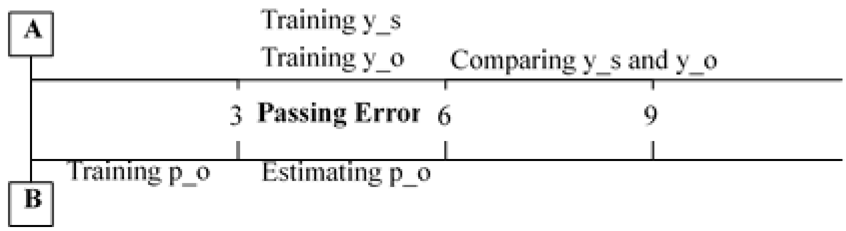
To evaluate the performance of estimation accuracy, we plan to utilize a rolling regression and compare the MAPEs generated from original models and those from peer models. To be specific, each regression model is trained over 36 months and is tested over the subsequent 12 months. Every model is estimated separately for each company based on its unique set of peer companies.

In the dynamic peer selection method discussed above, we need to match peers for each company in each year throughout our sample period. For example, to predict account balances for the year 1994, peers are selected based on data from the last quarter of 1993. Then, the data from 1991 to 1993 is used to generate predictions. In this manner, the process of selecting peers and estimating the models is done separately twenty times for each company from 1994 to 2015. At last, we are going to have 12 monthly predictions for each company for each year-account from 1994 to 2015. Considering different lifespans of the primary firm and peer firms, the estimation cases will be different and a detailed illustration is presented as follows.

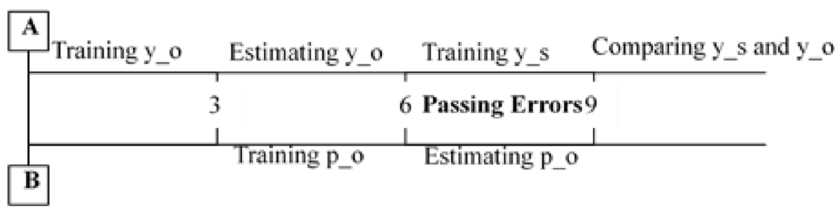
Case 1: The primary firm A has the same lifespan with peer company B. In this case, both firms use the first three years as the training period and start to estimate own prediction models in the fourth year. In the fourth year, peer company B starts to pass its aggregated residuals, prediction or actual data as sharing information to primary firm A and firm A begins to collect the sharing information as an input variable in the following three years. At the beginning of the seventh year, primary firm A has enough training samples (three years of consecutive sharing information as an independent variable) to estimate the peer-based sharing model y_s. This provides solid empirical evidence to compare the power of estimation between the original model y_o and the peer sharing models y_s.




Case 2: The primary firm A has a shorter lifespan than peer firm B. In this scenario, the difference from Case 1 is that for A the original three-year training period has been extended to six years with blank first three years. The rest of the process holds.




Case 3: The primary firm A has longer lifespan than peer firm B. In this case, the training period for firm B has been extended to six years with the first three years being blank, and the passing procedure has been delayed to the beginning of the seventh year correspondingly, so that the comparison process starts after the end of the ninth year.




The prediction performance is evaluated based on the mean absolute percentage error (MAPE) for each account-model. The MAPE is calculated for the test sample for each account-company-month. The MAPEs for the 12-month period are aggregated over company-year resulting in the aggregated measure of MAPE for each company-account-model. To compare the prediction performance of each model, results are aggregated over each account-industry, resulting in one MAPE for every account-model industry.

To compare the prediction performance between different estimation models, an upper triangular two tail t-test matrix is reported at industry level over prediction period. Specially, the first row of the matrix indicates whether the MAPEs generated by the peer model are significantly smaller than those generated by the original model. The rest of t-values in the upper triangular matrix identify whether the MAPEs generated by peer models are significantly different from each other.

**Error detection**

The evaluation of error detection is conducted by seeding artificial errors into account balances and comparing the error detection performance of all estimation models. In the context of this study, the detection capability of models is measured by the cost of errors (CE) via three basic metrics: the number of “false negative” errors (NFN), the number of “false positive” errors (NFP) and the cost ratio ($\frac{b}{a}$). The cost of errors is generated by the following function:

$$CE = a * NFN + b * NFP \quad (2)$$

Usually, auditors prefer to avoid the occurrence of false negatives, which implies potential undetected material misstatements and leads to audit failures and high litigation risks. However, with the reduction of false negatives, auditors normally face an increase in false positives, which raises the total audit cost and challenges the project budget. Therefore, an effective error detection model should keep both the number of false positive errors and the number of false negative errors at a reasonably low level. In addition, the choice of cost ratio also reflects the above mentioned concerns. Thus, for the litigation and cost reasons, auditors always set the value of b far less than a.

To assess the anomaly detection performance under different settings, we design and implement a controlled experiment by seeding artificial errors into initial account numbers. In the process of simulation of errors, we randomly pick up observations as "targets" and "seed" an error determined by initial account numbers and the magnitude parameter into the "target". We test how the error magnitude (e) can affect each model's anomaly detection capability with different magnitude settings in every round of error seeding ranging from 5% to 1%. In order to reduce the variance of the random choice, we repeat the selection of targets ten times for each setting.

Prior studies discuss several investigation rules to identify an anomaly (Stringer and Stewart 1986; Kinney and Salamon 1982; Kinney 1987; Knechel 1986). A modified version of the statistical rule (Kinney 1987, Kogan et al. 2014) is used in this study. Prediction intervals (PI) are used as the acceptable thresholds of deviations. If the value of the prediction is either above the upper or below the lower bound of the PI, then the corresponding observation is flagged as an anomaly. In this study, we only focus on the overstatement of revenue or the underestimate of cost of goods sold, which is often related to manipulations and frauds.

The selection of PI is a critical issue impacting the detection performance of models. The size of the PI is determined by the value of the significance level $\alpha$. A large $\alpha$ means a narrower interval and a lower detection rate. In this study, we use $s$ instead of $\alpha$ to tune the interval size. The parameter $s$ is the z-value of the corresponding significance level $\alpha$, for example, when $\alpha = 50\%$, $s = 0$. As we discussed in the previous section, we expect to choose a pseudo-optimal anomaly detection model for each industry, so that we are ready to tune several related hyper parameters (the number of false negative and false positive errors, the cost ratio, the magnitude of errors and the significance level) and evaluate the performance of the model by comparing the cost of errors using the Eq. (2) discussed above.

**The choice of the best model**

In order to determine how the choice of the best model changes depending on different experimental settings, we compare the total cost of errors for different models varying five different cost ratios, three magnitudes of errors, and five different prediction intervals[20]. In our error detection experiment, for seven different detection models[21], we simulate as many as 75 (5*3*5) scenarios for each model. Since auditors can choose the most powerful model based on historical experience with the best error detection performance to test client's data with unknown level of errors, it is possible for an auditor to choose in advance the "best" model with an appropriate prediction interval. For each of the fifteen (3*5) parameter pairs[22], auditors can choose the most effective prediction interval with the smallest cost of errors for each model out of the seven specifications. Then, for each parameter pair (a certain auditing scenario), auditors can have a vector containing the "best" seven models using the most powerful prediction interval.

---

[20] The cost ratio is defined as the ratio between the cost of false positives and false negatives. We consider the following cost ratios: 1:1, 1:10, 1:20, 1:50 and 1:100. The magnitudes of errors are 5%, 2% and 1%. The prediction interval widths are 0.1, 0.05, 0.02, 0.01 and 0 times the standard deviation.

[21] The seven models include the original model without any sharing information (O), the low level model sharing the estimated residuals (errors) among peer firms (E), the medium level sharing model sharing the prediction value (P), the high level sharing model sharing the actual value of a certain account (A), the model sharing categorical information derived from the estimated residuals: the sign of prediction errors (S), the deviation level of prediction errors (L) and the combined model including both the sign and the deviation level (M).

[22] The parameter pair is defined as a parameter combination of the cost ratio and the magnitude of errors, which simulates a certain scenario in the audit practice. For instance, the parameter pair (1:1, 5%) means that the auditors calculate the cost of errors by summing up the numbers of false positives and false negatives directly, with cost ratio 1:1 and the magnitude of seeded errors equal to 5 %.

Under this "best case" scenario assumption, we rank the error detection performance among the seven different models within each vector under varying pairs of parameters and treat the rankings as preference ballots for different models. Specifically, the higher[23] the rankings of a certain model with predefined pairs of parameters, the higher the preference of utilizing such model. To investigate the model selection choice for a certain company, we need to take into account all the information from the preference ballots and aggregate the information to a desired level of granularity.

In this chapter, we adapt the Borda count[24] voting method to determine the most suitable model for each company based on the preference ballots with fifteen parameter pairs. The Borda count method has been widely used in evaluating error detection performance in decision-making literature (Lumini et al. 2006, García-Lapresta et al. 2009, Perez et al. 2011). We rank models' error detection performance based on the cost of errors and assign the highest score to the highest-ranking model. Then we sum up the preferences in a certain dimension to observe the change of the best model by choosing the dimension of interests, such as the cost ratio or the magnitude of errors.

Consider the following illustration. For a certain company with gvkey 006862 from SIC 6211, there are seven models provided with/without information sharing schemes. For each model, the auditors have prior experience in choosing the most reliable prediction

[23] Rank 1 is the highest ranking with the smallest cost of errors.
[24] The Borda count is a single-winner voting method in which voters rank options in order of preference. The Borda count determines the outcome by giving each option, for each ballot, a score corresponding to the number of options ranked lower. For example, if we have three options in total, then the first ranking option can get 2 points and the second can get 1 point based on the number of options ranked lower. It is better than the plurality method, which only considers the first rankings of the preference ballots and elects those preferred by the largest number of voters.

intervals under the fifteen circumstances simulated by pairs of parameters (the magnitude of errors and the cost ratio). To be specific, when utilizing the low-level sharing model (Model E), they can generate a cost matrix representing the error detection performance in the fifteen scenarios across the five different prediction intervals. Then, for each scenario, they choose the most powerful prediction interval with the smallest cost of errors. In this case (Table 5), the best choice of prediction interval for Model E is 0.01, when the cost ratio equals 1:1 and the magnitude of errors equals 5%.

**Table 5. The Ranking Result for 5 Prediction Intervals, with 15 Pairs of Parameters**

| (Example: SIC 6211, gvkey 006862) | | | | | | |
|---|---|---|---|---|---|---|
| PIs / Pairs | (1:1, 0.05) | (1:1,0.02) | (1:1, 0.01) | (1:10, 0.05) | … | (1:100, 0.01) |
| 0.1 | 3 | 5 | 2 | 2 | … | 5 |
| 0.05 | 4 | 3 | 5 | 1 | … | 3 |
| 0.02 | 5 | 2 | 3 | 3 | … | 2 |
| 0.01 | 1 | 1 | 1 | 4 | … | 1 |
| 0 | 2 | 4 | 4 | 5 | … | 4 |

The pair "(x, y)" represents the scenario that the cost ratio is x and the magnitude of errors is y; e.g., the pair (1:1, 0.05) indicates that the cost ratio is 1:1 and the magnitude of errors is 5%. The "PIs" is short for "Prediction Intervals", which evaluates the width of prediction intervals. The 5 values in each column represent the rankings of cost of errors within certain parameter pair "(x, y)". The highest ranking (rank 1) is the best choice (smallest cost of errors) that auditors can make in certain model specification (e.g. Model E). As discussed in this chapter, for each model specification, we have 15 different scenarios (pairs), where x is selected from 1:1, 1:10, 1:20, 1:50 and 1:100, and y is selected from 5%, 2%, and 1%.

Next, the auditors can take the cost of errors with the appropriate prediction intervals for each circumstance as the "best" candidate that a certain model specification can achieve under these circumstances. After recording all values of cost of errors for the seven different model specifications, the auditors can generate a table with 15 cells, where each cell is a vector containing seven costs of errors according to the seven model specifications. Before the auditors use the Borda count method to select the best model over a certain dimension of interests, they first sort the values within the vector and treat the rankings as a preference ballot. For the company with gvkey 00682 from SIC 6211, the preference ballots for the fifteen scenarios can be found in Table 6.

**Table 6. The Preference Ballots for a Certain Company in the Considered 15 Scenarios**

| (Example: SIC 6211, gvkey 006862) | | | | | |
|---|---|---|---|---|---|
| | 1:1 | 1:10 | 1:20 | 1:50 | 1:100 |
| 5% | [7,6,3,2,1,4.5,4.5] | [1,4,3,2,6,5,7] | [1,4,3,2,6,5,7] | [1,4,3,2,6,5,7] | [1,4,3,2,6,5,7] |
| 2% | [4,3,6,5,1,2,7] | [1,2,3,4,5,6,7] | [1,2,3,4,6,5,7] | [1,2,3,4,6,5,7] | [1,2,3,4,6,5,7] |
| 1% | [4.5,3,6,1,4.5,7] | [1,3,2,4,5,6,7] | [1,3,2,4,5,6,7] | [1,3,2,4,5,6,7] | [1,3,2,4,5,6,7] |

This table shows the results of ranking the 7 model specifications for the company (Gvkey 006862). The vector in each cell provides the ranks of the seven models. The presentation order of the values in the vector is the original model, the error sharing model, the prediction sharing model, the actual sharing model, the categorical sharing model with the sign of prediction errors, the model with the level of deviations and the mixed model contains both the sign and the deviations of prediction errors. For example, in the top left corner cell the number 3 means that the cost of errors of prediction model ranks as the third minimum. The existence of two 4.5s means the categorical information sharing model with the deviations of prediction errors and the mixed model have the same rank. Thus, we rank both of them as 4.5 instead of rank 4 or rank 5. The rows 1:1, 1:10, 1:20, 1:50 and1: 100 represent the cost ratios between false positives and false negatives, and the columns 5%, 2% and 1% represent the magnitudes of errors.

To aggregate the preference ballots over a certain dimension of interests, we add the vectors instance by instance according to either the row or the column. By aggregating the preference in the same row, we generate a table of candidates (minimizing the cost of errors) with different magnitudes of errors for companies within a certain industry. Additionally, we also investigate the change of the best model with the change of the cost ratios between false positives and false negatives, by aggregating the Borda count vectors down to the bottom of the column. Then we assign 6 points to the first ranking, 5 points to the second ranking, and so on. After that, we select the winners for each setting based on the largest total score. Lastly, we do a plurality voting[25] by counting the frequency of best models among companies in current industry with a certain directional aggregation.

## 2.4 Validation Results

### *2.4.1 Estimation Accuracy*

To evaluate the performance of our privacy-preserving analytical procedures in prediction accuracy, we first compare the MAPEs between the original model (Model 1) and all sharing models (Model 3, 5, 7, 9, 11 and 13) for the revenue account. The comparison results can be found in Table 7. Intuitively, as displayed in the first four columns in Panel A, we observe that the MAPE of the three sharing models with different levels of privacy is usually (except for SIC 2834, 2836 and 3845) smaller than that of the original model, suggesting that our proposed sharing schemes utilizing contemporaneous peer data indeed improve the prediction accuracy.

Then, we observe that the prediction accuracy using the sharing model based on categorical information derived from residuals is reduced compared to the low level sharing scheme in estimating the revenue account balance. Specially, when we share only the sign of prediction error, 8 out of 10 industries (except for SIC 2834 and 2836) receive larger MAPEs than when we share residuals. The case gets worse when we only share the level of deviation with threshold $\delta$=3. In this case, all industries receive larger MAPEs. Additionally, utilizing both categorical variables with threshold $\delta$ =3 leads to an

[25] For the Plurality Method, the candidate with the most first place votes wins.

unsatisfactory result comparing to the low-level sharing model. As mentioned above, the value of threshold affects the usefulness of the level of deviation. The undesired result indicates a lack of information due to the insensitive threshold so that we tune the threshold downward and make it sensitive enough to capture more information. After we tune the threshold from 3 to 1, we find the estimation accuracy is improved. Moreover, the estimation accuracy of this categorical sharing scheme utilizing both categorical variables becomes as good as the low-level sharing scheme.

Since extreme outliers in the sample can significantly impact the mean of the MAPE, we use the median of MAPE as a robustness test. In Panel B, we get a consistent but stronger result. We observe that the prediction accuracy using the sharing models with three different levels of privacy receive improvements in all industries. Additionally, the prediction accuracy using the sharing model based on categorical information derived from residuals is reduced compared to the low level sharing scheme in all industries.

In order to statistically confirm the evaluation results above, in Panel C, we present an upper triangular t-test matrix that indicates whether our proposed sharing models are superior to the original model and whether these sharing models can achieve improvements in estimation accuracy at a comparable level. Without of loss generality, we present the matrix for SIC 7372 as an illustration and others can be found in the Supplementary Appendix A. In the first row of the matrix, we observe that the sharing model A, P, and E outperforms the original model with a significant smaller MAPE indicated by a two-tails t-test. As confirmed by three two-tails t-tests between these three sharing models, the improvements in prediction accuracy of these three models are not significant different from each other, suggesting that these sharing models are superior to the original model at a comparable level. Except for the SIC 2834, other SICs follow a similar pattern. In addition, the t-test results of categorical sharing models show that the model S improves the estimation accuracy at a relatively lower level comparing to the A, P and E in most of SICs, except for 2834, 3845 and 4931. Moreover, the model L outperforms the original model in half of the SICs and the model L3 seldom improves the estimation performance due to the loss of information as we predicted.

In the SIC 7372, the sharing model SL barely outperforms the original model O but is significantly better than other categorical sharing models except for the model S, implying that the model SL may be further improved by tuning the threshold $\delta$. In the rest of nine SICs, except for the SIC 3845, the t-test results of model "SL" show that the model SL always significantly outperforms the original model O and other categorical sharing models with one variable. Further, the improvements from utilizing the "SL" model are at a comparable level to the "E" model in most of SICs, except for SIC 7370, 5812, 4911 and 4931.

**Table 7. The Evaluation of Prediction Accuracy in Estimating Revenue Account**

Panel A. The Comparison of MAPEs among Estimation Models (Industry Mean)

| SIC | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| 7372 | 0.43 | 0.23 | 0.30 | 0.30 | 0.59 | 0.35 | 0.37 | 0.37 | 0.29 |
| 1311 | 1.56 | 1.06 | 0.99 | 1.24 | 1.62 | 1.16 | 1.30 | 1.97 | 2.50 |
| 7370 | 0.12 | 0.06 | 0.09 | 0.08 | 0.10 | 0.09 | 0.11 | 0.11 | 0.10 |
| 2834 | 1.07 | 0.69 | 1.45 | 1.15 | 1.34 | 0.79 | 2.22 | 0.76 | 0.89 |
| 3674 | 0.17 | 0.11 | 0.11 | 0.11 | 0.15 | 0.12 | 0.17 | 0.14 | 0.16 |
| 4911 | 0.16 | 0.10 | 0.12 | 0.11 | 0.18 | 0.14 | 0.17 | 0.15 | 0.14 |
| 5812 | 0.12 | 0.08 | 0.09 | 0.09 | 0.11 | 0.09 | 0.11 | 0.10 | 0.11 |
| 2836 | 1.32 | 0.92 | 1.14 | 1.68 | 1.42 | 0.70 | 1.40 | 0.85 | 1.13 |
| 3845 | 0.58 | 0.30 | 0.59 | 0.58 | 0.69 | 0.51 | 1.10 | 0.52 | 0.60 |
| 4931 | 0.14 | 0.10 | 0.11 | 0.11 | 0.18 | 0.12 | 0.19 | 0.14 | 0.13 |

Panel B. The Comparison of MAPEs among Estimation Models (Industry Median)

| SIC | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| 7372 | 0.08 | 0.06 | 0.05 | 0.05 | 0.07 | 0.06 | 0.07 | 0.07 | 0.08 |
| 1311 | 0.19 | 0.13 | 0.13 | 0.13 | 0.15 | 0.14 | 0.17 | 0.16 | 0.19 |
| 7370 | 0.07 | 0.05 | 0.05 | 0.05 | 0.06 | 0.05 | 0.06 | 0.06 | 0.06 |
| 2834 | 0.13 | 0.09 | 0.10 | 0.10 | 0.12 | 0.11 | 0.13 | 0.12 | 0.12 |
| 3674 | 0.11 | 0.07 | 0.07 | 0.07 | 0.10 | 0.08 | 0.10 | 0.09 | 0.09 |
| 4911 | 0.09 | 0.06 | 0.07 | 0.06 | 0.10 | 0.08 | 0.09 | 0.08 | 0.10 |
| 5812 | 0.07 | 0.05 | 0.05 | 0.05 | 0.07 | 0.06 | 0.07 | 0.06 | 0.06 |
| 2836 | 0.13 | 0.08 | 0.08 | 0.08 | 0.08 | 0.08 | 0.10 | 0.10 | 0.08 |
| 3845 | 0.15 | 0.07 | 0.11 | 0.11 | 0.14 | 0.11 | 0.13 | 0.11 | 0.11 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 4931 | 0.07 | 0.06 | 0.06 | 0.05 | 0.10 | 0.07 | 0.09 | 0.07 | 0.08 |

Panel C. The t-tests of MAPEs among Estimation Models

| | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.007 | 0.021 | 0.021 | 0.908 | 0.126 | 0.273 | 0.210 | 0.050 |
| A | | | 0.198 | 0.041 | 0.003 | 0.004 | 0.209 | 0.003 | 0.989 |
| P | | | | 0.856 | 0.005 | 0.059 | 0.315 | 0.020 | 0.732 |
| E | | | | | 0.003 | 0.027 | 0.280 | 0.022 | 0.857 |
| S&L3 | | | | | | 0.002 | 0.091 | 0.236 | 0.008 |
| SL | | | | | | | 0.810 | 0.394 | 0.333 |
| L3 | | | | | | | | 0.967 | 0.089 |
| L | | | | | | | | | 0.282 |
| S | | | | | | | | | |

This table displays the comparison of the MAPEs of all estimation models for revenue account. Panel A depicts the comparison of the industry mean of MAPEs in estimating revenues. Panel B shows the comparison of the industry median of MAPEs in revenue account as a robustness check. Panel C is an upper triangular t-test matrix. In Panel C, the p values in the first row are generated by one-tail t-tests, indicating whether sharing models are superior to original model in prediction accuracy; the rest of p values are generated by two-tail t-tests, examining whether there is significant difference in prediction accuracy between any two models.

Next, we compare the MAPEs between the original model (Model 2) and all sharing models (Model 4, 6, 8, 10, 12, and 14) for the cost of goods sold account. In table 8 Panel A, we observe that when comparing the three sharing models to the original models in the first four columns, all industries experience accuracy improvements, suggesting that the utility of our proposed three levels of sharing schemes is still held in estimating cost of goods sold account.

Panel A depicts the improvement from using the categorical sharing models (model 10, 12 and model 14) in the cost of goods sold account as well. Consistent with the evaluation results for estimating the revenue account, sharing both categorical variables and setting the threshold of the level of deviation to 1 leads to a similar improvement in estimation accuracy with the low-level sharing scheme. However, sharing only one categorical variable or tuning the threshold to 3, results in a worse performance than the low-level sharing scheme. Similar, to eliminate the impact of extreme outliers on the mean of the MAPE, we use the median of MAPE as a robustness check in Panel B for the cost of goods sold account and get a similar result with Panel A.

In the upper triangular matrix presented in the Panel C and the Supplementary Appendix B, we see that a similar patter as what we observed in estimating the revenue account: sharing model A, P, E and SL outperforms the original model O with a significant smaller MAPE in all industries confirmed by two-tails t-test. The difference of improvements in prediction accuracy between model A, P and E is not significant. The t-test results of "SL" indicate that the sharing model SL is significantly better than other categorical sharing models but inferior to the numerical sharing models A, P and E due to the loss of information. Other categorical sharing models with only one variable or the threshold equal to three, outperform the original model in several SICs respectively.

**Table 8. The Evaluation of Prediction Accuracy in Estimating Cost of Goods Sold**

Panel A. The Comparison of MAPEs among Estimation Models (Industry Mean)

| SIC | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| 7372 | 1.37 | 0.54 | 0.61 | 0.61 | 1.46 | 0.93 | 1.50 | 1.61 | 2.33 |
| 1311 | 5.19 | 2.88 | 2.12 | 3.03 | 2.24 | 2.61 | 5.49 | 7.02 | 5.46 |
| 7370 | 0.26 | 0.27 | 0.15 | 0.15 | 0.19 | 0.17 | 0.21 | 0.22 | 0.21 |
| 2834 | 0.46 | 0.29 | 0.32 | 0.34 | 0.51 | 0.38 | 0.54 | 0.42 | 0.50 |
| 3674 | 0.28 | 0.16 | 0.18 | 0.18 | 0.24 | 0.19 | 0.24 | 0.22 | 0.21 |
| 4911 | 0.28 | 0.14 | 0.16 | 0.15 | 0.22 | 0.17 | 0.23 | 0.20 | 0.21 |
| 5812 | 0.12 | 0.10 | 0.09 | 0.09 | 0.13 | 0.10 | 0.12 | 0.12 | 0.11 |
| 2836 | 0.19 | 0.80 | 0.14 | 0.14 | 0.17 | 0.15 | 0.19 | 0.18 | 0.17 |
| 3845 | 0.89 | 0.30 | 0.43 | 0.45 | 0.50 | 0.47 | 0.62 | 0.55 | 0.48 |
| 4931 | 0.16 | 0.12 | 0.13 | 0.13 | 0.20 | 0.15 | 0.21 | 0.16 | 0.16 |

Panel B. The Comparison of MAPEs among Estimation Models (Industry Median)

| SIC | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| 7372 | 0.14 | 0.10 | 0.09 | 0.09 | 0.12 | 0.10 | 0.13 | 0.12 | 0.13 |
| 1311 | 0.29 | 0.22 | 0.21 | 0.20 | 0.26 | 0.23 | 0.29 | 0.27 | 0.26 |
| 7370 | 0.13 | 0.08 | 0.08 | 0.08 | 0.10 | 0.09 | 0.11 | 0.11 | 0.11 |
| 2834 | 0.16 | 0.11 | 0.11 | 0.12 | 0.13 | 0.11 | 0.14 | 0.14 | 0.15 |
| 3674 | 0.13 | 0.09 | 0.09 | 0.09 | 0.11 | 0.09 | 0.12 | 0.11 | 0.11 |
| 4911 | 0.11 | 0.08 | 0.09 | 0.08 | 0.13 | 0.10 | 0.12 | 0.11 | 0.13 |
| 5812 | 0.07 | 0.05 | 0.05 | 0.06 | 0.06 | 0.06 | 0.07 | 0.06 | 0.06 |
| 2836 | 0.13 | 0.12 | 0.10 | 0.10 | 0.11 | 0.10 | 0.11 | 0.11 | 0.11 |
| 3845 | 0.18 | 0.10 | 0.14 | 0.14 | 0.17 | 0.14 | 0.19 | 0.17 | 0.17 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 4931 | 0.09 | 0.07 | 0.07 | 0.06 | 0.11 | 0.09 | 0.10 | 0.09 | 0.10 |

Panel C. The t-tests of MAPEs among Estimation Models

| | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.680 | 0.000 | 0.766 | 0.903 | 0.986 |
| A | | | 0.889 | 0.889 | 0.000 | 0.000 | 0.003 | 0.006 | 0.010 |
| P | | | | 0.498 | 0.000 | 0.000 | 0.004 | 0.007 | 0.008 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.002 |
| S&L3 | | | | | | 0.005 | 0.771 | 0.551 | 0.082 |
| SL | | | | | | | 0.005 | 0.004 | 0.005 |
| L3 | | | | | | | | 0.594 | 0.064 |
| L | | | | | | | | | 0.051 |
| S | | | | | | | | | |

This table displays the comparison of the MAPEs of all estimation models for cost of goods sold account. Panel A depicts the comparison of the industry mean of MAPEs in estimating cost of goods sold. Panel B shows the comparison of the industry median of MAPEs in revenue account as a robustness check. Panel C is an upper triangular t-test matrix. In Panel C, the p values in the first row are generated by one-tail t-tests, indicating whether sharing models are superior to original model in prediction accuracy; the rest of p values are generated by two-tail t-tests, examining whether there is significant difference in prediction accuracy between any two models.

Based on the validation results above, we conclude that sharing adjustment errors (residuals) can help auditors benefit from sharing contemporaneous information from peer companies and improve their estimation accuracy without violating clients' confidentiality. The benefits from sharing errors (residuals) are similar to sharing predictions or even real account numbers, even after converting numerical residuals to categorical dummies with suitable parameters.

### *2.4.2 Error Detection*

Without loss of generality, we present the result for SIC 7372 as an example, the others can be found in the Supplementary Appendix C. Usually, the categorical model sharing the level of deviations with δ=1 can achieve a better result, thus we remove two model specifications that share the level of deviations with δ=3 in our error detection evaluations.

As expected and shown in Panel A for the case of overestimating revenues, all peer models sacrifice a small amount of false positive errors for a significant reduction of false negative errors at all magnitudes of errors, which leads to a notable reduction in the cost of errors. Except for SIC 1311, 4931, 5812 and 4931, the error-detection performance of the peer models is better than the original model regardless of the magnitude of errors. In these SICs, when the magnitude of errors goes down to 1%, the original model achieves a better result with the prediction interval parameter s equal to 0.1. In addition, we see the improvements of error detection performance from sharing models are nearly at a comparable level with each other.

In the panel B and Supplementary Appendix D, the peer models have consistently superior false negative detection performance over the original model in the case of underestimating the cost of goods sold. However, the performance of peer models is sensitive to the magnitude of errors in regard to all SICs. Specifically, when the magnitude of errors is large enough (larger than 2%), the peer model outperforms the original model with fewer false negatives, but when the magnitude of errors gets smaller (e.g. 1%), the effectiveness of peer models suffers. Except for SIC 3845 and 5812, most SICs follow this pattern.

Apparently, Table 9 shows that our proposed sharing models indeed have ~~a~~ better error detection performance than the original model at a comparable level.

**Table 9. The Evaluation of Error Detection**

Panel A. The Error Detection Performance in Revenue Account

Example SIC 7372 (%)

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_p | FP_p | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 14.9 | 26.4 | 11.9 | 27.1 | 12.6 | 27.1 | 12.2 | 26.8 | 12.0 | 27.1 | 11.6 | 27.6 | 12.2 | 27.6 |
| 0 | 0.02 | 19.7 | 26.3 | 17.8 | 26.8 | 17.8 | 27.0 | 17.9 | 26.7 | 17.6 | 26.8 | 17.0 | 27.6 | 17.6 | 27.8 |
| | 0.01 | 21.4 | 26.1 | 20.3 | 26.8 | 20.2 | 26.8 | 20.3 | 26.6 | 20.1 | 26.8 | 19.8 | 28.1 | 20.0 | 27.5 |
| | 0.05 | 14.7 | 26.4 | 11.7 | 26.9 | 12.4 | 27.0 | 12.2 | 26.9 | 11.8 | 26.9 | 11.9 | 27.6 | 12.3 | 27.7 |
| 0.01 | 0.02 | 20.3 | 26.3 | 18.6 | 26.8 | 18.3 | 26.8 | 18.4 | 26.7 | 18.4 | 26.8 | 17.3 | 27.2 | 17.7 | 27.5 |
| | 0.01 | 21.5 | 26.1 | 20.6 | 26.9 | 20.5 | 26.8 | 20.5 | 26.7 | 20.5 | 26.8 | 20.0 | 27.6 | 19.9 | 27.5 |
| | 0.05 | 14.8 | 26.1 | 11.9 | 26.8 | 12.5 | 26.6 | 12.2 | 26.6 | 12.1 | 26.6 | 11.9 | 27.5 | 12.4 | 27.5 |
| 0.02 | 0.02 | 20.3 | 26.1 | 18.5 | 26.8 | 18.3 | 26.6 | 18.3 | 26.5 | 18.3 | 26.7 | 17.5 | 27.4 | 17.7 | 27.2 |
| | 0.01 | 21.7 | 25.8 | 20.8 | 26.6 | 20.8 | 26.4 | 20.8 | 26.4 | 20.6 | 26.4 | 19.9 | 27.5 | 20.2 | 27.3 |
| | 0.05 | 15.4 | 25.6 | 12.5 | 26.0 | 13.1 | 26.0 | 12.8 | 26.0 | 12.6 | 25.9 | 11.6 | 27.6 | 12.2 | 27.7 |
| 0.05 | 0.02 | 20.3 | 25.3 | 19.1 | 25.9 | 18.7 | 25.9 | 18.8 | 25.9 | 18.8 | 25.9 | 17.1 | 27.7 | 17.3 | 27.6 |
| | 0.01 | 22.3 | 25.4 | 21.2 | 25.9 | 21.4 | 25.8 | 21.4 | 25.8 | 21.4 | 25.8 | 19.8 | 27.7 | 19.7 | 27.6 |
| | 0.05 | 16.0 | 25.0 | 13.1 | 25.2 | 13.8 | 25.3 | 13.4 | 25.3 | 13.3 | 25.1 | 12.9 | 25.5 | 13.3 | 25.8 |
| 0.1 | 0.02 | 21.2 | 24.9 | 19.8 | 25.3 | 19.6 | 25.3 | 19.6 | 25.3 | 19.7 | 25.2 | 18.9 | 25.5 | 18.9 | 26.2 |
| | 0.01 | 23.0 | 24.7 | 21.9 | 25.1 | 21.9 | 25.0 | 22.0 | 25.0 | 21.9 | 24.9 | 21.4 | 25.8 | 21.5 | 26.0 |

Panel B. The Error Detection Performance in Cost of Goods Sold Account

Example SIC 7372 (%)

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_p | FP_p | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.9 | 28.1 | 15.7 | 27.5 | 15.4 | 28.0 | 15.8 | 27.5 | 15.7 | 27.4 | 14.9 | 27.7 | 16.1 | 27.0 |
| 0 | 0.02 | 20.0 | 28.0 | 19.5 | 27.3 | 19.1 | 28.0 | 19.9 | 27.2 | 19.7 | 27.4 | 18.8 | 27.9 | 19.3 | 27.2 |
| | 0.01 | 20.6 | 27.8 | 20.9 | 27.3 | 20.5 | 27.8 | 21.2 | 27.3 | 20.9 | 27.3 | 20.7 | 27.9 | 21.6 | 26.7 |
| | 0.05 | 17.2 | 28.1 | 16.1 | 27.4 | 15.6 | 27.9 | 15.9 | 27.3 | 16.1 | 27.4 | 15.2 | 28.2 | 16.3 | 27.1 |
| 0.01 | 0.02 | 19.9 | 27.9 | 19.6 | 27.5 | 19.0 | 27.8 | 20.0 | 27.3 | 19.7 | 27.5 | 19.2 | 27.7 | 20.1 | 26.9 |
| | 0.01 | 20.9 | 27.7 | 21.1 | 27.0 | 20.7 | 27.5 | 21.3 | 26.9 | 21.2 | 27.0 | 20.8 | 27.9 | 21.5 | 26.9 |
| | 0.05 | 16.8 | 27.6 | 15.8 | 26.8 | 15.4 | 27.5 | 15.7 | 26.8 | 15.8 | 26.9 | 15.2 | 27.4 | 16.4 | 26.9 |
| 0.02 | 0.02 | 20.0 | 27.8 | 19.8 | 27.1 | 19.3 | 27.6 | 20.1 | 27.0 | 19.9 | 27.0 | 19.4 | 27.2 | 20.4 | 26.6 |
| | 0.01 | 21.0 | 27.6 | 21.3 | 26.9 | 21.0 | 27.4 | 21.5 | 26.8 | 21.4 | 26.9 | 20.7 | 27.7 | 21.8 | 26.6 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 17.5 | 27.7 | 16.5 | 26.7 | 16.3 | 27.5 | 16.6 | 27.0 | 16.6 | 26.7 | 14.9 | 27.8 | 16.0 | 26.9 |
| 0.05 | 0.02 | 20.5 | 27.6 | 20.4 | 26.6 | 20.1 | 27.2 | 20.7 | 26.6 | 20.5 | 26.5 | 19.1 | 28.1 | 19.8 | 27.0 |
| | 0.01 | 21.4 | 27.6 | 21.7 | 26.5 | 21.3 | 27.1 | 21.8 | 26.5 | 21.8 | 26.4 | 20.5 | 28.0 | 21.4 | 26.9 |
| | 0.05 | 18.3 | 27.1 | 17.4 | 25.8 | 17.0 | 26.1 | 17.4 | 25.7 | 17.6 | 25.5 | 16.8 | 26.0 | 17.7 | 25.3 |
| 0.1 | 0.02 | 20.6 | 27.1 | 21.1 | 26.0 | 20.7 | 26.3 | 21.3 | 25.8 | 21.2 | 25.6 | 20.6 | 26.4 | 21.9 | 25.7 |
| | 0.01 | 22.0 | 26.9 | 22.4 | 25.4 | 22.3 | 26.0 | 22.7 | 25.5 | 22.9 | 25.4 | 22.4 | 26.2 | 22.9 | 25.2 |

This table displays (overestimating revenues & underestimating cost of goods sold) error detection performance of sharing models (sharing actual, prediction, error, either the sign of predictions and the level of deviations or both of them) and the benchmark model by percentage respectively, with different magnitudes of errors (e: from 1% to 5%) and different significance (s: determined by α) and width of prediction interval (PI) for companies with four digit SIC 7372. The term “FN” represents “False Negative” and FP represents “False Positive”. Additionally, the subscript “o” means original model, and “a”, “p”, “e”, “s”, “l” and “m” are short for “actual”, “prediction”, “error”, “the sign of prediction” “the level of deviation” and “mix” respectively (with the latter indicating sharing both the sign of predictions and the level of deviations).

### *2.4.3 The Choice of the Best Model*

Table 10 Panel A presents the selection of the best models for the overestimated revenue account with the change of the magnitudes of errors and Panel B shows the result for the cases of underestimated cost of goods sold account in ten industries. Similarly, in Table 11 Panel A, we show the change of the best models for the overestimated revenue account with the change of the cost ratios, and depict the case of the underestimated cost of goods sold account for ten industries in Panel B.

Consistent with prior findings, in Panel A (the detection of overestimated revenue account), the best model is usually the combined categorical information-sharing model that shares both the sign and the level of deviations of prediction errors. The change of model selections has little co-movement with the change of the magnitudes of errors. The best models are usually model M, occasionally model A, and in a few cases other models, except for SIC 5812 and 2836.

At the same time, in Panel B (the detection of underestimated cost of goods sold account), some of the information-sharing models are inferior to the original model when the magnitudes of errors are at 2% in SIC 5812 and 2836. In other SICs, the sharing models can beat the original model with no regards to the magnitudes of errors. In sum, the selection of best models in this scenario are similar (e.g. always model M) but differs according to different industrial economic structures and operational procedures (e.g. 5812 and 2836).

**Table 10. The Change of Best Models According to Different Magnitudes of Errors**

| | Panel A. Overestimated Revenue | | | Panel B. Underestimated COGS | | |
|---|---|---|---|---|---|---|
| 7372 | M | M | A | M | M | M |
| 1311 | M | M | M | M | M | M |
| 7370 | M | M | A/P/L | M | M | M |
| 2834 | M | M | M | M | M | M |
| 3674 | M | M | A | M | M | M |
| 4911 | M | M | A | M | M | A |
| 5812 | A | S | S | L | O | E |
| 2836 | A | L | L | M | O | L |
| 3845 | M | M | M | M | M | M |
| 4931 | M | A | A | A/M | A | A |

In this table, the 1:1 to 1:100 represent the cost ratios. “O” is short for “Original”, “E” means the error sharing model, “P” is for the prediction model, “A” is the actual sharing model, “S” stands for the “Sign” and “L” stands for the “Level” of deviations of prediction errors. At last, “M” represents the combined/ mixed model containing both sign and the level of deviations of prediction errors.

Further, in Table 11, in the Panel A (the detection of overestimated revenue account), the best model is always model M without any changes with the change of cost ratios from 1:10 to 1:100. However, when the cost ratio is 1:1, the choice of best models starts to vary among a group of the sharing models, which indicates that model M is the most stable model that sacrifices the least number of false positives to achieve fewer false negatives in our experiment. In panel B (the detection of underestimated cost of goods sold account), the selection of best models is different. When the cost ratio is 1:1, we find that the sharing models outperform the original model in all ten industries but the choice of best models varies among different models in a similar way as we observed in Panel A.

However, when we put more weight on false negatives, the choice converges to the model M as we expected.

**Table 11. The Change of Best Models According to Different Cost Ratios**

| | | | | | |
|---|---|---|---|---|---|
| Panel A. Overestimated Revenue | | | | | |
| | 1:01 | 1:10 | 1:20 | 1:50 | 1:100 |
| 7372 | L | M | M | M | M |
| 1311 | S | M | M | M | M |
| 7370 | L | M | M | M | M |
| 2834 | A/L | M | M | M | M |
| 3674 | A/L | M | M | M | M |
| 4911 | S | M | M | M | M |
| 5812 | S | M | M | M | M |
| 2836 | S | E | E | E | E |
| 3845 | E/L | M | M | M | M |
| 4931 | E | M | M | M | M |
| Panel B. Underestimated COGS | | | | | |
| | 1:01 | 1:10 | 1:20 | 1:50 | 1:100 |
| 7372 | L/S | M | M | M | M |
| 1311 | L | M | M | M | M |
| 7370 | L | M | M | M | M |
| 2834 | A | M | M | M | M |
| 3674 | L | M | M | M | M |
| 4911 | S | M | M | M | M |
| 5812 | A/E | M | M | M | M |

| | | | | | |
|---|---|---|---|---|---|
| 2836 | A/L | M | M | M | M |
| 3845 | E/L | M | M | M | M |
| 4931 | E | M | M | M | M |

In this table, the 1:1 to 1:100 represent the cost ratios. "O" is short for "Original", "E" means the error sharing model, "P" is for the prediction model, "A" is the actual sharing model, "S" stands for the "Sign" and "L" stands for the "Level" of deviations of prediction errors. At last, "M" represents the combined/ mixed model containing both sign and the level of deviations of prediction errors.

Interestingly, when we expand our sample to twenty industries presented in a online supplementary file, during the detection of overestimated revenue account, the selection of best models (M) is homogeneous. However, in detecting the underestimated cost of goods sold account, the result is heterogeneous. This finding may indicate varied effectiveness of the implementation of analytical procedures for different types of accounts. More specifically, the revenue account is easier to predict based on historical revenues and related revenue accounts, and the economic role of the revenue account does not vary across industries. Therefore, the selection of best models does not change significantly across industries or parameter values. On the other hand, the economic role of cost of goods sold is more divergent due to varying economic structures and operational procedures in different industries. For example, it is obviously dissimilar between companies in manufacturing versus companies in the financial services industry. Therefore, the selection of best models for the cost of goods sold account varies more than for the revenue account.

### 2.5 Concluding Remarks

This study develops a set of artifacts that could benefit auditors in performing analytical procedures through sharing peer data in a privacy-preserving way. We use peer models in various ways at different sharing levels and observe that peer data are extremely useful in helping auditors reduce their estimation errors and achieve better error detection performance. We also observe a comparable level of improvement within the three different sharing schemes. Namely, auditors can benefit from sharing self-generated regression residuals (errors) with peer companies, obtaining a better estimation and error detection performance. Additionally, after converting the numerical estimation errors into categorical dummy variables, we still can achieve a comparable level of improvement with higher-level information sharing schemes by fine-tuning parameters. Our results strongly indicate that our proposed artifact is beneficial for improving the performance of analytical procedures, which can contribute to the improvement of the overall audit quality. Furthermore, the results indicate the power of sharing within the same audit firm. Last but not the least, the discussion on the choice of the best model provides auditors the “best” sharing model with the least cost of errors under multiple auditing scenarios. In the future, the sharing procedures may “break the boundaries” between audit firms to utilize the power of “Big Data” and the emerging high-tech applications such as block chains.

It is important to note that the reported results have a number of limitations. First, companies that have no peers after the first three years or do not have uninterrupted peer errors are dropped from our sample. However, these companies still need to be audited. It is likely that practicing auditors will be able to identify peers for these companies based on a more elaborate algorithm or a larger scope of unlisted clients. Otherwise, they may simply charge higher audit fees as compensations for increasing litigation risks and additional audit efforts. Second, the evaluation procedures in this study are based on interpolated data points and not on real data. Thus, there may be some outliers in our data set causing serious problems (e.g. outlier values of MAPE). While our evaluation results show significant improvement of prediction accuracy and the superior performance of error detection, the accuracy of these predictions may not be sufficient for the practitioners. Third, as Leitch and Chen (2003) examine the error detection performance of analytical procedures by looking at coordinated errors, it is also reasonable to evaluate the difference in error detection performance when coordinated errors exist. The marginal contribution of contemporaneous information from peer companies to error detection performance with different sharing schemes may change due to the existence of coordinated errors.

# CHAPTER 3: GEOGRAPHIC INDUSTRY CLUSTERS AND AUDIT QUALITY

## 3.1 Introduction

Since the Enron debacle and the subsequent collapse of Arthur Anderson, a large body of research investigated the antecedents and consequences of poor audit quality. After the SOX (Sarbanes Oxley Act of 2002), regulators, practitioners, and academic researchers have paid considerable attention to various determinant factors that may affect the perception of audit quality (e.g. Kallapur et al. 2010; Skinner et al. 2012; Gul et al. 2013; Francis et al. 2013 (a)). Specially, a growing number of studies (e.g. Balsam et al. 2003; Ferguson et al. 2003) emphasized the importance of industry experience/ expertise. As noted by Reichelt et al. (2010), auditors' national positive network synergies and the individual auditors' deep industry knowledge at the office level are jointly important factors in delivering higher audit quality. Recently, a stream of research motivated by the importance of geographic proximity between economic agents (Defond et al. 2011; Kedia and Rajgopal 2009), has investigated the audit-client relationship using geographic proximity and suggested that informational advantages associated with local audits enable auditors to better constrain management's biased earnings reporting (Choi et al. 2012; Jensen et al. 2015; Sarka et al. 2016). These studies provided evidence on the effectiveness of information about industry similarities and local links, however, geographic industry clusters, as the interaction of industry expertise and geographic proximity, have not been studied in auditing research. On one hand, the interaction of industry similarities and local links may allow auditors to achieve information advantages in industry experience and local connections, facilitating audit efficiency and improving audit quality. On the other hand, with lower communication costs and more connection opportunities, the geographic agglomeration of the certain industry may change clients' bargaining power and trigger a spillover effect on the adoption of aggressive accounting policies in a locality. Therefore, it is not trivial to identify the association between industry clusters and audit quality. To our knowledge, this research is the first one studying the effect of geographic industry clusters on audit quality.

Specifically, we examine whether there is a difference in audit quality between firms within certain "geographic industry clusters" and those firms outside clusters. Further, if there is a significant effect of geographic industry clusters on audit quality, we also plan to find out the reasons that foster such quality gap. As noted previously, the agglomeration of clients from the same industry may benefit the auditors by enabling the collection of more relevant industry and local evidence, resulting in a positive combined effect. However, the low-cost connections in a local area within the same industry may provide opportunities for clients to share experiences on the adoption of questionable accounting policies, lower "perceived" cost of misconduct, change audit market competitions environment, escalate their bargaining power over auditors and convince auditors to accept questionable industry practice, resulting in a compromised audit quality. To complete the investigation on auditors' compromises, we also test whether auditor will charge an audit fee premium to compensate the raising litigation risks since they sacrifice a part of audit quality for those clients within a geographic industry cluster and whether such premium is higher when there is an existence of local industry competitors' connection.

Our empirical results using over 42,000 firm-year observations collected over the years from 2000 to 2015 reveal the following. First, after controlling a comprehensive set of variables known to affect the extent of opportunistic earnings management from prior literature, we find that the geographic industry cluster has a negative association with audit quality, indicating that the clients located in certain geographic industry cluster have a lower level of audit quality as opposed to those clients outside the cluster. To further gauge the moderating factor on the association between geographic industry clusters and audit quality, we find that, for stronger connections measured by the logarithm of number of local industry competitors, the negative relationship between geographic industry clusters and audit quality is more pronounced. As we expected, auditors are more likely to be convinced to accept questionable industry practice when they are facing local industry clients with a solid local connection and such connection also provides clients more opportunities to learn and spread questionable industry practice in the clusters. Following our hypothesis on the effect of geographic industry clusters on audit pricing, we find that auditors charge higher audit fees to the clients within a particular geographic industry cluster, using over 40,000 firm-year observations. Lastly, we examine the moderating effect of the existence of local connections through sharing the same auditor on the relation between the geographic industry clusters and audit fees. We use a dummy variable which equals one if there is at least one local industry competitor within the same MSA [1]

[1] In the United States, a metropolitan statistical area (MSA) is a geographical region with a relatively high population density at its core and close economic ties throughout the area. Such regions are neither legally incorporated as a city or town would be, nor are they legal administrative divisions like counties or separate entities such as states. As such, the precise definition of any given metropolitan area can vary with the source. A typical metropolitan area is centered on a single large city that wields substantial influence over the region (e.g., Chicago or Atlanta). However, some metropolitan areas contain more than one large city with no single

(Metropolitan Statistical Area), to measure the existence of the local connections and find that the audit fee premium is even higher if the client has a local connection in a particular cluster. These results support our hypotheses that the agglomeration of local clients within the same industry makes auditors become more lenient with clients' questionable industry practice due to the fear of losing clients, resulting in a lower audit quality. As the compensations for potential rising litigation risks, auditors charge clients within the clusters higher audit fees. For those clients with the local connections through sharing the same auditors, the auditors charge higher fee premiums and when the local connections become stronger, the audit quality of clients within the clusters declines more.

To validate our base results, we perform two robustness checks including considering the geographic proximity between auditor and client as well as utilizing the restatement as a surrogate measure for audit quality. We obtain similar results.

We believe this study can add value to current auditing research and practice in the following ways. First, as an important regulatory tool of the PCAOB, the inspection program leads to an improvement in audit quality. However, as suggested in prior literature (Gunny et al. 2013), the annual inspection program does not successfully target the most problematic candidates who have a higher level of discretionary accruals, and a greater propensity to restate and receive going concern opinions. We expect this research could be useful for the PCAOB's selections of engagement team by considering the agglomeration of firms within the same industry and distinguishing the inherent risk of auditing

municipality holding a substantially dominant position. Sources are from the US Census Metropolitan Statistical Area Delineations engagement between the firms within and outside clusters to identify better inspection candidates. In addition, the geographic industry clusters lower the communication cost, which may largely expedite auditing process in evidence collection, but at the same time may encourage the collusion of clients and threaten the independence of auditors. A better understanding of the role of client-auditor relationship in the geographic industry clusters can help regulators to support reliable connections (e.g. debates on auditor/partner rotation) and foresee potential deteriorations due to excessive collaborations.

The next section reviews the extant literature and develops research hypotheses. The third section discusses the details of research design including measure definitions and model specifications. The fourth section describes our sample and presents descriptive statistics. The empirical results can be found in the fifth section. The final section concludes this chapter.

### 3.2 Literature Review and Hypotheses Development

According to agglomeration economies literature (Duranton and Puga, 2004), the geographic agglomeration of industry clusters is due to advantages from sharing local labor markets, inputs-outputs relationship and knowledge spillovers. The underlying sharing also forces firms within industry clusters to become similar enough to take a share of the spoils. Firms within a certain industry cluster are more similar than firms within same industry but outside the cluster, after controlling the variations from locality. For instance, as argued in prior literature, firms within clusters behave in ways similar to their local peers, such as similar investment patterns (Dougal Parsons, and Titman 2015), strong co-movement in stock returns (Pirinsky and Wang 2006), and a great degree of co-movement in fundamentals (Engelberg et al. 2013). The similarities of local/neighboring firms allow auditors to collect more useful, relevant and timely information to generate effective benchmarks in audit analytical procedures, resulting in a better audit quality.

On the other hand, as argued by extant research (Kedia et al. 2007 & 2009), the perceived cost of adopting aggressive accounting practice by a certain firm is largely influenced by its' neighboring firms. The probability of a firm adopting/using aggressive accounting practices is positively associated with the increasing number of wrongdoing neighboring firms. Thus, within an industry cluster, the spread of aggressive accounting practices may provide auditors biased or unreliable accounting information, which weakens the effectiveness of audit analytics based on accounting numbers. Further, Beatty et al. (2013) provided evidence that high-profile accounting frauds have a signaling effect on peer firms' investment and distort real financial decisions of industry peers. As an expected consequence, these real adversely distortions intensified the bias in accounting information. This argument is generalized to a large population of fraudulent financial reporting not limited only to high-profile scandals and to a wider scope of company policies including capital expenditures and R&Ds, by Li et al. (2015). Within industry clusters, firms can easily observe economic behaviors of their competitors, and have stronger incentives to manipulate self-performance to pool with others in a fight for resource allocation. Thus, the manipulation phenomenon can be more prevalent among peer firms within the clusters comparing to firms outside the clusters. The manipulated accounting information will cause an ineffectiveness of utilizing benchmarks for auditors, resulting in higher false positives and false negatives.

Otherwise, the collaboration of local industry competitors forms an ally to convince auditors to accept questionable industry practice. The logic is simple: in a certain local area, with the growing number of clients agree on similar questionable industry practice, an invisible pressure begins to hangs over the auditors and such pressure makes auditors difficult to challenge their clients on questionable practice and easy to accept clients' explanation.

In sum, the geographic agglomeration of firms within the same industry has a countervailing effect on audit quality. However, we believe the negative effects of geographic industry clusters on audit quality will be the dominant. Thus, our hypothesis states as follows:

**Hypothesis 1:** There is a negative effect of the geographic industry cluster on audit quality.

We next posit that the negative effect of geographic industry clusters on audit quality is stronger for clients with more local industry competitors whom they share the same auditors with. As the agglomeration of companies within the same industry facilitates a face-to-face communication between local industry companies (Choi et al. 2012), we believe such connection imposes an insidious plot in persuading auditors to forsake strict inspections and hold back qualified opinions on questionable industry practice. In this chapter, we treat the number of local industry companies sharing the same auditor as a measure of connection between local companies. To be specific, a large number of local industry companies audited by the same auditor fuel a higher possibility for certain client to learn questionable industry practice from other peer companies and join an informal alliance of local industry companies against auditors. In such manner, when a client successfully negotiates with a certain auditor on a questionable industry practice, other clients who share the same auditor, consequently become free riders. Moreover, auditors may notch up the pressure from clients' collaborations, and such collaborations make auditors bogged down in a fear of losing clients. Likewise, the fear of client loss can drive auditors to become more lenient with their clients' questionable accounting practice, resulting in an inevitable compromised trajectory of lower audit quality. Therefore, when there is a positive effect of geographic industry clusters on audit quality, the local "connections" become a strong source of opposition and neutralize the positive effect from a more similar and relevant peer companies' information advantage. As we hypothesized, if the effect of geographic industry clusters on audit quality is negative, then the local "connections" shore up a pronounced negative result. All in all, we expect the degree of local "connection" between local industry competitors to moderate the effects of the geographic industry clusters on audit quality. To provide empirical evidence of this prediction, we test the following hypothesis:

**H2：** The negative effect of geographic industry clusters on audit quality is more pronounced for clients with more local industry competitors, whom they share the same auditors with, all else equal.

Since the geographic industry clusters may negatively affect the quality of audit service, it is not uncommon to investigate whether the agglomeration of companies within the same industry has a sequential effect on audit pricing. Prior studies documented that audit fees are mainly determined by the input efforts and the risk exposure. (Blankley et al. 2009) On one hand, the agglomeration of companies within the same industry allows auditors to profit from economies of scale because a more similar and relevant pool of local peers can allow auditors to take information advantages and save their costs by reducing repetitive procedures such as generating industry benchmark and gathering local information. The reduced input efforts lead to lower audit fees. Additionally, the agglomeration of companies within the same industry geographically combines disparate clients' interests together and escalates the bargaining power of clients within the clusters over auditors. The increasing bargaining power of clients may drive auditors to lower their audit fees and share their cost savings with their clients. On the other hand, the uncertainty raised up by the acceptance of questionable industry practice may leave a higher litigation risk for which auditors may charge higher audit fees to compensate themselves. Moreover, the agglomeration of companies within the same industry may provide more opportunities for clients to spread and learn questionable industry practice within the clusters, leading to a contaminated accounting information environment, as we argued previously. Intuitively, confronted by the coordination of clients within the clusters, auditors need to put much more efforts into the auditing process as well as to take higher litigation risks. Consistent with prior literature, excessive audit efforts plus higher litigation risk exposures lead to a higher audit price. Following our previous hypothesis, we believe the contaminated accounting information environment and the decreasing audit quality within the geographic industry clusters will lead the auditors to charge higher audit fees to compensate for their extra efforts and excessive litigation risks. Thus we expect that:

**H3:** The auditors will charge the clients within the geographic industry clusters higher audit fees than those clients outside the clusters.

In a similar vein, our fourth hypothesis is going to investigate the moderating effects of the local "connections" on the association between geographic industry clusters and audit fees. Unlike using the number of local industry competitors whom a client share the same auditor with as the measure of local "connection", we use the existence of local industry competitors as the measure of local "connection".[2] Consistent with our second hypothesis, we anticipate that the existence of local "connection" has possibilities to herd clients towards offering higher audit fees on their own. To be specific, when a client successfully negotiates with the auditor on an industry questionable practice by ceding the power of asking for a lower audit fee, other local industry competitors can easily learn such behaviors and offer higher audit fees to relish the opportunity to stay with its questionable accounting practice. Under this circumstance, the audit fee premiums become the bargain chips for clients, who want to adopt the questionable accounting practice. For auditors who face the clients within the clusters, connected with local industry competitors, they hardly refuse the offers from the clients due to the loss of clients. Therefore, we hypothesize that:

**H4:** The auditors will charge the clients with local connections within geographic industry clusters the fee premiums comparing to other clients.

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[2] This change is because the degree of local "connection" measured by the number of local industrial competitors is not necessary linearly associated with the audit fees. For example, for a certain area (MSA), the number of industrial competitors may vary from 1 to over 100, it is less likely that the audit fee will significantly different between the area with 100 industrial competitors and that with only 1. It is likely that the bargaining power from local "connection" will be enhanced if there is large enough participants but an overwhelming number of participants may split a single large connection structure into several separate small connection structures, resulting in a non-linear form. To wipe out such concerns, we use a dummy variable indicating the existence of local industrial competitors as a surrogate of local "connection".

## 3.3 Research Design

### *3.3.1 Measures*

#### Definition of geographic industry clusters

Following prior studies (Coval and Moskowitz 1999; Francis et al. 2005; Pirinsky and Wang 2006), we use the location of corporate headquarters as the client company location, since the corporate headquarters is likely to be the center of information exchange between the firm and its suppliers, service providers and investors. Thus, it is reasonable to believe auditors, especially local auditors (office-level), do most of their jobs there. We adopt the MSA-based (Metropolitan Statistical Area) geographic boundary, and embed each corporate headquarters in certain MSA according to its real location (city and state). We define those companies (clients) within the same MSA as local companies and the companies in a certain MSA within the same industry as local industry competitors. Since some MSAs in eastern U.S, located within a narrow geographic boundary but some MSAs in western states are much larger, there are some cases that some auditors, located in different MSA, are physically (based on real geographic distance) closer than the auditors within the same MSA. For this reason, in the robustness checks, we expand the definition of the local auditor and treat those auditors located less than 100 kilometers as the local auditors as well.

To capture the essence of geographic industry clustering, we define our variable of interests, “CLUSTER”, using three surrogate measurements of industry clusters, adapted from Almazan et al. (2010). The first measure ROF captures the degree of agglomeration of firms within certain industry by calculating the number of firms with the same three-digit SIC in a Metropolitan Statistical Area (MSA) divided by the total number of firms with the same three-digit SIC. But this measure is so crude that it is not reliable when there are very few firms within a certain industry. For instance, if for a firm-year there is only one valid observation within an industry, the ratio will take the value of maximum 1, which indicates 100% degree of agglomeration. The second measure DUM, excludes such concern by constraining a large enough number of firms within the same industry. We generate a dummy variable "DUM" that takes the value of one for firm-years in which a firm's headquarters is located within an MSA that has both 10 or more firms with the same three-digit SIC and at least 3% of the market value of the industry, and zero otherwise. Further, in the third measure CMV, we take into account the contribution of firms within the industry clusters to industry market values. The third measure CMV is also a dummy variable that takes the value of one for firm-years a firm's headquarters is located in an MSA that represents at least 10% of market value of the firm's industry and has at least three firms with the same three-digit SIC, and zero otherwise.

**Measurement of audit quality**

As in many other studies, the first challenge for researchers is how to empirically measure the term - "audit quality". The widely used definition of "audit quality" is described as the market assessed joint probability that auditors both "discover a breach in the client's accounting system" and "report the breach" (DeAngelo 1981). As the main two output-based audit quality measures, accruals and audit opinions (restatement and going-concern) are appropriate but not perfect proxies for audit quality. In line with similar studies, we use accruals rather than audit opinions to proxy for audit quality for the following reasons: as argued in Myers et al. (2003), audit opinion is an extreme measure of audit quality with only a small fraction of sample. Unlike accrual-based measures, audit opinions do not address audit quality differentiation for a broad cross section of firms. In such manner, the little cross-sectional variations will lead us to nowhere in an empirical tests due to the lack of statistical power. In addition, as we will illustrate in our secondary test, auditors may become easier to be convinced to accept the questionable industry practice due to the collaboration of local industry companies. These undetectable changes may not be captured in the sample of going-concern or restatement database. As a robustness check, we use restatement as an alternative measure for audit quality and the results qualitatively still hold. In the future, we plan to utilize a more clean, direct and reasonable proxy from PCAOB inspection data. The inspection data not only provides output-based reporting quality but also the input-based discovered quality.

As in many other studies, we use absolute discretionary accruals as an outcome of opportunistic earnings management. To alleviate the concerns that traditional Jones (1991) model is noisy, we choose two alternative commonly used measures of discretionary accruals: one is from the augmented Jones model developed by Ball and Shivakumar (2006), which takes the conditional conservatism into consideration, and the other is estimated by performance-matched modified Jones model (Kothari et al. 2005). We multiply the absolute value of the discretionary accruals by -1, and denote these two measures as DA_1 and DA_2, respectively.

The augmented Jones model of Ball and Shivakumar (2006) in Eq. (3) explains the computation of our first measure:

$$\frac{ACCR_{i,t}}{A_{i,t-1}} = \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{\Delta REV_{i,t}}{A_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{A_{i,t-1}} + \beta_4 \frac{CFO_{i,t}}{A_{i,t-1}} + \beta_5 DCFO_{i,t} + \beta_6 \frac{CFO_{i,t}}{A_{i,t-1}} * DCFO_{i,t} + \varepsilon_{i,t} \quad (3)$$

Where, for firm i and year t (or t-1), ACCR denotes total accruals (income before extraordinary items minus cash flow from operations); A, ΔREV, and PPE represent total assets, changes in net sales, and gross property, plant, and equipment, respectively; CFO represents cash flows from operations; DCFO is an indicator variable that equals one if CFO is negative, and zero otherwise; and $\varepsilon$ is the error term. We estimate Eq. (3) for each two-digit SIC industry and year with at least 10 observations. Our first measure of abnormal accruals, DA_1, is absolute value of the difference between actual value and the fitted values of Eq. (3), multiplied by -1.

Our second measure of abnormal accruals is computed as follows. For each two-digit SIC industry and year with at least 10 observations, we estimate the cross-sectional version of the modified Jones model as

$$\frac{ACCR_{i,t}}{A_{i,t-1}} = \beta_1 \frac{1}{A_{i,t-1}} + \beta_2 \frac{\Delta REV_{i,t}}{A_{i,t-1}} + \beta_3 \frac{PPE_{i,t}}{A_{i,t-1}} + \varepsilon_{i,t} \quad (4)$$

where the residuals are discretionary accruals before adjusting for firm performance. Following the procedures proposed by Kothari et al. (2005), we match each firm-year observation with another from the same two-digit SIC industry with the closest return on assets (ROA) in previous year. We then compute performance-matched abnormal accruals, DA_2, by taking the absolute value of the difference between the unadjusted discretionary accruals and the ROA matched ones.

### *3.3.2 Model Specifications*

**The effect of geographic industry clusters on audit quality**

To test our first hypothesis, we propose to estimate a multivariate regression model that links audit quality with our variable of interest, that is, a variable indicating whether the firm is located in a geographic industry cluster.

$$AQ_{i,t} = \beta_0 + \beta_1 CLUSTER_{it} + \beta_2 LNTA_{it} + \beta_3 CHGSALE_{i,t} + \beta_4 BTM_{i,t} + \beta_5 LOSS_{i,t} + \beta_6 Z_{i,t} + \beta_7 ISSUE_{i,t} + \beta_8 CFO_{i,t} + \beta_9 LACCR_{i,t} + \beta_{10} TENURE_{i,t} + \beta_{11} NAS_{i,t} + \beta_{12} BIGN_{i,t} + \beta_{13} INSPEC_{i,t} + \beta_{14} CONCENT_{i,t} + \varepsilon_{i,t} \quad (5)$$

For firm i in year t, all variables are defined in the Appendix A. The audit quality AQ can be proxyed by two measures of discretionary accruals. One is obtained from the augmented Jones (1991) model of Ball and Shiyakumar (2006), which takes into account the role of conditional accounting conservatism. The other one is performance-adjusted discretionary accruals using the model suggested by Kothari et al. (2005). Consistent with prior literature, we multiply our proxy for audit quality by -1.

Extant literature has shown that audit quality is affected by observable client and auditor characteristics. In this chapter, the control variables cover factors that may significantly affect audit quality based on auditors' incentives, clients' uncertainty and uniqueness, process and professional judgement of audit practice, suggested by prior literature (Knechel et al. 2013). Considering the uniqueness of clients, we include SIZE to control for the client size effect (e.g. Dechow and Dichev 2002), CHGSALE and BTM to control for growth, AGE to control for changes in firm life cycle (Anthony and Ramesh, 1992). For the concerns of uncertainty, we include LOSS to control for potential differences in earnings management between loss and profit firms, Z score, and ISSUE to control for potential financial distress, CFO to control for the potential correlation between accruals and cash flows (Kothari et al. 2005), and LACCR to control for the reversal of accruals overtime (Ashbaugh et al. 2003). Auditors' incentives are also controlled in our empirical study by including TENURE for concerns of long-term client-auditor relationship (Johnson et al. 2002; Myers et al. 2003), NAS and CLTIMP (Client importance) for incentives to compromise independence (Frankel et al. 2002; Chung and Kallapur 2003). Finally, we include BIGN and INSPEC (Industry specialist) to control for the effect of auditor reputation and industry expertise at the MSA level, and control CONTRA for the effect of auditor market concentration on our results (Kallapur et al. 2010; Kedia and Rajgopal 2007).

In the second hypothesis, we plan to examine an interaction effect that may explain why there is an audit quality difference between companies within geographic industry clusters and those firms outside the clusters. Therefore, we plan to modify our multivariate regression model by adding an explaining (moderating) term "LCONNECT" and an interaction term "CLUSTER*LCONNECT", where LCONNECT indicates the logarithm of number of local industry competitors for a certain client. The number of local industry competitors implies the degree of "local connection", because a large number of local industry competitors provide clients more opportunities to learn from other competitors, spread experience, and at the meanwhile form an ally to convince auditors to accept questionable industry practice. We estimate the following regression model:

$$AQ_{i,t} = \beta_0 + \beta_1 CLUSTER_{i,t} + \beta_2 LCONNECTION_{i,t} + \beta_3 CLUSTER_{i,t} * LCONNECTION_{i,t} + \beta_4 LNTA_{i,t} + \beta_5 CHGSALE_{i,t} + \beta_6 BTM_{i,t} + \beta_7 LOSS_{i,t} + \beta_8 Z_{i,t} + \beta_9 ISSUE_{i,t} + \beta_{10} CFO_{i,t} + \beta_{11} LACCR_{i,t} + \beta_{12} TENURE_{i,t} + \beta_{13} NAS_{i,t} + \beta_{14} BIGN_{i,t} + \beta_{15} INSPEC_{i,t} + \beta_{16} CONCENT_{i,t} + \varepsilon_{i,t} \quad (6)$$

**The effect of geographic industry clusters on audit pricing**

To investigate the effect of geographic industry clusters on audit fees, we use an audit fee model adapted from recent prior studies. (e.g. DeFond et al. 2002; Whisenant et al. 2003; Francis and Wang 2005; Krishnan et al. 2005; Ghosh and Pawlewicz 2009; Choi et al. 2010) We regress logged audit fees (LAF) on variables controlling for both audit efforts and risk exposures. We control for within-firm correlation of the residuals, and use the robust cluster technique suggested by Peterson (2009). The model is:

$$LAF_{i,t} = \beta_0 + \beta_1 CLUSTER_{i,t} + \beta_2 LNTA_{i,t} + \beta_3 EMPLOYEE_{i,t} + \beta_4 ARINV_{i,t} + \beta_5 CR_{i,t} + \beta_6 CATA_{i,t} + \beta_7 ROA_{i,t} + \beta_8 LEV_{i,t} + \beta_9 LOSS_{i,t} + \beta_{10} FOREIGN_{i,t} + \beta_{11} ISSUE_{i,t} + \beta_{12} BUSY_{i,t} + \beta_{13} INTANG_{i,t} + \beta_{14} SEG_{i,t} + \beta_{15} OPINION_{i,t} + \beta_{16} MERGE_{i,t} + \beta_{17} BIGN_{i,t} + +\beta_{17} INDSPE_{i,t} + +\beta_{17} CONCENT_{i,t} + \varepsilon_{i,t} \quad (7)$$

Consistent with prior literature, we include total assets (LTA), the number of employees (EMPLOYEE), the foreign operations (FOREIGN), the presence of mergers and acquisitions (MERGE), the number of business segments and the issuance of a going concern opinion (OPINION) to control for audit efforts. To control for audit risk, we include commonly used fundamental characters: CR, CATA, ARINV, ROA, LOSS and INTANG. We also include the leverage (LEV), to control the long-term financial structure of the client, the BUSY to control seasonal variations, the BIGN to control the size of audit firms, and INDSPEC and CONTENT to control industry expertise and audit market concentration respectively.

Similarly, we also test whether the local "connections" have a moderating effect on the association between geographic industry clusters and audit pricing by estimating the following modified regression model with interaction term "CLUSTER*CONNECT_DUM". As we argued previously, we use a dummy variable CONNECT_DUM instead of using LCONNECT to test the moderating effect of the existence of local industry competitors rather than the magnitude of such local connections on the association between geographic industry clusters and audit fees.

$$\mathrm{LAF}_{i,t} = \beta_0 + \beta_1 CLUSTER_{i,t} + \beta_2 CONNECTION\_DUM_{i,t} + \beta_3 CLUSTER * CONNECTION\_DUM_{i,t} + \beta_4 LNTA_{i,t} + \beta_5 EMPLOYEE_{i,t} + \beta_6 ARINV_{i,t} + \beta_7 CR_{i,t} + \beta_8 CATA_{i,t} + \beta_9 ROA_{i,t} + \beta_{10} LEV_{i,t} + \beta_{11} LOSS_{i,t} + \beta_{12} FOREIGN_{i,t} + \beta_{13} ISSUE_{i,t} + \beta_{14} BUSY_{i,t} + \beta_{15} INTANG_{i,t} + \beta_{16} SEG_{i,t} + \beta_{17} OPINION_{i,t} + \beta_{18} MERGE_{i,t} + \beta_{19} BIGN_{i,t} + +\beta_{20} INDSPE_{i,t} + +\beta_{21} CONCENT_{i,t} + \varepsilon_{i,t} \quad (8)$$

## 3.4 Sample Selection and Descriptive Statistics

### *3.4.1 Sample*

The initial list of our sample consists of all firms included in the Audit Analytics database from 2000 to 2015. We identify the state and city information for each local office and corporate headquarters from the Audit Analytics database. Then we match each state-city locations to the country codes of Federal Information Processing Standards (FIPS) using the U.S Census Bureau's 2000 Places file. Following Francis et al. (2005), we delete observations if auditors or clients are not located in one of the 280 MSAs defined in the U.S. census of 2000. We also obtain the latitude and longitude data for the state-city locations in our sample, using the U.S Census Bureau's Gazetteer file. With these data, we compute the real geographic distances between any two cities and make a robustness check considering the effects of geographic proximity between auditor and client.

Then we retrieve all other financial data from Compustat Annual file and exclude financial institutions and utility firms with SIC codes in the ranges 6000-6999 and 4900-4999, respectively. We also obtain audit fees, audit opinions data from the Audit Analytics database. After basic data selection, cleaning and merging, we obtain 42,066 firm-year observations located in 195 MSAs for our first two hypotheses. These observations are audited by auditors from 1089 unique audit practice offices located in 114 MSAs. The sample size for the third and the fourth hypotheses slightly decreases to 40101, due to data merging.

### *3.4.2 Descriptive Statistics and Univariate Tests*

Panel A of table 12 presents the descriptive statistics for our two discretionary accrual measures, DA_1 and DA_2, separately, for the "within geographic industry clusters group" (ROF>median (ROF), DUM=1 and CMV=1) and the "outside the clusters group" (ROF<=median (ROF), DUM=0 and CMV=0), along with univariate test results for differences in the mean between the two samples. As shown in Panel A of table 12, both DA_1 and DA_2 are significantly lower for the clients located in geographic industry clusters than for clients outside the clusters. The results hold for three different measures of geographic industry clusters. For instance, the mean value of DA_1 for those clients outside the clusters is -0.074 and -0.082 for those clients within geographic industry clusters, by using the measure CMV to identify whether a client is located in a geographic industry cluster. The differences are significant at the 1% level with t = 7.217.

**Table 12. Descriptive Statistics**

Panel A. Results of Univariate Tests

| | | Outside Clusters Group | | | Inside Clusters Group | | | Test for Equality |
|---|---|---|---|---|---|---|---|---|
| Variable | | Mean | Obs | S.D | Mean | Obs | S.D | (t-value) |
| CMV | DA_1 | -0.074 | 32725 | 0.095 | -0.082 | 9341 | 0.105 | 7.22 *** |
| | DA_2 | -0.101 | 32725 | 0.110 | -0.107 | 9341 | 0.116 | 4.92 *** |
| DUM | DA_1 | -0.070 | 33920 | 0.091 | -0.097 | 8146 | 0.119 | 18.85*** |
| | DA_2 | -0.097 | 33920 | 0.106 | -0.124 | 8146 | 0.130 | 17.37*** |
| ROF | DA_1 | -0.072 | 21721 | 0.095 | -0.082 | 20345 | 0.100 | 7.06 *** |
| | DA_2 | -0.099 | 21721 | 0.109 | -0.105 | 20345 | 0.114 | 5.40 *** |

Panel B. Descriptive Statistics for Variables in Audit Quality Specification

| Variable | Obs | Mean | S.D | 25% | Median | 75% |
|---|---|---|---|---|---|---|
| DA_1 | 42066 | -0.76 | 0.1 | -0.09 | -.042 | -0.02 |
| DA_2 | 42066 | -0.1 | 0.11 | -0.13 | -0.07 | -0.03 |
| LCONNECTION | 42066 | 0.80 | 0.97 | 0 | 0.69 | 1.39 |
| ROF | 42066 | 0.16 | 0.17 | 0.06 | 0.11 | 0.20 |
| DUM | 42066 | 0.19 | 0.40 | 0.00 | 0.00 | 0.00 |
| CMV | 42066 | 0.22 | 0.42 | 0.00 | 0.00 | 0.00 |
| LNTA | 42066 | 5.88 | 2.06 | 4.36 | 5.83 | 7.30 |
| BTM | 42066 | 0.61 | 0.64 | 0.23 | 0.44 | 0.77 |
| Z | 42066 | -1.09 | 2.22 | -2.61 | -1.48 | -0.20 |
| BIGN | 42066 | 0.76 | 0.43 | 1.00 | 1.00 | 1.00 |

| | | | | | | |
|---|---|---|---|---|---|---|
| LOSS | 42066 | 0.38 | 0.49 | 0.00 | 0.00 | 1.00 |
| ISSUE | 42066 | 0.78 | 0.41 | 1.00 | 1.00 | 1.00 |
| CONCENT | 42066 | 0.18 | 0.10 | 0.12 | 0.18 | 0.22 |
| TENURE | 42066 | 1.39 | 0.75 | 0.69 | 1.39 | 1.95 |
| BOTH | 42066 | 0.13 | 0.33 | 0.00 | 0.00 | 0.00 |
| CFO | 42066 | 0.04 | 0.20 | 0.00 | 0.08 | 0.14 |
| LACCR | 42066 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| NAS | 42066 | 0.78 | 0.27 | 0.79 | 0.87 | 0.92 |
| CHGSALE | 42066 | 0.16 | 0.58 | -0.04 | 0.07 | 0.21 |

Panel C. Descriptive Statistics for Variables in Audit Pricing Specification

| Variable | Obs | Mean | S.D | 25% | Median | 75% |
|---|---|---|---|---|---|---|
| LAF | 40101 | 13.23 | 1.34 | 12.20 | 13.23 | 14.15 |
| CONNECTION_DUM | 40101 | 0.52 | 0.50 | 0.00 | 1.00 | 1.00 |
| EMPOLYEE | 40101 | 1.68 | 2.04 | 0.40 | 0.92 | 2.07 |
| ARINV | 40101 | 0.25 | 0.19 | 0.09 | 0.21 | 0.36 |
| CR | 40101 | 3.12 | 3.39 | 1.33 | 2.09 | 3.49 |
| CATA | 40101 | 0.52 | 0.25 | 0.33 | 0.53 | 0.73 |
| ROA | 40101 | -0.03 | 0.28 | -0.06 | 0.05 | 0.11 |
| LEV | 40101 | 0.17 | 0.21 | 0.00 | 0.09 | 0.27 |
| INTANG | 40101 | 0.17 | 0.20 | 0.00 | 0.10 | 0.28 |
| SEG | 40101 | 0.58 | 0.69 | 0.00 | 0.00 | 1.10 |
| FOREIGN | 40101 | 0.54 | 0.50 | 0.00 | 1.00 | 1.00 |
| MERGE | 40101 | 0.35 | 0.48 | 0.00 | 0.00 | 1.00 |
| BUSY | 40101 | 0.69 | 0.46 | 0.00 | 1.00 | 1.00 |
| OPINION | 40101 | 0.06 | 0.24 | 0.00 | 0.00 | 0.00 |

Panel B of table 12 reports the descriptive statistics for all control variables included in our audit quality regression models. The average client size is 5.88, which is equivalent to about 190 million of total assets. About 76% of clients are audited by one of the Big N auditors, and the average logged auditor tenure is 1.39, which is interpreted as about 4 years of auditor tenure. On average, non-audit service fees are about 78% of total fees, and about 13% of clients hire auditors with both national and local industry specialists. Our descriptive statistics are quite comparable to those in prior studies (Choi et al. 2010; Francis and Yu 2009), when we truncate our sample to fit the time period.

Similarly, Panel C of table 12 reports the descriptive statistics for variables in our audit pricing model specifications. The average audit fees charged is 13.23, approximately 0.56 million dollars. About 54% of clients have foreign operations, 35% of clients are involved in merges and acquisitions and 69% clients are audited in a busy season in current year. On average each client has 1.78 business segments and only 6% of them have received going concern opinions.

### *3.4.3 Pearson Correlation Matrix*

Panel A of table 13 presents the Pearson correlation matrix for all the variables included in Eq. (5). The two abnormal accrual measures, DA_1 and DA_2, are highly correlated 0.52 ($p<0.01$). The "cluster" variables are negatively correlated with DA_1 and DA_2 ($p<0.01$) except ROF. As we expected, the regression result using ROF is the worst of three measures. Finally, we note that the correlations between the control variables are mostly not very high except for those between BIGN and LNTA (0.48), and between CFO and LOSS (-0.51). This finding suggests that multicollinearity is unlikely to be a serious problem in our model.

# Table 13. Pearson Correlation Matrix

## Panel A. Pearson Correlations between Discretionary Accruals, Geographic Industry Clusters and Control Variables

| | DA_1 | DA_2 | ROF | DUM | CMV | LNTA | BIGN | TENURE | NAS | CHGSALE | BTM | LOSS | Z | ISSUE | CFO | LACCR | INDSPEC | CONCENT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DA_1 | 1.00 | | | | | | | | | | | | | | | | | |
| DA_2 | 0.52 | 1.00 | | | | | | | | | | | | | | | | |
| ROF | 0.06 | 0.05 | 1.00 | | | | | | | | | | | | | | | |
| DUM | -0.11 | -0.10 | 0.22 | 1.00 | | | | | | | | | | | | | | |
| CMV | -0.04 | -0.02 | 0.36 | 0.55 | 1.00 | | | | | | | | | | | | | |
| LNTA | 0.29 | 0.26 | 0.14 | -0.03 | 0.11 | 1.00 | | | | | | | | | | | | |
| BIGN | 0.15 | 0.12 | 0.04 | 0.04 | 0.04 | 0.48 | 1.00 | | | | | | | | | | | |
| TENURE | 0.14 | 0.12 | 0.02 | -0.04 | 0.00 | 0.28 | 0.18 | 1.00 | | | | | | | | | | |
| NAS | 0.06 | 0.05 | 0.01 | -0.02 | 0.01 | 0.22 | 0.26 | 0.00 | 1.00 | | | | | | | | | |
| CHGSALE | -0.16 | -0.13 | -0.02 | 0.08 | 0.03 | -0.03 | 0.00 | -0.08 | 0.00 | 1.00 | | | | | | | | |
| BTM | 0.05 | 0.06 | 0.03 | -0.08 | -0.05 | -0.10 | -0.08 | -0.08 | -0.03 | -0.11 | 1.00 | | | | | | | |
| LOSS | -0.29 | -0.22 | -0.06 | 0.13 | 0.02 | -0.34 | -0.13 | -0.15 | -0.09 | 0.02 | 0.12 | 1.00 | | | | | | |
| Z | -0.23 | -0.15 | 0.00 | -0.04 | -0.03 | -0.02 | -0.03 | -0.05 | -0.02 | -0.03 | -0.10 | 0.39 | 1.00 | | | | | |
| ISSUE | -0.06 | -0.05 | 0.01 | 0.07 | 0.04 | 0.13 | 0.10 | -0.05 | 0.04 | 0.08 | -0.10 | 0.10 | 0.22 | 1.00 | | | | |
| CFO | 0.29 | 0.25 | 0.07 | -0.12 | 0.01 | 0.34 | 0.12 | 0.11 | 0.08 | -0.09 | -0.01 | -0.51 | -0.37 | -0.11 | 1.00 | | | |
| LACCR | 0.27 | 0.19 | 0.07 | -0.04 | 0.01 | 0.34 | 0.21 | 0.11 | 0.09 | -0.11 | 0.06 | -0.21 | -0.17 | -0.04 | 0.30 | 1.00 | | |
| INDSPEC | 0.07 | 0.06 | 0.06 | 0.01 | 0.08 | 0.21 | 0.21 | 0.09 | 0.08 | -0.01 | -0.04 | -0.05 | 0.01 | 0.03 | 0.04 | 0.06 | 1.00 | |
| CONCENT | 0.05 | 0.04 | -0.04 | -0.05 | -0.06 | 0.04 | 0.11 | 0.02 | 0.06 | -0.01 | 0.02 | -0.04 | -0.05 | 0.00 | 0.02 | 0.04 | -0.02 | 1.00 |

## Panel B. Pearson Correlations between Audit Fees, Geographic Industry Clusters and Control Variables

| | LAF | ROF | LNTA | EMPLOYEE | ARINV | CR | CATA | ROA | LEV | LOSS | FOREIGN | ISSUE | BUSY | INTANG | SEG | OPINION | MERGE | BIGN | INDSPEC | CONCENT |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| LAF | 1.00 | | | | | | | | | | | | | | | | | | | |
| ROF | 0.13 | 1.00 | | | | | | | | | | | | | | | | | | |
| LNTA | 0.83 | 0.14 | 1.00 | | | | | | | | | | | | | | | | | |
| EMPLOYEE | 0.63 | 0.05 | 0.73 | 1.00 | | | | | | | | | | | | | | | | |
| ARINV | -0.05 | 0.05 | -0.11 | 0.02 | 1.00 | | | | | | | | | | | | | | | |
| CR | -0.21 | -0.04 | -0.19 | -0.24 | -0.17 | 1.00 | | | | | | | | | | | | | | |
| CATA | -0.22 | -0.05 | -0.39 | -0.27 | 0.39 | 0.44 | 1.00 | | | | | | | | | | | | | |
| ROA | 0.29 | 0.09 | 0.44 | 0.30 | 0.24 | -0.12 | -0.22 | 1.00 | | | | | | | | | | | | |
| LEV | 0.20 | 0.05 | 0.27 | 0.16 | -0.13 | -0.23 | -0.42 | 0.06 | 1.00 | | | | | | | | | | | |
| LOSS | -0.25 | -0.07 | -0.37 | -0.30 | -0.17 | 0.10 | 0.13 | -0.59 | 0.01 | 1.00 | | | | | | | | | | |
| FOREIGN | 0.44 | 0.10 | 0.38 | 0.25 | 0.11 | -0.11 | -0.03 | 0.27 | 0.00 | -0.20 | 1.00 | | | | | | | | | |

| | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ISSUE | 0.10 | 0.01 | 0.10 | 0.04 | -0.17 | -0.07 | -0.16 | -0.14 | 0.27 | 0.12 | -0.01 | 1.00 | | | | | | | | |
| BUSY | 0.07 | 0.00 | 0.04 | -0.05 | -0.19 | 0.01 | -0.10 | -0.10 | 0.10 | 0.08 | -0.04 | 0.11 | 1.00 | | | | | | | |
| INTANG | 0.25 | -0.02 | 0.23 | 0.16 | -0.16 | -0.23 | -0.46 | 0.12 | 0.18 | -0.06 | 0.15 | 0.12 | 0.05 | 1.00 | | | | | | |
| SEG | 0.35 | 0.06 | 0.35 | 0.31 | 0.12 | -0.18 | -0.20 | 0.23 | 0.11 | -0.18 | 0.22 | 0.00 | -0.01 | 0.20 | 1.00 | | | | | |
| OPINION | -0.19 | -0.03 | -0.27 | -0.14 | -0.06 | -0.10 | -0.05 | -0.40 | 0.00 | 0.26 | -0.15 | 0.06 | 0.04 | 0.01 | -0.09 | 1.00 | | | | |
| MERGE | 0.33 | 0.03 | 0.34 | 0.25 | 0.01 | -0.14 | -0.21 | 0.21 | 0.09 | -0.19 | 0.23 | 0.08 | -0.01 | 0.39 | 0.26 | -0.12 | 1.00 | | | |
| BIGN | 0.47 | 0.04 | 0.52 | 0.32 | -0.11 | -0.03 | -0.08 | 0.17 | 0.11 | -0.15 | 0.22 | 0.09 | 0.06 | 0.05 | 0.14 | -0.19 | 0.17 | 1.00 | | |
| INDSPEC | 0.21 | 0.05 | 0.21 | 0.18 | -0.02 | -0.03 | -0.05 | 0.06 | 0.04 | -0.06 | 0.07 | 0.03 | 0.02 | 0.02 | 0.08 | -0.05 | 0.05 | 0.22 | 1.00 | |
| CONCENT | 0.02 | -0.03 | 0.07 | 0.06 | 0.01 | 0.01 | -0.01 | 0.05 | 0.00 | -0.05 | 0.01 | 0.00 | -0.02 | -0.03 | 0.03 | -0.04 | 0.02 | 0.13 | 0.00 | 1.00 |

Similarly, Panel B of table 13 presents the Pearson correlation matrix for all the variables included in Eq. (5). The cluster variables are positively correlated with LAF. Except for the correlation between INTANG and CATA (-0.46), the correlation between control variables are mostly independent to each other. This finding suggests that multicollinearity is not a problem in this model specification as well.

## 3.5 Empirical Results

### *3.5.1 Main Results*

**Geographic industry clusters and audit quality**

The results of the regression in Eq. (5) are displayed in table14. The dependent variable is the absolute value of discretionary accruals multiplied by -1. We use two measures of discretionary accruals: DA_1 is the discretionary accruals from the augmented Jones (1991) model of Ball and Shiyakumar (2006) and DA_2 is performance-adjusted discretionary accruals using the model suggested by Kothari et al. (2005). The variable of interest is the industry cluster variable (CMV, DUM and ROF). As shown in Column 1 and Column 2 the coefficients of CMV and DUM are negative and significant at 0.01 level (-0.008 with t=-5.05 and -0.006 with t=-3.10), showing that firms in the industry cluster have lower overall audit quality. This is consistent with our hypothesis that due to the communication between companies in the geographic industry cluster, auditors are less likely to deter opportunistic earnings management or biased reporting and become easier to accept questionable industry practice endorsed by their clients. Since the coefficient of CMV (DUM) is -0.008(-0.006) and mean of absolute accruals (DA_1) is about -0.076, on average, the company in industry cluster has 10.5 (7.9) percent higher absolute discretionary accruals (lower audit quality) than the one outside industry cluster. Therefore, the economic significance of industry cluster on audit quality is not trivial. As expected, bigger firms with higher market valuation, higher cash flow, lower bankruptcy risk, no loss in the operation, smaller sale change and lower total accruals are associated with higher auditor quality. Big N auditors with lower local market competition, longer tenure are associated with higher audit quality. Though insignificant, the coefficient of client importance is negative and the coefficient of industry expertise is positive, which is consistent with prior literature (Column 1).

Since our geographic industry cluster classification may be subjective, we also use industry density (ROF) to capture industry concentration effect. The coefficient of ROF is also -0.01 and significant at 5% level (See Column 3). Additionally, using the alternative measure of auditor quality (DA_2), we obtain similar results. All coefficients of industry cluster (CMV, DUM, and ROF) are negative and significant (Column 4-6).

**Table 14. Geographic Industry Cluster and Audit Quality**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | DA_1 | DA_1 | DA_1 | DA_2 | DA_2 | DA_2 |
| CMV | -0.008*** | | | -0.006*** | | |
| | (-5.05) | | | (-3.91) | | |
| DUM | | -0.006*** | | | -0.006*** | |
| | | (-3.10) | | | (-2.69) | |
| ROF | | | -0.010** | | | -0.012** |
| | | | (-2.15) | | | (-2.19) |
| LNTA | 0.008*** | 0.007*** | 0.007*** | 0.009*** | 0.009*** | 0.009*** |
| | (19.59) | (19.23) | (19.13) | (20.53) | (20.19) | (20.11) |
| BIGN | 0.004** | 0.005*** | 0.004*** | 0.002 | 0.002 | 0.002 |
| | (2.48) | (2.73) | (2.61) | (0.92) | (1.11) | (1.01) |
| TENURE | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (3.57) | (3.53) | (3.64) | (2.95) | (2.90) | (2.99) |
| NAS | -0.003 | -0.003 | -0.003 | -0.000 | -0.000 | -0.000 |
| | (-1.41) | (-1.39) | (-1.36) | (-0.09) | (-0.08) | (-0.05) |
| CHGSALE | -0.020*** | -0.020*** | -0.020*** | -0.016*** | -0.016*** | -0.016*** |
| | (-13.70) | (-13.68) | (-13.70) | (-10.03) | (-10.01) | (-10.02) |
| BTM | 0.006*** | 0.006*** | 0.006*** | 0.008*** | 0.008*** | 0.008*** |
| | (6.28) | (6.31) | (6.31) | (8.32) | (8.35) | (8.34) |
| LOSS | -0.016*** | -0.016*** | -0.016*** | -0.012*** | -0.012*** | -0.012*** |
| | (-11.23) | (-11.22) | (-11.29) | (-7.42) | (-7.39) | (-7.44) |
| Z | -0.007*** | -0.007*** | -0.007*** | -0.004*** | -0.004*** | -0.004*** |
| | (-16.52) | (-16.47) | (-16.45) | (-9.61) | (-9.59) | (-9.56) |
| ISSUE | -0.000 | -0.000 | -0.001 | -0.006*** | -0.006*** | -0.006*** |
| | (-0.38) | (-0.33) | (-0.42) | (-4.42) | (-4.36) | (-4.44) |
| CFO | 0.030*** | 0.030*** | 0.030*** | 0.037*** | 0.037*** | 0.037*** |
| | (5.06) | (5.07) | (5.10) | (5.13) | (5.14) | (5.16) |
| LACCR | 1.847*** | 1.856*** | 1.858*** | 1.093*** | 1.101*** | 1.103*** |
| | (11.16) | (11.19) | (11.21) | (6.35) | (6.39) | (6.40) |
| INDSPEC | 0.000 | -0.000 | -0.000 | 0.000 | -0.000 | -0.000 |
| | (0.12) | (-0.11) | (-0.13) | (0.10) | (-0.05) | (-0.05) |
| CONCENT | 0.012** | 0.013*** | 0.013*** | 0.010 | 0.010 | 0.010 |
| | (2.57) | (2.72) | (2.70) | (1.56) | (1.64) | (1.62) |
| Industry & Year Fixed Effect | YES | YES | YES | YES | YES | YES |
| Obs | 42,066 | 42,066 | 42,066 | 42,066 | 42,066 | 42,066 |
| R Square | 0.2254 | 0.2249 | 0.2246 | 0.1530 | 0.1528 | 0.1526 |

This table reports the preliminary result for the regressions of the audit quality on geographic clusters, using absolute value of discretionary accruals multiplied by -1 as a proxy for audit quality. DA_1 represents the discretionary accruals generated from Ball and Shiyakumar (2006) model and DA_2 represents Kothari's (2005) performance matched discretionary accruals. All continuous variables are winsorzied at 1% level. ***, **,* represent significance at 0.01, 0.05 and 0.1 levels, respectively. Standard errors were clustered at firm level.

One possible explanation for the decrease in audit quality is that the local industry peers learn questionable accounting practice from each other and form alliances to convince auditors to accept their flexible adjustments to their accounting information. In this sense, this effect should be more pronounced for industry competitors audited by the same auditor. For instance, if one client successfully negotiates with its auditor about opportunistic earnings management, the information may be spread in the cluster and the local industry peers are likely to start to negotiate with the same auditor. As the result, the auditor has to compromise to retain clients and the overall audit quality in the cluster is lower. The more firms within the cluster share the same auditor, the more likely that the auditor quality is lower. To examine this hypothesis, we use the logarithm of number of local connection (LCONNECTION) to capture the possibility of learning between companies in geographic industry clusters and the existence of the auditors' compromises. The local connection is defined as the number of local industry competitors sharing the same auditor. Table 15 displays the empirical results. Both the coefficient of CMV*LCONNECTION and the coefficient DUM*LCONNECTION are negative and significant at 10% level and 1% level respectively (-0.002 with t=-1.65 and -0.005 with t=-2.79). This indicates that the stronger networks within the geographic industry clusters lead to lower auditor quality. We also use the cluster intensity, the crude measure of industry cluster and the alternative measure of discretionary accruals (DA_2) as robustness checks and our results still hold (See Column 3-6). Overall, our findings support that the connection through sharing the same auditor can act as a conduit of information for companies located in the geographic industry cluster. The firms are more likely to learn from each other, spread negotiation experience and persuade auditors to clam up about their earnings management, resulting in lower auditor quality.

**Table 15. Local Connection and Audit Quality**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | DA_1 | DA_1 | DA_1 | DA_2 | DA_2 | DA_2 |
| CMV*LCONNECTION | -0.002* | | | -0.003* | | |
| | (-1.65) | | | (-1.67) | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| DUM*LCONNECTION | | -0.005*** | | | -0.006*** | |
| | | (-2.79) | | | (-3.08) | |
| ROF*LCONNECTION | | | -0.007* | | | -0.010** |
| | | | (-1.67) | | | (-2.20) |
| CMV | -0.003 | | | -0.001 | | |
| | (-1.37) | | | (-0.36) | | |
| DUM | | 0.003 | | | 0.005 | |
| | | (1.01) | | | (1.38) | |
| ROF | | | 0.004 | | | 0.008 |
| | | | (0.80) | | | (1.52) |
| LCONNECTION | -0.00138 | -0.000768 | -0.00179 | -0.00168 | -0.000631 | -0.00135 |
| | (-1.43) | (-0.80) | (-1.54) | (-1.54) | (-0.59) | (-1.04) |
| LNTA | 0.008*** | 0.007*** | 0.007*** | 0.009*** | 0.009*** | 0.009*** |
| | (19.45) | (19.14) | (19.15) | (20.37) | (20.12) | (20.11) |
| BIGN | 0.005*** | 0.006*** | 0.006*** | 0.003 | 0.003 | 0.003 |
| | (3.03) | (3.35) | (3.39) | (1.37) | (1.58) | (1.60) |
| TENURE | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** | 0.003*** |
| | (3.36) | (3.41) | (3.46) | (3.06) | (3.09) | (3.14) |
| NAS | -0.002 | -0.002 | -0.002 | 0.001 | 0.001 | 0.001 |
| | (-0.95) | (-0.91) | (-0.91) | (0.31) | (0.34) | (0.34) |
| CHGSALE | -0.019*** | -0.019*** | -0.019*** | -0.016*** | -0.016*** | -0.016*** |
| | (-13.62) | (-13.58) | (-13.61) | (-9.85) | (-9.80) | (-9.85) |
| BTM | 0.006*** | 0.006*** | 0.006*** | 0.008*** | 0.008*** | 0.008*** |
| | (5.83) | (5.83) | (5.84) | (8.51) | (8.49) | (8.50) |
| LOSS | -0.015*** | -0.015*** | -0.015*** | -0.011*** | -0.011*** | -0.011*** |
| | (-10.43) | (-10.37) | (-10.45) | (-6.90) | (-6.85) | (-6.92) |
| Z | -0.007*** | -0.007*** | -0.007*** | -0.004*** | -0.004*** | -0.004*** |
| | (-16.54) | (-16.56) | (-16.51) | (-9.83) | (-9.89) | (-9.81) |
| ISSUE | -0.000 | -0.000 | -0.000 | -0.005*** | -0.005*** | -0.005*** |
| | (-0.10) | (-0.05) | (-0.11) | (-4.08) | (-4.04) | (-4.08) |
| CFO | 0.028*** | 0.028*** | 0.028*** | 0.035*** | 0.035*** | 0.035*** |
| | (4.70) | (4.70) | (4.72) | (4.81) | (4.81) | (4.83) |
| LACCR | 1.863*** | 1.872*** | 1.872*** | 1.105*** | 1.111*** | 1.108*** |
| | (10.94) | (10.99) | (10.96) | (6.45) | (6.48) | (6.46) |
| INDSPEC | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.69) | (0.42) | (0.59) | (0.86) | (0.64) | (0.77) |
| CONCENT | 0.014*** | 0.015*** | 0.014*** | 0.012** | 0.014** | 0.012** |

| | | | | | | |
|---|---|---|---|---|---|---|
| | (2.82) | (3.13) | (2.86) | (2.15) | (2.43) | (2.18) |
| Industry Fixed Effect(3 Digit SIC) | YES | YES | YES | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES | YES | YES | YES |
| Obs | 41,854 | 41,854 | 41,854 | 41,854 | 41,854 | 41,854 |
| R Square | 0.226 | 0.226 | 0.226 | 0.156 | 0.156 | 0.156 |

This table reports the empirical result for the regressions of the audit quality on the interaction of geographic clusters and the logarithm of the number of local industry competitors (local connection), using absolute value of discretionary accruals multiplied by -1 as a proxy for audit quality. DA_1 represents the discretionary accruals generated from Ball and Shiyakumar (2006) model and DA_2 represents Kothari's (2005) performance matched discretionary accruals. All continuous variables are winsorzied at 1% level. ***, **,* represent significance at 0.01, 0.05 and 0.1 levels, respectively. Standard errors were clustered at firm level.

**Geographic industry clusters and audit pricing**

Table 16 reports the result of the regression in Eq. (7), where we investigate the effect of geographic industry clusters on audit fees. All reported t-statistics are on an adjusted basis by including both industry (3-digits SIC) and year fixed effect and using standard errors corrected for clustering at the firm level and heteroscedasticity. As shown in the column 1, 2, and 3, the dependent variable is logarithm of audit fees and the variables of our interests are three different measures of geographic industry clusters CMV, DUM and ROF, respectively. The coefficients are all positive and significant at 1% level in two tailed tests. These results indicate that, on average, auditors are more likely to charge the clients within a geographic industry clusters higher audit fees than to the clients outside the clusters. The results support our expectations that auditors charge higher audit fees to the clients within the clusters, because within the clusters, auditors need to charge higher audit fee to compensate extra efforts on collecting and verifying evidence and ascending risk exposures. Specially, the clients can easier learn and copy questionable industry accounting practice from other local industry competitors, which makes auditors hard to collect reliable local industry information, leading to excessive audit efforts and higher litigation risk. To examine the economic significance of our results, we find that the estimated coefficients of the variables of our interests (CMV, DUM and ROF) are around 0.1, which indicates that for certain clients within a geographic industry cluster, auditors will charge on average 10% higher audit fees than clients outside the clusters.

**Table 16. Geographic Industry Cluster and Audit Fee**

| | (1) | (2) | (3) |
|---|---|---|---|
| | LAF | LAF | LAF |
| CMV | 0.105*** | | |
| | (7.11) | | |
| DUM | | 0.135*** | |
| | | (8.13) | |
| ROF | | | 0.434*** |
| | | | (8.79) |
| LNTA | 0.441*** | 0.442*** | 0.441*** |
| | (67.06) | (67.10) | (67.45) |
| EMPLOYEE | 0.051*** | 0.052*** | 0.053*** |
| | (8.15) | (8.24) | (8.34) |
| ARINV | 0.132*** | 0.142*** | 0.136*** |
| | (2.87) | (3.07) | (2.97) |
| CR | -0.033*** | -0.033*** | -0.033*** |
| | (-16.83) | (-16.82) | (-16.67) |
| CATA | 0.605*** | 0.595*** | 0.601*** |
| | (13.88) | (13.78) | (13.87) |
| ROA | -0.287*** | -0.289*** | -0.286*** |
| | (-12.09) | (-12.12) | (-12.07) |
| LEV | 0.132*** | 0.126*** | 0.131*** |
| | (4.60) | (4.41) | (4.56) |
| LOSS | 0.125*** | 0.122*** | 0.123*** |
| | (13.20) | (12.92) | (13.04) |
| FOREIGN | 0.204*** | 0.204*** | 0.204*** |
| | (16.24) | (16.22) | (16.22) |
| ISSUE | 0.0538*** | 0.0520*** | 0.0539*** |
| | (5.12) | (4.95) | (5.13) |
| BUSY | 0.125*** | 0.126*** | 0.124*** |
| | (8.72) | (8.77) | (8.67) |
| INTANG | 0.245*** | 0.249*** | 0.246*** |
| | (5.95) | (6.07) | (5.98) |
| SEG | 0.111*** | 0.111*** | 0.113*** |
| | (11.76) | (11.78) | (11.93) |

| | | | |
|---|---|---|---|
| OPINION | 0.073*** | 0.075*** | 0.077*** |
| | (3.61) | (3.73) | (3.83) |
| MERGE | 0.033*** | 0.032*** | 0.033*** |
| | (3.61) | (3.50) | (3.62) |
| BIGN | 0.418*** | 0.413*** | 0.415*** |
| | (25.75) | (25.53) | (25.77) |
| INDSPEC | 0.073*** | 0.074*** | 0.074*** |
| | (4.67) | (4.73) | (4.74) |
| CONCENT | -0.280*** | -0.282*** | -0.271*** |
| | (-4.60) | (-4.64) | (-4.44) |
| Industry Fixed Effect (3 Digit SIC) | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES |
| Obs | 40,101 | 40,101 | 40,101 |
| R Square | 0.853 | 0.853 | 0.853 |

This table reports the empirical result for the regressions of audit fees on the geographic clusters. All continuous variables are winsorzied at 1% level. ***, **,* represent significance at 0.01, 0.05 and 0.1 levels, respectively. Standard errors were clustered at firm level.

As we argued previously, the learning spillover effects among local industry competitors, especially those competitors sharing the same auditor, may impose a fear of losing clients and force auditors to sit on their hands. Auditors may ramp up their tolerance of questionable industry practice and charge a higher level audit fees as compensations for potential litigate risks. To further examine our expectation based on a positive effect of geographic industry clusters on audit pricing, we investigate whether the excessive raising audit fees can be explained by an existence of local industry connection through sharing the same auditor. Table 17 introduces a dummy variable CONNECTION_DUM, which indicates whether a client has a local industry competitor sharing the same auditor. The dependent variable is still logarithm of audit fees, and the variables of our interests are three interaction terms CMV*CONNECTION_DUM, DUM*CONNECTION_DUM and ROF*CONNECTION_DUM. The coefficients of CMV*CONNECTION_DUM and DUM*CONNECTION_DUM are positive and significant at 5% level, which indicates that auditors charge clients who are located in a geographic industry clusters and have local competitors sharing the same auditor higher audit fees (0.040+0.060*1=0.1; 0.05+0.086*1=0.136). In the column 3, the coefficient of ROF*CONNECTION_DUM is positive but not significant, which is not very surprising, since ROF is the most crude measure out of our three measures. These results support our expectation that, when there is a local "connection" within industry clusters, auditors may compromise their independence due to a fear of losing clients. To be specific, auditors tolerate possible misconduct of clients, sacrifice an acceptable level of audit quality and charge higher audit fees as compensations for potential litigation risks. These results also provide a reasonable explanation that why auditors provide a lower audit quality for clients from the geographic industry clusters but charge higher audit fees.

**Table 17. Local Connection and Audit Fees**

| | (1) | (2) | (3) |
|---|---|---|---|
| | LAF | LAF | LAF |
| CMV*CONNECTION_DUM | 0.060** | | |
| | (2.05) | | |
| DUM*CONNECTION_DUM | | 0.086** | |
| | | (2.44) | |
| ROF*CONNECTION_DUM | | | 0.047 |
| | | | (0.72) |
| CMV | 0.040 | | |
| | (1.50) | | |
| DUM | | 0.050 | |
| | | (1.45) | |
| ROF | | | 0.255*** |
| | | | (5.08) |
| CONNECTION_DUM | 0.070*** | 0.065*** | 0.074*** |
| | (5.54) | (5.09) | (4.89) |
| LNTA | 0.440*** | 0.440*** | 0.441*** |
| | (67.68) | (67.64) | (68.11) |

| | | | |
|---|---|---|---|
| EMPLOYEE | 0.053*** | 0.054*** | 0.054*** |
| | (8.49) | (8.60) | (8.61) |
| ARINV | 0.169*** | 0.186*** | 0.160*** |
| | (3.74) | (4.12) | (3.56) |
| CR | -0.032*** | -0.032*** | -0.033*** |
| | (-17.05) | (-17.06) | (-17.04) |
| CATA | 0.575*** | 0.558*** | 0.580*** |
| | (12.88) | (12.67) | (13.05) |
| ROA | -0.274*** | -0.275*** | -0.276*** |
| | (-11.55) | (-11.55) | (-11.64) |
| LEV | 0.136*** | 0.135*** | 0.133*** |
| | (4.68) | (4.64) | (4.59) |
| LOSS | 0.122*** | 0.119*** | 0.120*** |
| | (12.77) | (12.48) | (12.64) |
| FOREIGN | 0.200*** | 0.199*** | 0.200*** |
| | (15.84) | (15.73) | (15.87) |
| ISSUE | 0.049*** | 0.047*** | 0.050*** |
| | (4.78) | (4.55) | (4.82) |
| BUSY | 0.122*** | 0.123*** | 0.121*** |
| | (8.44) | (8.58) | (8.42) |
| INTANG | 0.219*** | 0.219*** | 0.217*** |
| | (5.29) | (5.30) | (5.26) |
| SEG | 0.114*** | 0.115*** | 0.114*** |
| | (12.10) | (12.14) | (12.12) |
| OPINION | 0.092*** | 0.095*** | 0.095*** |
| | (4.61) | (4.74) | (4.74) |
| MERGE | 0.034*** | 0.034*** | 0.034*** |
| | (3.75) | (3.68) | (3.68) |
| BIGN | 0.396*** | 0.392*** | 0.395*** |
| | (23.94) | (23.73) | (24.05) |
| INDSPEC | 0.056*** | 0.067*** | 0.057*** |
| | (3.54) | (3.82) | (3.56) |
| CONCENT | -0.265*** | -0.266*** | -0.255*** |
| | (-4.27) | (-4.30) | (-4.12) |
| Industry Fixed Effect(3 Digit SIC) | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES |
| Obs | 40,055 | 40,055 | 40,055 |
| R Square | 0.853 | 0.853 | 0.853 |

This table reports the empirical result for the regressions of audit fees on the geographic clusters. All continuous variables are winsorzied at 1% level. ***, **,* represent significance at 0.01, 0.05 and 0.1 levels, respectively. Standard errors were clustered at firm level.

The coefficients of the control variables are, overall, significant in line with the evidence reported in prior research. The coefficients of variables representing complexity, such as LNTA, EMPLOYEE and SEG, are highly significant, with a positive sign across all columns, suggesting that a large/complex client tends to consume more auditing resource than a small/simple one. The coefficients on the operation performance of certain clients, including ARINV, CR, CATA, ROA, LEV, INTANG and LOSS are consistent with prior studies, suggesting that better financial performances lower the audit fees being charged. The coefficients on special events, including FOREIGN, ISSUE, BUSY, MERGE and OPINION, are all positive and significant, implying that the enrollments in special events such as opening foreign branches, issuing new finance, taking merge or acquisitions and receiving qualified opinions increase the audit fees. Finally, the coefficient of the size, industry expertise and market concentration of auditors also significantly affect the value of audit fees.

## 3.6 Robustness Checks

### *3.6.1 Concerns on Geographic Proximity between Auditor and Client*

In a prior similar study, Choi et al. (2012) find that local auditors provide higher-quality audit services than non-local auditors by utilizing the geographic proximity between audit and client to identify a "local" auditor. In this chapter, we find that clients within geographic industry clusters have lower audit quality comparing to those outside the clusters. One possible explanation is that clients within the clusters may be not able to hire local auditors, who as predicted will provide higher audit quality. As a robustness check, to exclude the influence from geographic proximity between auditor and client, we re-estimate our main regression models in Eq. (5) and Eq. (7) by controlling for the benefits from local auditor. We include a dummy variable "LOC", which equal one if the auditor located in the same MSA with the client or the distance between auditor and client is less than 100 kilometers.

Table 18 Panel A shows that the negative association between geographic industry clusters and accrual-based proxies of audit quality is not effected by controlling the geographic proximity between auditor and client at all. A positive and significant coefficient of LOC is consistent with prior literature and indicates that local auditors indeed provide higher audit quality. Similarly, in Panel B, the association between geographic industry clusters and audit fees still holds after controlling the benefits from local auditors. In our sample, nearly 80% clients are audited by local auditors, which is also comparable to prior literature. These results support our expectation that our results are robust after controlling the geographic proximity between auditor and client. For Eq. (6) and Eq. (8), the results are not changed since there is no influence of adding additional control variable in our first stage result.

**Table 18. Robustness Checks – Geographic Proximity**

Panel A. Geographic Proximity between Auditor and Client and Audit Quality

| | DA_1 | DA_1 | DA_1 | DA_2 | DA_2 | DA_2 |
|---|---|---|---|---|---|---|
| CMV | -0.008*** | | | -0.007*** | | |
| | (-5.22) | | | (-3.99) | | |
| DUM | | -0.007*** | | | -0.006*** | |
| | | (-3.25) | | | (-2.76) | |
| ROF | | | -0.011** | | | -0.012** |
| | | | (-2.36) | | | (-2.28) |
| LOC | 0.003** | 0.003** | 0.003* | 0.002 | 0.002 | 0.002 |
| | (2.19) | (2.04) | (1.96) | (1.03) | (0.95) | (0.90) |

| | | | | | | |
|---|---|---|---|---|---|---|
| R Square | 0.226 | 0.225 | 0.225 | 0.153 | 0.153 | 0.153 |
| Obs | 42,066 | 42,066 | 42,066 | 42,066 | 42,066 | 42,066 |

Panel B. Geographic Proximity between Auditor and Client and Audit Pricing

| | LAF | LAF | LAF |
|---|---|---|---|
| CMV | 0.101*** | | |
| | (6.84) | | |
| DUM | | 0.130*** | |
| | | (7.85) | |
| ROF | | | 0.419*** |
| | | | (8.46) |
| LOC | 0.475 | 0.460 | 0.043 |
| | (3.13) | (3.06) | (2.86) |
| R Square | 0.853 | 0.853 | 0.853 |
| Obs | 40,101 | 40,101 | 40,101 |

This table reports the empirical result for the regressions of our base results after controlling the geographic proximity between auditor and client. All continuous variables are winsorzied at 1% level. ***, **,* represent significance at 0.01, 0.05 and 0.1 levels, respectively. Standard errors were clustered at firm level.

### *3.6.2 Restatements*

Along with abnormal accruals, restatements are commonly used as an alternative proxy for audit quality. To test the robustness of our results, we re-estimate our regression using restatements as the dependent variable. We obtain restatements from Audit Analytics from 2000 to 2015. As auditors may change their attitudes, strategies and behaviors after the restatement is made public, we only focus on the first time when the firm restated and exclude all firm-years after the first restatement. In this sense, we can identify 2,438 unique restatements. With available financial controls and audit characteristics, our final sample consists of 33,695 observations. All results are reported in Table 19. The dependent variable is RES, which is equal to 1 if the firm-year is during the restatement period, otherwise 0. All controls in Table 14 are included.

**Table 19. Robustness Checks - Restatement**

| | Res | Res | Res |
|---|---|---|---|
| CMV | 0.0674 | | |
| | (0.81) | | |
| DUM | | 0.206** | |
| | | (2.06) | |
| ROF | | | 0.630* |
| | | | (1.84) |
| LNTA | 0.0444** | 0.0432** | 0.0513** |
| | (2.07) | (2.03) | (2.46) |
| BIGN | 0.229** | 0.222** | 0.126 |
| | (2.40) | (2.32) | (1.39) |
| TENURE | 0.0317 | 0.0346 | -0.00559 |
| | (0.66) | (0.72) | (-0.13) |
| NAS | 0.280** | 0.286** | 0.0770 |
| | (2.38) | (2.44) | (0.86) |
| CHGSALE | 0.117*** | 0.114*** | 0.128*** |
| | (3.48) | (3.40) | (3.95) |
| BTM | 0.0306 | 0.0317 | 0.00219 |
| | (0.75) | (0.78) | (0.06) |
| LOSS | 0.142** | 0.137** | 0.145** |
| | (2.24) | (2.16) | (2.36) |
| Z | 0.0161 | 0.0165 | 0.0132 |
| | (1.04) | (1.07) | (0.88) |
| ISSUE | 0.147** | 0.142** | 0.117* |
| | (2.13) | (2.06) | (1.75) |
| CFO | 0.257 | 0.263 | 0.180 |
| | (1.51) | (1.54) | (1.06) |
| LACCR | 9.814** | 9.773** | 12.98*** |
| | (2.16) | (2.15) | (2.95) |
| INDSPEC | 0.112 | 0.114 | 0.0948 |
| | (1.34) | (1.36) | (1.09) |
| CONCENT | -0.820** | -0.823** | -0.629* |
| | (-2.24) | (-2.24) | (-1.76) |
| Industry Fixed Effect(3 Digit SIC) | YES | YES | YES |
| Year Fixed Effect | YES | YES | YES |
| Obs | 33,695 | 33,695 | 33,695 |
| R Square | 0.0838 | 0.0843 | 0.0839 |

This table reports the empirical result for the regressions of our base results using restatement as the alternative measure for audit quality. All continuous variables are winsorzied at 1% level. ***, **,* represent significance at 0.01, 0.05 and 0.1 levels, respectively. Standard errors were clustered at firm level.

The coefficients of DUM and ROF are positive and significant at 5% level and 10% level respectively (Column 2 and Column 3). It provides evidence that the firms in industry clusters are more likely to announce a restatement (lower audit quality) compared with those outside clusters. Surprisingly, the CMV has no significant effect on audit quality (Column 1). The possible reason is that due to the restriction on the total market share, CMV may capture the large firms, which are less likely to announcement a restatement. In this sense, DUM and ROF are more appealing because they measure the concentration of the number of firms, regardless of the firm size. In a word, the above findings are aligned with our base results.

## 3.7 Conclusion

In this chapter, we investigate the effect of the geographic industry clusters on audit quality. Though there's a growing literature that has examined the role of the local audit market and geographic proximity in audit quality, little attention has been paid to the issue in the context of geographic proximity of clients. Our results provide strong evidence that the geographic agglomeration of companies within the same industries has a negative impact on audit quality by facilitating accrual based earnings management and restatements. We also find the impact is pronounced for the clients with the stronger industry networks through sharing the same auditor. It suggests that due to the lower communication cost in the geographic industry clusters, clients are more likely to learn questionable accounting practices and form alliances to negotiate with auditors and convince them to tolerate questionable accounting practices. Lastly, we also find that auditors charge higher audit fees for clients located in the geographic industry clusters and such phenomenon is more pronounced for clients with the industry networks through sharing the same auditor.

Our research has several contributions. First, this study sheds some light on the importance of local communications among firms in the context of auditing. While the prior literature mainly focuses on the interactions between clients and auditors, we show the interaction between firms may also be vital to influence the auditor judgment and audit quality. It also helps the regulator identify the prospects for inspection more efficiently by considering the impact of industrial cluster and internalize the audit risks in the industrial cluster. Lastly, a better understanding of client-auditor relation in the industrial cluster can help the regulators to design and enforce a new regulation to enhance the auditor interdependence and mitigate the deterioration in auditor quality due to excessive collaborations.

# CHAPTER 4: AUDITOR REPUTATION AND THE DURATION OF CUSTOMER-SUPPLIER RELATIONSHIPS

## 4.1 Introduction

This chapter examines the effect of the reputation of suppliers' auditors on the duration of customer-supplier relationships by investigating three research questions. First, does a poor reputation for the supplier's auditor increase the likelihood of the customer terminating the supply chain relationship? Second, does the information sharing cost, specifically the geographic distance or the existence of a shared auditor between the two parties, have a mediating effect on the association between auditor reputation and the duration of supply chain relationships? Third, does a supplier's remediation by switching from a low reputation auditor to a high reputation auditor in the current year reduce the likelihood of customer-supplier relationship breakdowns in the following year?

The nature and economic consequences of supply chain relationships is a topic that attracts a lot of attention in academic research. In the realm of accounting, prior literature focuses on how the customer-supplier relationship, especially the dependency of customers (customer concentration), affects participants' operational and financial performance (Gavirneni, Kapusckinski, and Tayur 1999; Lee, So, and Tang 2000; Baiman and Rajan 2002; Hertzel et al. 2008; Fee and Thomas 2006; Johnstone, Li, and Luo 2014). Prior literature explains that information asymmetry is the source of supply chain risks (Akerlof 1970; Jensen and Meckling 1976), and demonstrates the increasing needs for reliable information between the two parties (Gulati 1995; Costello 2013; Cen 2017). Moreover, as concentrated supply chain ties grow (e.g. Choi and Krause 2006; Patatoukas 2011), the quality and reliability of information sharing between suppliers and customers becomes the key factor that drives the benefits of collaboration.

By reducing information asymmetry and ensuring the quality of information sharing in supply chains, we believe that auditors play important role in maintaining the customer-supplier relationships. As an important external monitoring mechanism, auditors provide reliable and independent assurance on clients' financial reporting and bridge the gap between suppliers and customers by providing audit opinions. Auditors also act as trusted watchdogs for suspicious financial frauds. Since the firm with the unveiling financial fraud may face major penalties from the stock and product markets, these effects increase the likelihood that suppliers' production will collapse, impairing the benefits to downstream customers. Thus, auditors can protect customers from the unexpected collapse of their upstream partner by detecting and revealing the misreporting. In addition, for customers who are connected with multiple suppliers from different regions, monitoring each supplier would be a heavy burden that exceeds the benefits it may bring. Therefore, the certified accounting information from trusted auditors would be an optimal information source to mitigate information asymmetry between suppliers and customers.

In response to calls for studies to investigate mechanisms that may mitigate information asymmetry and ensure the reliable exchange of information (Baiman and Rajan 2002), we extend the literature that examines the role of auditors in maintaining supply chain relationships, emphasizing the effect of publicly available information on the reputation of the supplier's auditor as an early warning mechanism that signals potential supply chain risks to customers. We explore "negative critical incidents" that push customers to terminate supply chain relationships and provide evidence on how such signaling affects the duration of customer-suppliers relationships.

The announcement of a client's restatement is a relatively common signal of an audit failure that may damage the auditor's reputation (Swanquist and Whited 2015), which may decrease the level of customers' perceived trust in the supplier's auditor if that auditor is responsible for a restatement. Based on prior literature that investigates the association between auditor reputation and the choice of an auditor (Francis et al. 2012, Swanquist and Whited 2015, Li et al. 2016), we believe that publicly available auditor reputation, measured by the number of announcements of restatements, can be a proper proxy for a customer's perceived level of trust in the auditor

To examine our research questions, we build our supply chain relationship data set from Compustat Segment file, based on the requirements of SAFS 131 (Fee, Hadlock and Thomas 2006; Raman and Shahrur 2008). We adapt Swanquist and Whited's (2015) method of generating auditor reputation at the office level and adjust the measure by considering firm size and market competition within the MSA[1]. The variable of interest, the auditor reputation, is a relative measure that captures an abnormal level of responsibility for clients' restatements in certain office compared to the average level of involvement in clients' restatements within the MSA. Thus, if an auditor's reputation is negative, it means that the auditor is less likely to be involved in clients' restatements, implying a good reputation. By contrast, if an auditor's reputation is positive, it means the

[1] In the United States, a metropolitan statistical area (MSA) is a geographical region with a relatively high population density at its core and close economic ties throughout the area, defined by US census bureau.

auditor is more likely to be associated with clients' restatements, representing a bad reputation. Additionally, to capture the real "customer termination" instead of "customer defection" (Hollmann et al. 2015), we define relationship termination as occurring when the name of major customers no longer exists in the supplier's disclosure for the next consecutive three years. The control variables are collected from Computstat and Audit Analytics since 2000. Thus, as we test the association between disclosed auditor reputation and supply chain relationship termination, our sample runs from 2000 to 2011 because we measure subsequent relationship termination in the third year. In sum, we include 4,232 observations in our empirical tests.

We design our base model by utilizing hazard models[2] including logistic regression, Cox model and the Weibull regression, where the dependent variable is an indicator for supply chain relationship termination. Across our model specifications, we include vectors of controls for suppliers' general financial performance, operating status, and factors that may affect supply chain relationships, such as suppliers/customers concentration, market share, and the length of relationships. Consistent with our expectation, we find a significantly positive association between poor reputation of the supplier's auditor and supply chain relationship termination ($p<0.01$) in all models, implying that poor reputation of supplier's auditor increases the risk of relationship termination.

[2] Proportional hazards models are a class of survival models in statistics. Survival models relate the time that passes before some event occurs to one or more covariates that may be associated with that quantity of time. In a proportional hazards model, the unique effect of a unit increase in a covariate is multiplicative with respect to the hazard rate. From the book written by John O' Quigley.

To extend our main results, we examine whether changes in information sharing between the two parties may enhance/mitigate the effectiveness of the reputation of the suppliers' auditor in signaling customers' termination decisions. Specifically, we focus on two information-sharing costs: geographic distance and the occurrence of the two parties sharing an auditor. Consistent with DeWitt et al. (2006), who find operation benefits within a geographically concentrated region, customers who choose a "flexible supply base" strategy[3] can easily obtain private local information from suppliers directly at low cost if the two parties are relatively nearby. The effect of a poor reputation for the supplier's auditor is mitigated, since the cost of tracking such information becomes smaller. Thus, we expect that increases in geographic distance between customers and suppliers will increase the importance of the reputation of the supplier's auditor on the decision to terminate the customer-supplier relationship. Research finds that shared auditors between customers and suppliers mitigates information asymmetry (Bugeja et al. 2011; Xie, Yi, and Zhang 2013; Francis, Pinnuck, and Watanabe 2013 (b); DeFranco, Kothari, and Verdi 2011). Based on this work, we expect that shared auditors between the two parties reduces the importance of the reputation of the supplier's auditor in signaling customers, since the shared auditor can provide a better interpretation of the seller's financial performance, internal controls and other related operational assessments. Our results are consistent with our conjecture that sharing auditors can help customers to interpret suppliers' financial information and evaluate supply chain risks, leading to less information asymmetry and mitigating the

[3] The concept can be found in the book "Supply Chain Risk Management Tools for Analysis" written by David L. Olson.

importance of the publicly available reputation of suppliers' auditors on supply chain management. In addition, we show a positive mediating effect of geographic distance between the two parties on our main results, implying that when customers and suppliers are located far away from each other, the additional cost of private local information increases the importance of publicly available auditor reputation in determining the future of the customer-supplier relationship.

Next, we consider how suppliers' remediation by dismissing low reputation auditors influences the duration of supply chain relationships. As argued by Hollmann et al. (2015), the decision to continue a relationship is influenced by the accumulation of both positive and negative signals. If the supplier's engagement with a low reputation auditor is a negative signal (e.g. such supplier may have problematic financial reporting) that may motivate customers to terminate the supply chain relationship, then the seller's remediation by switching to a high reputation auditor sends a positive signal (e.g. such supplier is actively willing to isolate from low quality financial reporting and provide more reliable financial information) to their customers. The combined effect of receiving both good and bad signals is ambiguous, which leaves open an empirical question of whether suppliers' remediation by switching from low reputation auditors to high reputation auditors in the current year reduce the likelihood of customer-supplier relationship breakdowns in the following year. We find a significant negative association between auditor dismissals and relationship termination, implying that suppliers' remediation in the current year gives customers a positive signal about suppliers' accounting information, which increases their level of confidence about future cooperation in the following year. Thus, the likelihood of terminating customer-supplier relationships will decrease. This result helps us to dispel concerns that customers may not observe or care about the reputations of the suppliers' auditors, and eliminates the weakness that could arise from omitted, unobservable, correlated characteristics related to supply chain management.

This study contributes to current research in two ways. First, it documents the importance of public information about the reputation of suppliers' auditors in signaling customers either to maintain or terminate supply chain relationships. We respond to calls for more research on the reliable exchange of information within supply chain relationships (Baiman and Rajan 2002) by considering the role of auditors in maintaining these relationships. Unlike studies that focus on audit quality and audit fees, our evidence suggests that customers can utilize publicly available information on auditor reputation as a signal to evaluate potential supply chain risks and prospects for future cooperation, especially when customers and suppliers are located far away from each other. Our results also provide evidence on the benefits of sharing common auditors in maintaining supply chain relationships. In addition, since the measure of auditor reputation used in this chapter is dynamic and easily available, it is also predictive because it can serve as an early warning about potential supply chain disruption. By contrast, in related studies on restatements (Bauer et al. 2017), the use of disclosure of internal control weakness as the signal is more defensive, leaving less time for customers to respond.

Second, our study provides insights for managers and practitioners. Given the significant role of auditors in maintaining stable supply chain relationships, managers should be aware that the choice of auditors affects their ability to stay connected with major customers. In our analysis, we find that suppliers with major customers tend to hire auditors with high reputations. Additionally, suppliers' remediation by switching auditors from low reputation to higher reputation sends positive signals to customers, and such timely remediation activities help to salvage key customers relationships.

This chapter proceeds as follows. In Section 4.2, we provide a literature review and hypothesis development. Research methodology including data, measures, and model specifications can be found in Section 4.3. The empirical results are presented in Section 4.4. We also conduct additional analyses in Section 4.5, and offer conclusions in Section 4.6.

### 4.2 Literature Review and Hypothesis Development

Broadly categorized, two main risks affect supply chain design and management (Chopra et al. 2004; Kleindorfer et al. 2005): 1) delay risks arising from the problem of coordinating the balance between supply and demand; and 2) disruption risks arising from events that interfere with normal activities (e.g. financial distress and natural disasters). Unfortunately, no single strategy can decrease both risks simultaneously; there is always a tradeoff between them. For example, customers can distribute their orders to multiple suppliers located in different regions to lower their disruption risk. However, that strategy increases the delay risk due to problems in forecasting for multiple suppliers. By contrast, if customers rely on only a few key suppliers, they benefit from lower delay risks, but face higher disruption risks. As Christopher and Lee (2014) argue, improved "end-to-end" visibility can mitigate supply chain risks, increase supply chain "confidence" between the two parties and improve the quality of supply chain information, regardless of strategies.

In the realm of accounting studies, such risks can be explained as the consequence of information asymmetry due to adverse selection (Akerlof 1970; Jensen and Meckling 1976; Costello 2013). Specifically, the supplier has an information advantage over its customer on product quality and quantity, but at the meanwhile concerns with product demand held by the customer (Costello 2013). This information asymmetry may lead to a hold-up problem (Christensen et al. 2016) that can increase customers' delay risks. Additionally, when each party's actions are not perfectly observable, the risk of opportunistic behavior increases (Holmstrom 1979). For example, suppliers' use of discretion in accounting information to induce investments in relationship-specific assets (Raman and Shahrur 2008) may increase future customers' disruption risks because of the increased uncertainty about suppliers' financial performance. Thus, major customers will demand truthful information sharing to alleviate information asymmetry (Cen et al. 2016), particularly in relationships in which repeated transactions are expected (Gulati 2015).

Supply chains have become more concentrated due to enhanced direct economic ties and mutual dependence (e.g. Choi and Krause 2006; Patatoukas 2012). A growing number of studies show that an integrated system of information sharing over supply chains allows both the supplier and the customer to reap net benefits from the relationship (Lanier, Wempe, and Zacharia 2010). For instance, Matsumura and Schloetzer (2016) find that suppliers with high customer sales concentration achieve higher accounting rates of return. However, the benefits of collaboration are contingent on the reliability of the information shared over supply chains. Baiman and Rajan (2002) argue that the supply chain relationship can be treated as the amount and type of information exchanged between suppliers and customers, which allows for greater production efficiency, but increases the potential for information appropriation (e.g. earnings manipulation, overproduction, and overinvestment). Therefore, the enhanced economic ties and mutual dependence in a modern independent supply chain lead to an increasing demand for trustworthy information, especially from the customer side, since customers are more likely to lack trust in their suppliers (Kumar 1996).

Auditors play an important role in reducing information asymmetry and ensuring that reliable information is shared between customers and suppliers. As a key external monitoring mechanism, auditors provide reliable and independent assurance on clients' financial positions and act as a trusted watchdog over suspicious financial dealings by issuing qualified opinions, going-concern opinions, and opinions on material internal control weaknesses. Prior studies provide evidence that suppliers' financial reporting quality decreases if the suppliers depend on major customers, since dependent suppliers have more incentives to manage earnings to influence major customers' perception (Raman and Shahrur 2008), to choose a risky tax planning strategy (Huang et al. 2016), and to avoid corporate tax (Cen et al. 2017). These increased business risks will affect the supplier's financing policy, production capability, product quality, and future operation planning. In addition, Dhaliwal et al. (2015) argue that dependent suppliers face the risk of losing a key customer, which creates higher cash flow risk. Customer dependency increases the supplier's business risk, so auditors are more likely to issue going-concern opinions for dependent suppliers and help customers to get rid of potential business disruptions (Krishnan et al. 2016). Moreover, Bauer et al. (2017) document that internal control quality will affect the supplier's ability to contract with key customers reliably. Thus, the auditor's assurance over financial reporting becomes a major information channel to help not only investors, but also supply chain participants to evaluate business risks and reconsider prospects for collaboration.

Auditors also act as trusted watchdog for potential financial frauds. Prior literature shows that the unveiling of financial fraud is a shock to a firm's operating performance, since the firm may face major penalties from both the stock and product markets, such as soaring borrowing costs, stock price slumps, and loss of intangible value. These performance shocks increase the likelihood that production could collapse, which would impair the benefits to downstream customers. Thus, auditors can protect customers from the unexpected collapse of their supplier by detecting the misreporting in the first place.

If customers deal with multiple suppliers from different regions to lower their delay risks, they have a heavy burden to track and monitor each supplier's behavior directly. Even if customers manage concentrated supply chain relationships and can monitor key suppliers, the suppliers may distort their accounting information due to the customers' inability to monitor them effectively (Holmstrom 1979). Therefore, certified accounting information from trusted auditors would be an optimal information source for major customers to make business decisions because it mitigates information asymmetry. The perceived trust in the supplier's auditor will be a direct, ex ante, and observable signal for the customer to identify potential supply chain risks.

The announcement of a client's restatement signals an audit failure that may damage the certifying auditor's reputation (Swanquist and Whited 2015). Consequently, the customer will have less trust in the supplier's auditor if that auditor is responsible for an announced restatement. Prior literature suggests that office-level characteristics contribute to audit quality (Choi, et al. 2010; Francis, Stokes, and Anderson 1999; Francis and Yu 2009; Francis, Michas, and Yu 2013), and a number of studies document the existence of contagion effects (e.g. the systematical audit deficiency in certain local office) from low quality audits (Francis et al. 2012; Swanquist and Whited 2015; Li et al. 2016). Therefore, observable auditor reputation, measured by announcements of restatements, can be a suitable proxy for customers' perceived level of trust in the auditor. When the supplier is audited by a low reputation auditor, the customer can easily observe the signal and re-evaluate the supply chain relationship. As suggested by Kinney (2000), customers and suppliers may view transaction conditions more favorably and prefer to sustain a longer relationship if they are assured of the quality of information that is shared between supply chain participants. Consistent with Costello's (2013) finding that information asymmetry between suppliers and customers leads to supply contracts with shorter durations, impairment of the customer's trust in the supplier's auditor may cause the customer to question the reliability of the supplier's information and possibly end the supply chain relationship. Additionally, Raman and Shahrur (2008) provide evidence that supply chain relationships have a shorter duration when either party engages in opportunistic earnings manipulation. In un-tabulated analysis, Bauer et al. (2017) provide strong evidence on the positive association between restatements and customer-supplier relationship termination, implying that customers strongly repel their suppliers with restatements. when they observe audit failures (restatements). Based on this argument, we conjecture that the reputation of the supplier's auditor is negatively associated with the termination of supply chain relationships, stated as follows:

**H1:** A poor reputation for the supplier's auditor increases the likelihood of termination of the customer-supplier relationship.

Extending for our main hypothesis, we also consider the potential mediating effect of information sharing on the association between the reputation of the supplier's auditor and the duration of the supply chain relationship. As discussed above, customers may choose a flexible supply base strategy to manage their supply chain risks by engaging with suppliers across multiple geographic regions (Tang et al. 2006). Consistent with prior literature (DeWitt et al. 2006) showing the positive impact of operating within an integrated supply chain in a geographically concentrated cluster, we believe that customers can easily trace suppliers' operating, financial, and local information within a geographically concentrated region through inexpensive and comprehensive monitoring. Therefore, the cost of tracking the public reputation of the supplier's auditor becomes larger, compared to the easily obtained private local information. By contrast, if customers are remote from their suppliers, the monitoring costs start to outweigh the benefits. To fill the gap arising from information asymmetry between the two parties in a supply chain, the public reputation of the supplier's auditor becomes an optimal signal for customers to evaluate risks and manage relationships. In sum, we expect that with greater geographic distance between customers and suppliers, the reputation of the supplier's auditor will become more important to the decision whether to terminate the customer-supplier relationship. We propose the following hypothesis:

**H2 (a):** The association between the reputation of the supplier's auditor and the likelihood of customer-supplier relationship termination will be stronger with increased geographic distance between suppliers and customers.

Prior literature shows that having shared auditors appears to enhance information flow between two parties and improve corporate outcomes (Bugeja et al. 2011; Xie, Yi and Zhang 2013; Francis, Pinnuck, and Watanabe 2014; DeFranco, Kothari, and Verdi 2011). For example, Cai et al. (2016) examine the impact of shared auditors on mergers and acquisitions. They show that having a common auditor helps to reduce information uncertainty during the acquisition process. In a more relevant study, Dhaliwal et al. (2017) show that having a common auditor reduces information asymmetry in supply chains and mitigates inefficiency of investments in relationship-specific assets. In addition, Cai et al. (2015) argue that client firms of a shared auditor can better understand the assumptions and accounting choices underlying the financial statements of other client firms of that auditor. We apply these arguments to our study and expect that having a common auditor will mitigate the importance of the reputation of the supplier's auditor in signaling customers to evaluate supply chain risks and terminate potentially dangerous relationships. We propose the following hypothesis:

**H2 (b):** The association between the reputation of the supplier's auditor and the likelihood of customer-supplier relationship termination will be mitigated when supplier and customer share a common auditor.

Next, we consider how suppliers' remediation by dismissing low reputation auditors influences the duration of supply chain relationships. As argued in Hollmann et al.

(2015), the decision to continue a relationship is influenced by the accumulation of both positive and negative signals. If the supplier's engagement with a low reputation auditor is a negative signal for the customer to terminate a supply chain relationship, then remediation by switching to a higher reputation auditor sends a positive signal for the customer to consider continuing the collaboration based on the future reliability of information about the supplier's financial performance. In a related study, Bauer et al. (2017) provide evidence that suppliers who make investments to address internal control issues can salvage relationships by providing positive signals to their customers.

However, it is difficult to identify the real effects of positive or negative signals on customers' termination decisions. Customers who are highly risk averse may end supply chain relationships immediately, leaving no time for suppliers to engage in remediation activities. Alternatively, customers may not believe that suppliers' remediation activities are sufficient to make up for the bad impressions created by suppliers' previous choice of low reputation auditors. In reality, customers may observe the auditor reputation of suppliers only at the season of preparing financial statements and future budgets. At that time, suppliers who are eager to disassociate with bad reputation auditors have successfully changed auditors to signal their confidence and reliability on financial reporting. Thus, customers may have higher probability to take such remediation activities positive. Therefore, we propose our last hypothesis as follows:

**H3:** The supplier's remediation by replacing a low reputation auditor with a higher reputation auditor will reduce the likelihood of customer-supplier relationship termination

## 4.3 Research Design

### *4.3.1 Sample*

To test our hypotheses, we use all U.S. public firms with the necessary data to identify major customer-supplier relationships. Our sample starts from 2000 (the beginning of Audit Analytics) to 2014[4]. We use disclosed announcements of restatements as the best publicly available proxy for our measure of auditor reputation. Major customers could have access to private information regarding their suppliers' operating and financial status, and such private information biases away from finding a negative relationship between auditor reputation and supply chain relationship termination. However, as discussed previously, using the reputation of the suppliers' auditor benefits the customer because it serves as an early warning mechanism. The average time to discover and confirm a restatement is around two years (Palmrose et al. 2004; Gleason et al. 2008), which may be too late for customers to reconsider the supply chain risks.

Following Bauer et al. (2017), we identify customers within supply chains by matching customer names to firm names in Compustat. SFAF 131 requires that firms identify each customer that represents more than 10 percent of sales. SEC regulations also require firms to disclose the identities of such customers. First, we match disclosed customer names to Compustat identifiers by parsing the disclosed customer names. Then, we then investigate the remaining unmatched customer names by manually searching for a customer name match among all U.S firms within Capital IQ. We match suppliers to

[4] We measure relationship termination in year t+3, so our testing period ends in 2011.

restatement and dismiss data from Audit Analytics and obtain control variables from Compustat. All variables are defined in Appedix B.

### *4.3.2 Measures of Auditor Reputation*

We adapt the method used by Swanquist and Whited (2015) to generate auditor reputation at the office level. We use the number of restatements announced by clients in an office[5] during a calendar year as the proxy for audit failure that impairs auditor reputation. We identify restatements[6] related to misapplications of accounting principles and fraud as defined by Audit Analytics, since these irregularities are more associated with significant negative effects (Hennes, Leone, and Miller 2008). We also require restatements to be related to audited annual financial statements and exclude restatements of unaudited quarterly or interim financial statements. Each restatement announcement is linked to the last certifying audit office associated with the restated financials, whether or not that auditor is still the current auditor for that client since the restatement announcement date. The calculation for restatement "contamination" (e.g. the systematical auditing deficiency in certain local office) is performed as follows for each office-year:

$$\mathrm{CONTAMINATION}_{j,t} = (\sum_{k=1}^{N} RESTATE_{k,t})$$

[5] Audit offices are defined by the combination of each auditor's company name and the metropolitan statistical area (MSA), which is defined using the taxonomy from the U.S. Census Bureau's website. Refer to https://www.census.gov/population/metro/data/def.html for classifications. We eliminate MSAs where clients have only one auditor choice to avoid the effect from monopoly audit service.

[6] We also tried changing the sample of announcements of restatements according to Irani et al. (2015). We include all restatements resulting from misapplication of GAAP and reported in form 8-K item 4.02 disclosures from 2004 to 2014, but exclude restatements disclosed in venues such as 10-K or 10-Q if the disclosure date for the applicable venue precedes the Form 8-K Item 4.02 filing date. Our results still hold qualitatively.

Where:

j = office identifier

k= identifier for clients for office j

t = time period (calendar year);

$RESTATE_{k,t}$ = binary variable equal to k if client k announced a restatement during calendar year t, and 0 otherwise; and

N = number of clients audited by office j.

Since contamination is likely to be evaluated relative to local characteristics, we scale our reputation measure by office size and subtract the average level of contaminations in local MSA market competitions. Specifically, large auditor offices may be involved with more restatements because they engage with more clients. In addition, reputation may vary across different local auditing markets. Within a highly competitive MSA, the likelihood of being responsible for restatements may be affected by market competition or heavy workloads. Therefore, we subtract the restatement percentage across MSAs from the office-level restatement percentage as follows:

$$\mathrm{REPUTATION}_{j,t} = \frac{1}{N}\,CONTAMINATION_{j,t} - \frac{1}{M}\,CONTAMINATION_{q,t}$$

Where:

j = office identifier

q = MSA identifier for office j

t = time period (calendar year);

$\mathrm{CONTAMINATION}_{j,t}$ = restatement announcements for clients of office j

$CONTAMINATION_{q,t}$ = restatement announcements for clients in MSA q not audited by office j.

Thus, the variable $\mathrm{REPUTATION}_{j,t}$ captures the abnormal level of an office's audit reputation relative to the local level of audit reputations. For example, Office A in MSA 1 has ten clients, and two out of ten clients announce restatements in the year t (20% contamination). MSA 1 has 40 clients not audited by Office A during year t, and four of these clients announce restatements (10% contamination). Therefore, according to our measurement, the reputation for Office A will be 20% - 10% = 10%, indicating that Office A is relatively more contaminated than the average of its competitors in MSA 1.

### *4.3.3 Model Specifications*

**Main tests**

To examine the usefulness of the reputation of the supplier's auditor in signaling a customer's supply chain management reaction, we employ a hazard design that models the probability of a relationship ending. Consistent with prior literature (Raman and Sharur 2008; Bauer et al. 2017), we regard a relationship that falls below the ten percent sales threshold prescribed by SFAS 131 as the cessation of the supply chain relationship. However, to capture the real "customer termination" instead of "customer defection" (Hollmann et al. 2015), we extent the rule by confirming the end of supply chain relationships if the name of that major customer is no longer listed in the supplier's disclosure for the next consecutive three years (t+3). Using logistic regression (Logit), as well as Cox proportional hazard model (Cox) and the accelerated failure time model assuming a Weibull distribution (Weibull), we estimate the signaling effect of the reputation of the supplier's auditor (our proxy for the customer's perceived trust in the supplier's auditor) on the probability of termination of a particular supply chain relationship. The Logit model is shown below. The only difference from the Cox and Weibull models is the omission of length of relationship (tenure) because the Cox and Weibull hazard analyses use the length of relationship to generate the "dead/failure" event.

$$\mathrm{TER}_{3\mathrm{YRS}_{\mathrm{i,t+1}}} = \beta_0 + \beta_1 REP_{i,t} + \mu(Relationship\ Controls)_{i,t} + \rho(Supplier\ controls)_{i,t} + \sigma(Customer\ Controls)_{i,t} + \sum industry_i + \sum year_{\ i} + \varepsilon_{i,t}$$

The dependent variable is an indicator that equals one if the customer-supplier relationship is terminated, based on that customer not being listed as a major customer in the supplier's disclosures in the following three years, and zero otherwise. For the Cox and Weibull models, we have censored data, where $\mathrm{TER}_{3\mathrm{YRS}_{\mathrm{i,t+1}}}$ is equal to one for an observation with failure and is equal to zero for all firm-years for a survival observation. We measure the time to failure from the year when each supply chain relationship is first identified in our dataset. We use three approaches (the base Logit model and the Cox and Weilbull models) to triangulate our results and to ensure that our results are robust to varying baseline hazard distributions.

The variable of interest is $REP_{i,t}$, which is a measure indicating an office-level auditor reputation relative to the average level of contamination within the same MSA. We expect the auditor reputation from the supplier side is negatively associated with the probability of relationship breakdown, implying that a poor reputation for the supplier's auditor can signal customers to terminate current supply chain relationships due to their decreased perceived trust in supplier's auditor.

In this model, we include three vectors of variables to control factors that may affect the relationship duration. To control for the relationships, we include customer concentration (measured as sales to the major customer divided by total supplier sales), supplier concentration (measured as supplier sales to the customer divided by that customer's cost of goods sold[7]), length of the supply chain relationship, and market share (measured as a percentage of all sales within firm's 4-digit SIC) in the vector of "Relationship Controls". Based on prior literature (Fee et al. 2006; Raman and Sharhrur 2008), we also control for supplier (customer) firm size, firm age, research and development expenditures, and negative free cash flow. In the vector of "Supplier Controls", we include variables related to suppliers' operations to control for underlying supplier problems that may increase supply chain risks and lead to supply chain breakdowns. These include inventory turnover, inventory holding period, fixed asset turnover, days in accounts receivable, accounts payable, and inventory, capital expenditure intensity, profit, and gross margins (Patatoukas 2012; Feng et al. 2015; Matsumura and Schloetzer 2016).

[7] Since the distribution of the supplier (customer) concentration is heavily skewed, we use the rank based on decile as the independent variables in our regression analysis.

Finally, we include industry and year fixed effect in all duration models, and cluster standard errors by supplier throughout the analysis. The variable definition can be found in the Appendix.

**Intermediation effects tests**

To investigate the mediating effects of information sharing on the association between auditor reputation and supply chain termination, we modify our main model by adding interaction terms between intermediating variables and the main variable. As discussed in section 2, we focus on two mediating variables: the geographic distance between the two parties and a dummy variable indicating whether suppliers and customers sharing common auditors.

To obtain the geographic distance between suppliers and customers, we first identify the city, state and country information for suppliers and customers, use Google Map to locate the addresses of their headquarters, and record the values of latitude and longitude. Based on the coordinate parameters, we calculate the geographic distance between the two parties and add an interaction term between distance and reputation into the regression. We also artificially classify the distance into two groups by generating a dummy variable FAR[8] that is equal to one if the distance between supplier and customer is larger than 100 miles. We estimate the following regression model to test H2 (a):

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[8] The introduction of the variable "FAR" investigates the sensitivity of the mediating effect of geographic distance on the association between auditor reputation and supply chain termination.

$$\mathrm{TER}_{\mathrm{3YRS}_{\mathrm{i,t+1}}} = \beta_0 + \beta_1 REP_{i,t} + \beta_2\, DISTANCE_{i,t}\,\left(FAR_{i,t}\right) + \beta_3 DISTANCE_{i,t}\,\left(FAR_{i,t}\right) * REP_{i,t} + \mu(Relationship\ Controls)_{i,t} + \rho(Supplier\ controls)_{i,t} + \sigma(Customer\ Controls)_{i,t} + \sum industry_i + \sum year_{\ i} + \varepsilon_{i,t}$$

The primary variable of interest is the interaction term: $DISTANCE_{i,t}\,\left(FAR_{i,t}\right) * REP_{i,t}$ and we expect a significant positive coefficient, implying that the greater the distance between two participants, the higher the likelihood of customer termination based on the observed low reputation of the supplier's auditor. To be consistent, we continue to use the control variables from our main model.

We also consider the mitigating influence of sharing common auditors, since common auditors can reduce the severity of information asymmetry in supply chains (Cai et al. 2016). We introduce the dummy variable SHARING, which is equal to one if customers and suppliers sharing the same auditor,[9] into our model and focus on the coefficient of interaction term between SHARING and our main variable. We expect a significant negative coefficient on the interaction term, since we believe that sharing auditors can mitigate the importance of customers' reliance on the reputations of their suppliers' auditors. We estimate the following regression model to test H2 (b):

[9] In this chapter, the sharing of an auditor means using the same auditor at the office level, not the national level.

$$\mathrm{TER}_{3\mathrm{YRS}_{\mathrm{i,t+1}}} = \beta_0 + \beta_1 REP_{i,t} + \beta_2\, SHARING_{i,t} + \beta_3 SHARING_{i,t} * REP_{i,t} + \mu(Relationship\ Controls)_{i,t} + \rho(Supplier\ controls)_{i,t} + \sigma(Customer\ Controls)_{i,t} + \sum industry_i + \sum year_{\ i} + \varepsilon_{i,t}$$

**Remediation tests**

To investigate the association between auditor reputation and supply chain termination after suppliers' remediation by replacing their low reputation auditors, we modify our main model by adding the variable DISMISS, consistent with the remediation model in Ashbaugh-Skaife et al. (2008). DISMISS is equal to one if the supplier dismisses its current low reputation auditor and switches to a high reputation auditor in the current year t. Low reputation auditors are defined as those auditors whose reputation (REP) are at the bottom twenty percent in the current year t. In our setting, only those dismissals that involve suppliers switching from low reputation to higher reputation auditors are counted as remediation behaviors. DISMISS represents an interaction term that captures the incremental remediation effect of switching from low reputation to high reputation auditors on the probability of customer termination.

$$\mathrm{TER}_{3\mathrm{YRS}_{\mathrm{i,t+1}}} = \beta_0 + \beta_1 REP_{i,t} + \beta_2\, DISMISS_{i,t} + \mu(Relationship\ Controls)_{i,t} + \rho(Supplier\ controls)_{i,t} + \sigma(Customer\ Controls)_{i,t} + \sum industry_i + \sum year_{\ i} + \varepsilon_{i,t}$$

## 4.4 Results

### *4.4.1 Descriptive Statistics*

Table 20 provides descriptive statistics for the variables used in the Logit and hazard models that predict the probability of relationship termination. We observe that twenty percent of supply chain relationships end within the next three years. With respect to our primary variable "REP", the average auditor reputation is around zero (-0.01), indicating that the average office-level auditor reputation is comparable to the MSA-level auditor reputation. For control variables, the major customers are larger than their suppliers with an average 4.23 size gap (10.11-5.88=4.23). The supply chain relationships last approximately 3.34 years from 1 year to 30 years. To adjust for the serious skewness of customer and supplier dependency, we utilize their rank based on deciles instead of the original level of the value.

**Table 20. Descriptive Statistics**

| | N | Mean | S.D | Min | 0.25 | Mdn | 0.75 | Max |
|---|---|---|---|---|---|---|---|---|
| TER_3YRS | 4232 | 0.20 | 0.40 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |
| REP | 4232 | -0.01 | 0.10 | -1.00 | -0.04 | -0.01 | 0.01 | 0.64 |
| SUP_SIZE | 4232 | 5.88 | 1.98 | -0.63 | 4.51 | 5.79 | 7.21 | 12.60 |
| SUP_AGE | 4232 | 2.70 | 0.80 | 0.00 | 2.20 | 2.71 | 3.30 | 4.13 |
| R&D | 4232 | 0.07 | 0.12 | 0.00 | 0.00 | 0.02 | 0.10 | 0.74 |
| NEGFCF | 4232 | 0.38 | 0.49 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| INV_TO | 4232 | 14.71 | 36.78 | 0.80 | 3.22 | 5.13 | 10.29 | 292.07 |
| IHLD | 4232 | 0.13 | 0.11 | 0.00 | 0.00 | 0.10 | 0.19 | 0.46 |
| PPE_TO | 4232 | 15.93 | 29.30 | 0.16 | 3.21 | 6.39 | 14.16 | 211.83 |
| DAYS_AR | 4232 | 57.00 | 31.29 | 1.28 | 37.87 | 52.89 | 68.37 | 270.49 |
| DAYS_AP | 4232 | 63.99 | 77.98 | 3.29 | 30.90 | 45.98 | 67.61 | 783.03 |
| DAYS_INV | 4232 | 88.75 | 77.12 | 0.00 | 36.14 | 72.46 | 116.58 | 446.94 |
| CAPEX | 4232 | 0.04 | 0.06 | 0.00 | 0.01 | 0.03 | 0.05 | 0.38 |
| PM | 4232 | -0.19 | 1.06 | -10.51 | -0.07 | 0.03 | 0.08 | 0.53 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| GM | 4232 | 0.36 | 0.45 | -5.66 | 0.23 | 0.37 | 0.56 | 0.95 |
| MKTSHARE | 4232 | 0.07 | 0.18 | 0.00 | 0.00 | 0.01 | 0.04 | 1.00 |
| CUS_DEP | 4232 | 5.38 | 2.84 | 1.00 | 3.00 | 5.00 | 8.00 | 10.00 |
| SUP_DEP | 4232 | 5.53 | 2.85 | 1.00 | 3.00 | 5.00 | 8.00 | 10.00 |
| TENURE | 4232 | 3.34 | 4.16 | 0.00 | 0.00 | 2.00 | 5.00 | 29.00 |
| CUS_SIZE | 4232 | 10.11 | 1.73 | 2.48 | 8.97 | 10.19 | 11.48 | 14.63 |

The definition of variables can be found in the Appendix B.

### *4.4.2 Multivariate Results*

**Hypothesis1**

Table 21 reports the results of the base Logit model (Column 1), the Cox model (Column 2), and the Weibull model (Column 3). Consistent with our expectation in Hypothesis 1, all models show a significantly positive association between the reputation of the supplier's auditor and supply chain relationship termination ($p<0.01$), which implies that a poor reputation for the supplier's auditor increases the risk of relationship termination. In column 2 and column 3, the positive hazard ratios indicate the same result as the Logit model.

Consistent with Bauer et al. (2017), we also find that customer dependency is negatively associated with relationship termination, which implies that relationships that are more important to suppliers are less likely to be terminated since suppliers may put more efforts into maintaining those relationships with their customers. By contrast, supplier dependency is positively associated with relationship termination, which implies that when suppliers are important to customers, the customers may become more concerned about their business risks and are easy to end up with suppliers due to increased supply chain risk. Furthermore, size, age, market power (measured by market shares), and relationship length are negatively associated with the likelihood of termination. Among other suppliers' operating controls, days in inventory and negative cash flows are positively associated with the probability of termination, but days in inventory is negatively related to the probability of termination. Overall, the results in Table 21 support our expectation that customers may utilize the early warning from auditor reputation as a signal to make decision about their future cooperation with their suppliers.

**Table 21. The Association between Auditor Reputation and Supply Chain Relationship**

| | (1) | (2) | (3) |
|---|---|---|---|
| | LOGIT | COX | WEIBULL |
| REP | 1.308*** | 1.234*** | 1.109*** |
| | (-2.77) | (-2.60) | (-2.36) |
| TENURE | -0.041*** | | |
| | (-2.79) | | |
| SUP_SIZE | -0.420*** | -0.357*** | -0.384*** |
| | (-9.10) | (-8.30) | (-7.70) |
| SUP_AGE | -0.122** | -0.119* | -0.288*** |
| | (-2.04) | (-1.88) | (-3.75) |
| R&D | -0.030 | -0.240 | -0.410 |
| | (-0.06) | (-0.56) | (-0.81) |
| NEGFCF | 0.214** | 0.178* | 0.251*** |
| | (-2.19) | (-1.91) | (-2.58) |
| INV_TO | 0.000 | 0.000 | 0.000 |
| | (-0.02) | (-1.07) | (-1.00) |
| IHLD | -1.682*** | -1.851*** | -2.109*** |
| | (-2.99) | (-3.48) | (-3.53) |
| PPE_TO | 0.003* | 0.000 | 0.000 |
| | (-1.90) | (-0.77) | (-0.84) |
| DAYS_AR | 0.000 | 0.000 | 0.000 |
| | (-1.08) | (-0.55) | (-0.18) |
| DAYS_AP | 0.001** | 0.001* | 0.000 |
| | (-2.28) | (-1.75) | (-1.50) |
| DAYS_INV | 0.002*** | 0.002*** | 0.002*** |
| | (-3.30) | (-3.46) | (-3.16) |
| CAPEX | 0.620 | -0.160 | -0.240 |
| | (-0.62) | (-0.15) | (-0.21) |

| | | | |
|---|---|---|---|
| PM | -0.060 | -0.080 | -0.107** |
| | (-1.12) | (-1.61) | (-2.05) |
| GM | -0.323*** | -0.267*** | -0.233*** |
| | (-2.57) | (-3.12) | (-2.44) |
| MKTSHARE | 0.795*** | 0.930*** | 0.868** |
| | (-2.45) | (-3.02) | -2.09 |
| CUS_DEP | -0.286*** | -0.232*** | -0.250*** |
| | (-15.39) | (-14.09) | (-14.03) |
| SUP_DEP | 0.166*** | 0.177*** | 0.196*** |
| | (-5.74) | (-6.23) | (-6.03) |
| CUS_SIZE | 0.077* | 0.123*** | 0.129*** |
| | (-1.95) | (-3.14) | (-2.87) |
| _CONS | 0.660 | | -1.579* |
| | (-0.72) | | (-1.76) |
| Year Fixed Effect | YES | YES | YES |
| Industry Fixed Effect | YES | YES | YES |
| Clustered by supplier | YES | YES | YES |
| R^2 | 0.16 | | |
| Chi^2 | | 1346.65 | |
| Ln_p | | | 0.314*** |
| | | | -10.64 |
| N | 4232 | 4232 | 4232 |

Z statistics in parenthesis. Significant two-tailed p-values denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

**Hypothesis 2**

We next examine whether the geographic distance between suppliers and customers and the sharing of common auditors between the two parties have mediating effects on the main results. The results for Model 2 are tabulated in Table 22. Column 1 shows a significant negative coefficient ($p<0.01$) of the interaction term, which implies that the sharing of common auditors between suppliers and customers has a negative moderating effect on the association between the auditor's reputation and supply chain relationship termination. This result is consistent with our expectation that sharing common auditors can help customers better interpret suppliers' financial position, acknowledge operating conditions, and evaluate supply chain risks, which leads to less information asymmetry between the two parties and mitigates the importance of the publicly available reputation of the supplier's auditor on supply chain management. Furthermore, Column 2 shows that the geographic distance between suppliers and customers has a positive mediating effect ($p<0.05$) on the main results. The positive coefficient implies that when customers and suppliers are located far away from each other, the increased cost of private local information makes the publicly available reputation of the auditor more important in determining future customer-supplier relationships. Consistent with this result, after the geographic distance is split into far and near groups[10], we get a similar but much stronger positive result ($p<0.01$) in Column 3, which provides additional evidence on the mitigating effects of geographic distance on the primary results.

**Table 22. The Impact of Information Sharing on the Association between Auditor Reputation and Supply Chain Relationship**

| | (1) | (2) | (2) |
|---|---|---|---|
| | TER_3YRS | TER_3YRS | TER_3YRS |
| INTER | -3.543*** | 0.072** | 2.617*** |
| | (-2.47) | (-2.26) | (-2.42) |
| REP | 1.427*** | 0.010 | 0.560 |
| | (-2.97) | (-0.01) | (-1.04) |
| SHARING | -0.190 | | |
| | (-0.80) | | |
| DISTANCE | | 0.000 | |
| | | (-1.52) | |

[10] The two groups were distinguished by a dummy variable "FAR", which is equal to one if the geographic distance falls in the top quartile of all supplier-customer distances, and zero otherwise.

| | | | |
|---|---|---|---|
| FAR | | | 0.170* |
| | | | (-1.67) |
| SUP_SIZE | -0.423*** | -0.426*** | -0.426*** |
| | (-9.16) | (-9.17) | (-9.18) |
| SUP_AGE | -0.130** | -0.129** | -0.128** |
| | (-2.16) | (-2.14) | (-2.13) |
| R&D | -0.010 | -0.070 | -0.060 |
| | (-0.03) | (-0.15) | (-0.13) |
| NEGFCF | 0.215** | 0.218** | 0.217** |
| | (-2.20) | (-2.22) | (-2.22) |
| INV_TO | 0.000 | 0.000 | 0.000 |
| | (-0.03) | (-0.01) | (-0.04) |
| IHLD | -1.703*** | -1.738*** | -1.739*** |
| | (-3.02) | (-3.07) | (-3.07) |
| PPE_TO | 0.003* | 0.003* | 0.003* |
| | (-1.90) | (-1.90) | (-1.88) |
| DAYS_AR | 0.000 | 0.000 | 0.000 |
| | (-1.05) | (-1.04) | (-1.02) |
| DAYS_AP | 0.001** | 0.001*** | 0.001** |
| | (-2.22) | (-2.37) | (-2.32) |
| DAYS_INV | 0.003*** | 0.003*** | 0.003*** |
| | (-3.32) | (-3.36) | (-3.37) |
| CAPEX | 0.590 | 0.640 | 0.610 |
| | (-0.60) | (-0.65) | (-0.62) |
| PM | -0.060 | -0.060 | -0.060 |
| | (-1.12) | (-1.07) | (-1.09) |
| GM | -0.323*** | -0.326*** | -0.322*** |
| | (-2.57) | (-2.62) | (-2.59) |
| MKTSHARE | 0.791*** | 0.815*** | 0.823*** |
| | (-2.43) | (-2.51) | (-2.54) |
| CUS_DEP | -0.286*** | -0.286*** | -0.286*** |
| | (-15.38) | (-15.42) | (-15.39) |
| SUP_DEP | 0.168*** | 0.170*** | 0.169*** |
| | (-5.82) | (-5.86) | (-5.83) |
| TENURE | -0.041*** | -0.040*** | -0.040*** |
| | (-2.77) | (-2.67) | (-2.71) |
| CUS_SIZE | 0.079** | 0.082** | 0.083** |
| | (-2.02) | (-2.08) | (-2.10) |
| _CONS | 0.680 | 0.530 | 0.590 |
| | (-0.75) | (-0.58) | (-0.64) |

| | | | |
|---|---|---|---|
| Year Fixed Effect | YES | YES | YES |
| Industry Fixed Effect | YES | YES | YES |
| Clustered by supplier | YES | YES | YES |
| R^2 | 0.16 | 0.16 | 0.16 |
| N | 4232 | 4232 | 4232 |

Z statistics in parenthesis. Significant two-tailed p-values denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

**Hypothesis 3**

Table 23 presents the results for our last hypothesis and provides evidence that suppliers' remediation by switching from low reputation auditors to higher reputation auditors influences the duration of supply chain relationships. Table 4 shows a significant negative association between auditor dismissals and relationship termination. This result implies that when suppliers switch to auditors with higher reputations in the current year t, customers will receive a positive signal about suppliers' accounting information that increases their level of confidence about future cooperation in the following year t+1. Therefore, the likelihood of terminating customer-supplier relationships decreases correspondingly.

Furthermore, this analysis helps to dispel concerns that customers may not observe or care about the reputation of suppliers' auditors, since the evidence shows that customers not only utilize the reputation of their suppliers' auditors as early signals of future disruption risks, but also consider suppliers' remediation positively when suppliers switch from low reputation to high reputation auditors. Additionally, these results help to eliminate the possibility of missing unobservable correlated characteristics in supply chain management. If unobservable issues that lead to relationship termination (e.g.: customer service problems or inefficient logistics) exist and are not mitigated by our vectors of controls, then we should have found no effects from remediation on the likelihood of termination.

**Table 23. The Impact of Auditor Dismissal on the Association between Auditor Reputation and Supply Chain Relationship**

| | (1) | (2) |
|---|---|---|
| | TER_3YRS | TER_3YRS |
| DISMISS | -0.647* | -0.788** |
| | (-1.75) | (-2.18) |
| REP | 1.070*** | 1.198*** |
| | (2.58) | (3.01) |
| SUP_SIZE | -0.199*** | -0.143*** |
| | (-7.00) | (-5.48) |
| SUP_AGE | -0.058 | -0.025 |
| | (-1.13) | (-0.49) |
| R&D | -0.038 | -0.032 |
| | (-0.10) | (-0.08) |
| NEGFCF | 0.215*** | 0.222*** |
| | (2.63) | (2.75) |
| INV_TO | 0.001 | 0.001 |
| | (0.51) | (0.53) |
| IHLD | -0.903* | -0.590 |
| | (-1.94) | (-1.32) |
| PPE_TO | -0.001 | -0.001 |
| | (-0.35) | (-0.71) |
| DAYS_AR | 0.001 | 0.0011 |
| | (0.54) | (0.95) |
| DAYS_AP | 0.002*** | 0.001** |
| | (3.05) | (2.39) |
| DAYS_INV | 0.001 | 0.000 |
| | (1.54) | (0.68) |
| CAPEX | 0.094 | -0.077 |
| | (0.12) | (-0.10) |
| PM | -0.027 | -0.028 |
| | (-0.53) | (-0.62) |
| GM | -0.314** | -0.188* |

| | | |
|---|---|---|
| | (-2.52) | (-1.86) |
| MKTSHARE | 0.672** | 0.625** |
| | (2.20) | (2.00) |
| CUS_DEP | -3.702*** | |
| | (-5.16) | |
| SUP_DEP | 0.005 | -0.033 |
| | (0.08) | (-0.50) |
| TENURE | -0.068*** | -0.089*** |
| | (-5.04) | (-6.68) |
| CUS_SIZE | -0.106*** | -0.117*** |
| | (-4.85) | (-5.36) |
| Year Fixed Effect | YES | YES |
| Industry Fixed Effect | YES | YES |
| Clustered by supplier | YES | YES |
| R^2 | 0.09 | 0.11 |
| N | 5,917 | 5,917 |

Z statistics in parenthesis. Significant two-tailed p-values denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

**4.5 Additional Analysis**

In our first hypothesis, we argue that major customers, who have stronger mutual economic ties with their partners, have incentives to ask for reliable and truthful information from their suppliers. To lower the costly burden of monitoring each supplier, customers may establish their confidence in their suppliers by observing the reputation of the suppliers' auditors. Customers may cut off the supply chain relationship if they feel uncertain about their future dealings with their current suppliers. Thus, the demand for stability in supply chain relationships may lead suppliers with major customers to choose auditors with higher reputation in the first place. The additional analysis explores whether suppliers with major customers choose higher reputation auditors compared to suppliers with no major customers.

In Table 24, after controlling factors that commonly affect auditor reputation (Francis et al. 2012; DeFond et al. 2016), we find a significant negative association between auditor reputation and the dummy variable indicating whether suppliers have major customers. This result is consistent with our expectation that suppliers with major customers tend to choose auditors with higher reputation compared to suppliers with no major customers. This result further consolidates our main results by supporting our assumption about customers' demand for high quality information from suppliers.

**Table 24. Whether Suppliers with Major Customers Tend to choose Auditors with Higher Reputations**

| | REPUTATION |
|---|---|
| CUS_REL | -0.004** |
| | (-2.11) |
| SIZE | 0.003*** |
| | (-3.81) |
| LEV | 0.000 |
| | (-0.97) |
| CF | -0.000*** |
| | (-3.11) |
| CF_SALE | 0.000** |
| | (-2.24) |
| TOBIN_Q | 0.000 |
| | (-0.92) |
| Z_SCORE | 0.000 |
| | (-0.07) |
| ROA | -0.003** |
| | (-2.15) |
| TAN | 0.002 |
| | (-0.47) |
| GROWTH | 0.006*** |
| | (-3.76) |
| LOSS | 0.002 |
| | (-1.06) |
| CLT_IMP | 0.004 |
| | (-0.57) |

| | |
|---|---|
| A_TENURE | 0.002 |
| | (-1.34) |
| GC | 0.005 |
| | (-1.57) |
| LAF | -0.002 |
| | (-1.23) |
| IND_NATION | 0.008*** |
| | (-3.99) |
| IND_CITY | 0.003* |
| | (-1.68) |
| _CONS | -0.005 |
| | (-0.12) |
| Year Fixed Effect | YES |
| Industry Fixed Effect | YES |
| Clustered by supplier | YES |
| R^2 | 0.01 |
| N | 51201 |

Z statistics in parenthesis. Significant two-tailed p-values denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

As robustness checks, we first relax the restriction of the definition of "major customers", by including those self-reported "major customers" whose sales ration are less than ten percent (10%). In Table 6 column (1) to column (3), we still observe a significant positive relationship between the reputation for the supplier's auditor and the duration of supply chain relationship. Second, we also replace our relative measure (REL) with an alternative absolute measure (RAB), which only adjust the size of audit firm. In Table 25 column (4) to column (6), we also find consistent and significant results in our base models.

**Table 25. Robustness Checks**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Logit | Cox | Weibull | Logit | Cox | Weibull |
| REL | 1.472*** | 1.115*** | 1.125*** | | | |
| | (3.27) | (3.11) | (3.06) | | | |
| RAB | | | | 1.003* | 1.138*** | 1.217*** |
| | | | | (1.94) | (2.90) | (3.09) |
| TENURE | -0.061*** | | | -0.061*** | | |
| | (-4.20) | | | (-4.21) | | |
| SIZE | -0.270*** | -0.203*** | -0.231*** | -0.269*** | -0.203*** | -0.232*** |
| | (-8.59) | (-8.23) | (-8.59) | (-8.53) | (-8.20) | (-8.58) |
| AGE | -0.0395 | -0.256*** | -0.333*** | -0.0421 | -0.257*** | -0.335*** |
| | (-0.70) | (-5.05) | (-5.73) | (-0.75) | (-5.09) | (-5.77) |
| R&D | -0.693 | -0.861** | -0.976*** | -0.704 | -0.876** | -0.988*** |
| | (-1.49) | (-2.52) | (-2.58) | (-1.52) | (-2.57) | (-2.62) |
| NEGFCF | 0.281*** | 0.243*** | 0.242*** | 0.282*** | 0.247*** | 0.246*** |
| | (2.91) | (3.03) | (2.85) | (2.93) | (3.07) | (2.90) |
| INV_TO | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.50) | (0.64) | (0.69) | (0.52) | (0.65) | (0.71) |
| IHLD | -1.566*** | -0.235 | -0.248 | -1.566*** | -0.227 | -0.238 |
| | (-2.84) | (-0.49) | (-0.47) | (-2.84) | (-0.48) | (-0.46) |
| PPE_TO | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 |
| | (1.09) | (0.98) | (1.14) | (1.08) | (1.02) | (1.19) |
| DAYS_AR | -0.000 | 0.000 | 0.000 | -0.000 | 0.000 | 0.000 |
| | (-0.08) | (0.18) | (0.35) | (-0.01) | (0.23) | (0.41) |
| DAYS_AP | 0.001* | 0.000 | 0.000 | 0.001* | 0.000 | 0.000 |
| | (1.88) | (1.05) | (1.01) | (1.85) | (1.00) | (0.96) |
| DAYS_INV | 0.001 | 0.000 | 0.000 | 0.001 | 0.000 | 0.000 |
| | (1.50) | (0.10) | (0.11) | (1.51) | (0.10) | (0.10) |
| CAPEX | 0.947 | 0.858 | 1.043 | 0.942 | 0.884 | 1.079 |
| | (1.04) | (1.26) | (1.39) | (1.04) | (1.30) | (1.44) |
| PM | -0.191*** | -0.105*** | -0.120*** | -0.192*** | -0.107*** | -0.123*** |
| | (-2.82) | (-2.69) | (-2.82) | (-2.83) | (-2.75) | (-2.88) |
| GM | -0.289* | -0.047 | -0.028 | -0.281* | -0.046 | -0.026 |
| | (-1.95) | (-0.50) | (-0.27) | (-1.89) | (-0.49) | (-0.25) |
| MKTSHARE | 1.209*** | 0.703** | 0.787** | 1.198*** | 0.704** | 0.791** |
| | (3.65) | (2.45) | (2.55) | (3.63) | (2.45) | (2.55) |

| | | | | | | |
|---|---|---|---|---|---|---|
| CUS_DEP | -5.061*** | -2.943*** | -3.077*** | -5.090*** | -2.964*** | -3.095*** |
| | (-7.36) | (-5.84) | (-5.82) | (-7.42) | (-5.90) | (-5.88) |
| SUP_DEP | 2.474** | 1.552 | 1.592 | 2.534** | 1.550 | 1.591 |
| | (2.22) | (1.57) | (1.47) | (2.29) | (1.58) | (1.48) |
| CUS_SIZE | -0.038 | 0.0050 | 0.007 | -0.037 | 0.004 | 0.007 |
| | (-1.39) | (0.24) | (0.31) | (-1.36) | (0.21) | (0.29) |
| Year Fixed Effect | | | | | YES | |
| Industry Fixed Effect | | | | | YES | |
| R Square | 0.1475 | | | 0.1461 | | |
| N | 5,274 | 4,355 | 4,355 | 5,274 | 4,355 | 4,355 |

Z statistics in parenthesis. Significant two-tailed p-values denoted as follows: *** p<0.01, ** p<0.05, * p<0.1

## 4.6 Conclusion

To lower the supply chain risks (e.g. delay risks and disruption risks) arising from information asymmetry between customers and suppliers, auditors satisfy the increasing demands of high quality information sharing over supply chains by issuing reliable opinions and detecting suspicious accounting misconducts in financial reporting. In this chapter, we emphasize the importance of auditors, and regard auditor reputation as an early warning signal for customers to evaluate current supply chain risks and future prospects for cooperation. We expect that the publicly available auditor reputation, measured by their clients' restatements, may significantly affect the confidence of customers in their suppliers. As suggested by prior literature, customers and suppliers may view transaction conditions more favorably and prefer to sustain a longer relationship if the customers are assured of the quality of suppliers' information that has been audited by trusted auditors. Therefore, we utilize a series of hazard models to investigate the association between the reputation of suppliers' auditors and customer-supplier relationship terminations. We find that a poor reputation for the supplier's auditor increases the likelihood of customer-supplier relationship termination, but that such association will be mitigated if customers and suppliers are located close to each other or they share common auditors. In addition, we document that suppliers who take remediation activities by switching from low reputation auditors to high reputation auditors, sending positive signals to customers, will reduce the likelihood of relationship breakdown in the following year. We answer the calls from prior literature to investigate the impact of "negative critical incidents" and other "mechanism" on supply chain relationships. We also extend the literature that examines the role of auditors in contract efficiency through providing assurance on financial reporting and detecting financial frauds.

This research has serval limitations. First, we identify major customers based on suppliers' 10-K disclosure under SFAS 131. This guidance only requires suppliers to disclose major customers who represent over ten percent of suppliers' total sales. Other significant customers that are close to the ten percent threshold will be unobservable. Second, we exclude any observations within a monopoly auditing market where clients have no choice among auditors. However, the number of dropped observations is trivial relative to the sample that was used in our regression models. Finally, even though we extensively control commonly used factors that may influence the duration of supply chain relationships, we cannot rule out the possibility of endogenous missing factors that may be correlated with variations in auditor reputation. Despite these limitations, we believe that this chapter sheds light on the importance of auditor reputation in signaling supply chain risks and maintaining stable supply chain relationships.

# CHAPTER 5: CONCLUSION

The purpose of this dissertation is to investigate the topic of information sharing in auditing practice by answering the following research questions. First, how auditors can benefit from information sharing without violating confidentiality problems, second, how auditors can cope with the influence of information diffusion between their clients on audit quality, and third, how auditors can act as information sharing intermediaries or repositories to reduce the information asymmetry and aid management decision making in multilateral business relationships.

Specially, the first essay examines the potential benefits of sharing peer information on analytical procedures. I introduce an approach for selecting peers for each client and perform a number of experiments to examine peers' information contribution to the performance of analytical procedures at different data sharing levels. I use peer models in various ways at different sharing levels and observe that peer data is extremely useful in helping auditors reduce their estimation errors and achieve better audit quality. I also observe a comparable level of improvement within the three different sharing schemes, implying auditors can benefit from sharing self-generated regression residuals (errors) with peer companies in a privacy-preserving manner. Additionally, after converting the numerical estimation errors into categorical dummy variables, the benefits still hold, by fine-tuning parameters. The results strongly indicate that sharing peer data is especially beneficial for improving the overall estimation prediction performance of analytical procedures, which can contribute to improving the overall audit quality. Furthermore, the results indicate the power of sharing within the same audit firm. Regarding research limitations, I point out three potential risks arising from sample selection, simulation process and the detection of coordinated error.

In my second essay, I investigate the effect of the geographic industry clusters on audit quality to bridge the gap in research regarding the role of the local audit market and geographic proximity in audit quality. This research is an attempt to study the effects of information sharing between clients on audit quality. The results provide strong evidence that the geographic agglomeration of companies within the same industries has a negative impact on audit quality by being associated with accrual based earnings management and restatements. I also find the impact is pronounced for the clients with the stronger industry networks through sharing the same auditor. It suggests that due to the lower communication cost in the geographic industry clusters, clients are more likely to learn questionable accounting practices and form alliances to negotiate with auditors and convince them to tolerate questionable accounting practices. Lastly, I also find that auditors charge higher audit fees to clients located in the geographic industry clusters and such phenomenon is more pronounced for clients with the industry networks through sharing the same auditor.

In the third essay, I emphasize the importance of auditors, and regard auditor reputation as an early warning signal for customers to evaluate current supply chain risks and future prospects for cooperation. I utilize a series of hazard models to investigate the association between the reputation of suppliers' auditors and customer-supplier relationship terminations. I find that a poor reputation for the supplier's auditor increases the likelihood of customer-supplier relationship termination, but that such association will be mitigated if customers and suppliers are located close to each other or they share auditors. In addition, I document that suppliers who use remediation activities by switching from low reputation auditors to high reputation auditors, thus sending positive signals to customers, will reduce the likelihood of relationship breakdown in the following year. This study answers the calls from prior literature to investigate the impact of “negative critical incidents” and other “mechanisms” on supply chain relationships and also extends the literature that examines the role of auditors in contract efficiency through providing assurance on financial reporting and detecting financial frauds. The limitation of this study is due to the data used, since I can only identify major customers based on suppliers’ 10-K disclosure under SFAS 131. In addition, the emergence of audit market monopoly in small MSA also results in these data limitations.

# APPENDICIES

## Appendix A.

| Variables Definition | |
|---|---|
| | ***Audit Quality Model*** |
| AQ | Audit Quality, measured by discretionary accrual or PCAOB inspection outputs |
| CLUSTER | Geographic industry clusters, measured by ROF, DUM, and CMV.<br>*ROF*: the number of firms with the same three-digit SIC in a Metropolitan Statistical Area (MSA) divided by the total number of firms with the same three-digit SIC;<br>*DUM*: the number of firms with the same three-digit SIC in a Metropolitan Statistical Area (MSA) divided by the total number of firms with the same three-digit SIC;<br>*CMV*: takes one if for firm-years a firm's headquarters is located in an MSA that represents at least 10% of market value of the firm's industry and has at least three firms with the same three-digit SIC, zero otherwise. |
| LNTA | Natural log of total assets in thousands of dollars. |
| CHGSALE | Changes in sales deflated by lagged total assets. |
| BTM | Book-to-market ratio, winsored at 0 and 4. |
| AGE | The age of listing firm since 1974. |
| LOSS | Indicator variable equal to 1 if firm reports a negative net income for the year, 0 otherwise. |
| Z | Zmijewski's (1984) financial distress score, winsored at +5 and -5. |
| ISSUE | Indicator variable equal 1 if the sum of debt or equity issue during the past three years is more than 5% of the total assets, 0 otherwise. |
| CFO | Operating cash flows taken from the cash flow statement, deflated by lagged total asset. |
| LACCR | One-year lagged total accruals. Accruals are defined as income before extraordinary items minus operating cash flows from the statement of cash flow deflated by lagged total assets. |
| TENURE | Auditor tenure, measured as the natural log of the number of years the incumbent auditor has served the client. |
| NAS | Relative importance of non-audit services, measured as the ratio of the natural log of non-audit fees over the natural log of non-audit fees over the natural log of total fees. |
| BIGN | Indicator variable equal 1 if auditor is one of the Big N firms, 0 otherwise. |
| INDSPEC | An indicator variable for auditor industry expertise that equals one if the audit firm is the industry leader for the audit year in both local level and national wide. |

| | |
|---|---|
| CONCENT | A measure of auditor concentration by each MSA, measured by the Herfindahl index of the number of clients for each audit office, based on auditor's location |
| | ***Audit Fees Model*** |
| EMPLOYEE | The square root of number of employees |
| ARINV | Sum of accounts receivable and inventory, scaled by total assets |
| CR | Current ratio, defined as current assets divided by current liabilities |
| CATA | The ratio of current assets to total assets |
| ROA | Return on assets, defined as earnings before interest and taxes divided by total assets |
| LEV | Ratio of long-term debt to total assets |
| FOREIGN | Indicator variable equal to 1 if the firm pays foreign income taxes, 0 otherwise. |
| BUSY | Indicator variable equal to 1 if a company's fiscal year is December 31st, 0, otherwise |
| INTANG | Ratio of intangible assets to total assets |
| SEG | Logarithm of number of business segments |
| OPINION | 1 if the auditor issues a going concern audit opinion, 0 otherwise. |
| MERGE | Indicator variable equal to 1 if the firm reported the impact of a merger or acquisition on net income, 0 otherwise. |

**Appendix B.**

| | |
|---|---|
| REP | The relative auditor reputation measured by subtracting the percentage of restatements in a given MSA from the percentage of restatements for a local office. (Swanquist and Whited 2015) |
| SUP_SIZE | Logarithm of a supplier's total assets (AT) |
| SUP_AGE | The number of years the supplier is listed in the Compustat |
| R&D | Supplier research and development expense (XRD) scaled by total assets (AT) |
| NEGFCF | Indicator variable equal to one if supplier's free cash flow (IB + DP - CAPX) is negative, and zero otherwise |
| INV_TO | Inventory turnover measured as cost of goods sold (COGS) divided by two-year average FIFO inventory (INVT) (Feng et al. 2015) |
| IHLD | Inventory holding period measured as inventory (INVT)divided by opening total assets (AT) |
| PPE_TO | Property, plant and equipment turnover measured as total revenue (RECT) divided by net property, plant and equipment (PPENT) |
| DAYS_AR | Days in accounts receivable measured as accounts receivable (RECT) divided by total revenue (REVT) multiplied by 365 |
| DAYS_AP | Days in accounts payable measured as accounts payable (AP) divided by cost of goods sold (COGS) multiplied by 365 |
| DAYS_INV | Days in inventory measured as inventory (INVT) divided by cost of goods sold (COGS) multiplied by 365 |
| CAPEX | Capital expenditure intensity measured as capital expenditures (CAPX) divided by total assets (AT) |
| PM | Profit margin measured as income before extraordinary items (IB) divided by total revenue (REVT) |
| GM | Gross margin measured as total revenue (REVT) less cost of goods of sold (COGS) divided by total revenue (REVT) |
| MKTSHARE | Total sales (REVT) in year t divided by total industry sales, defined as the sum of total sales by all firms in year t within that firm's 4-digit SIC code |
| CUS_DEP | The rank (decile) of customer concentration measured as sales to a specific major customer (CSALES) divided by total supplier sales (REVT) |
| SUP_DEP | The rank (decile) of supplier concentration measured as purchases from supplier (CSALES) divided by total customer cost of goods sold (COGS) |
| TENURE | The length of the customer-supplier relationship at the beginning of the year |
| CUS_SIZE | Logarithm of customer's total assets (AT) |

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## SUPPLEMENTARY APPENDICES

### Appendix A.

**The t-test of MAPEs among Estimation Models for Revenue Account**

| 1311 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.001 | 0.000 | 0.632 | 0.674 | 0.000 | 0.387 | 0.236 | 0.085 |
| A | | | 0.014 | 0.631 | 0.005 | 0.701 | 0.490 | 0.008 | 0.009 |
| P | | | | 0.055 | 0.001 | 0.517 | 0.109 | 0.006 | 0.007 |
| E | | | | | 0.087 | 0.636 | 0.522 | 0.003 | 0.004 |
| S&L3 | | | | | | 0.000 | 0.361 | 0.285 | 0.097 |
| SL | | | | | | | 0.502 | 0.023 | 0.017 |
| L3 | | | | | | | | 0.044 | 0.011 |
| L | | | | | | | | | 0.014 |
| S | | | | | | | | | |

| 7370 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.620 | 0.087 | 0.000 |
| A | | | 0.000 | 0.035 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.052 | 0.000 | 0.421 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.013 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.001 | 0.032 | 0.845 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.143 | 0.001 |
| L | | | | | | | | | 0.013 |
| S | | | | | | | | | |

| 2834 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.481 | 0.047 | 0.624 | 0.161 | 0.071 | 0.001 | 0.115 | 0.378 |
| A | | | 0.057 | 0.087 | 0.073 | 0.156 | 0.000 | 0.108 | 0.565 |
| P | | | | 0.139 | 0.660 | 0.016 | 0.012 | 0.021 | 0.045 |
| E | | | | | 0.406 | 0.027 | 0.000 | 0.027 | 0.036 |
| S&L3 | | | | | | 0.003 | 0.018 | 0.006 | 0.047 |
| SL | | | | | | | 0.000 | 0.672 | 0.422 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.212 |
| S | | | | | | | | | |

| 3674 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.199 | 0.000 | 0.002 |
| A | | | 0.158 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.276 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.000 | 0.003 | 0.343 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.000 |
| S | | | | | | | | | |

| 4911 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.006 | 0.000 | 0.000 |
| A | | | 0.000 | 0.819 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.001 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.376 | 0.000 | 0.000 |
| SL | | | | | | | 0.000 | 0.000 | 0.237 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.132 |
| S | | | | | | | | | |

| 5812 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.214 | 0.000 | 0.805 | 0.006 | 0.068 |
| A | | | 0.994 | 0.823 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.826 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.003 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.114 | 0.123 | 0.476 |
| SL | | | | | | | 0.000 | 0.011 | 0.006 |
| L3 | | | | | | | | 0.000 | 0.025 |
| L | | | | | | | | | 0.441 |
| S | | | | | | | | | |

| 2836 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.083 | 0.433 | 0.576 | 0.475 | 0.012 | 0.711 | 0.038 | 0.006 |
| A | | | 0.377 | 0.304 | 0.101 | 0.539 | 0.006 | 0.200 | 0.167 |
| P | | | | 0.217 | 0.130 | 0.323 | 0.524 | 0.503 | 0.964 |
| E | | | | | 0.662 | 0.267 | 0.733 | 0.338 | 0.416 |
| S&L3 | | | | | | 0.030 | 0.930 | 0.074 | 0.088 |
| SL | | | | | | | 0.000 | 0.006 | 0.046 |
| L3 | | | | | | | | 0.000 | 0.201 |
| L | | | | | | | | | 0.156 |
| S | | | | | | | | | |

| 3845 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.067 | 0.782 | 0.649 | 0.294 | 0.101 | 0.159 | 0.700 | 0.591 |
| A | | | 0.033 | 0.065 | 0.133 | 0.666 | 0.113 | 0.919 | 0.131 |
| P | | | | 0.361 | 0.311 | 0.286 | 0.130 | 0.692 | 0.932 |
| E | | | | | 0.251 | 0.335 | 0.125 | 0.727 | 0.777 |
| S&L3 | | | | | | 0.184 | 0.153 | 0.508 | 0.384 |
| SL | | | | | | | 0.145 | 0.968 | 0.028 |
| L3 | | | | | | | | 0.268 | 0.182 |
| L | | | | | | | | | 0.610 |
| S | | | | | | | | | |

| 4931 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.870 | 0.123 |
| A | | | 0.000 | 0.005 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.780 | 0.000 | 0.007 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.123 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.083 | 0.000 | 0.000 |
| SL | | | | | | | 0.000 | 0.000 | 0.119 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.137 |
| S | | | | | | | | | |

This table displays the comparison of the MAPEs of all estimation models for revenue account. Panel A depicts the comparison of the industry mean of MAPEs in estimating revenues. Panel B shows the comparison of the industry median of MAPEs in revenue account as a robustness check. Panel C is an upper triangular t-test matrix. In Panel C, the p values in the first row are generated by one-tail t-tests, indicating whether sharing models are superior to original model in prediction accuracy; the rest of p values are generated by two-tail t-tests, examining whether there is significant difference in prediction accuracy between any two models.

**Appendix B.**

**The t-test of MAPEs among Estimation Models for Cost of Goods Sold Account**

| 1311 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.004 | 0.000 | 0.011 | 0.008 | 0.644 | 0.137 | 0.836 |
| A | | | 0.081 | 0.150 | 0.767 | 0.069 | 0.002 | 0.004 | 0.004 |
| P | | | | 0.021 | 0.251 | 0.341 | 0.000 | 0.001 | 0.141 |
| E | | | | | 0.393 | 0.586 | 0.000 | 0.001 | 0.067 |
| S&L3 | | | | | | 0.097 | 0.019 | 0.015 | 0.005 |
| SL | | | | | | | 0.017 | 0.014 | 0.008 |
| L3 | | | | | | | | 0.058 | 0.984 |
| L | | | | | | | | | 0.329 |
| S | | | | | | | | | |

| 7370 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| A | | | 0.440 | 0.505 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.121 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.007 | 0.000 | 0.002 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.009 | 0.782 |
| L | | | | | | | | | 0.023 |
| S | | | | | | | | | |

| 2834 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.003 | 0.001 | 0.189 | 0.077 | 0.232 | 0.457 | 0.284 |
| A | | | 0.466 | 0.008 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.500 | 0.000 | 0.006 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.029 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.500 | 0.000 | 0.792 |
| SL | | | | | | | 0.000 | 0.006 | 0.001 |
| L3 | | | | | | | | 0.000 | 0.554 |
| L | | | | | | | | | 0.040 |
| S | | | | | | | | | |

| 3674 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| A | | | 0.000 | 0.056 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.886 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.722 | 0.000 | 0.013 |
| SL | | | | | | | 0.000 | 0.000 | 0.037 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.490 |
| S | | | | | | | | | |

| 4911 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.005 | 0.001 | 0.003 | 0.185 | 0.021 | 0.262 | 0.088 | 0.097 |
| A | | | 0.261 | 0.024 | 0.000 | 0.132 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.400 | 0.000 | 0.161 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.003 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.241 | 0.078 | 0.412 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.100 |
| S | | | | | | | | | |

| 5812 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.002 | 0.002 | 0.010 | 0.310 | 0.798 |
| A | | | 0.830 | 0.294 | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.245 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.117 | 0.019 | 0.002 |
| SL | | | | | | | 0.000 | 0.000 | 0.028 |
| L3 | | | | | | | | 0.167 | 0.024 |
| L | | | | | | | | | 0.208 |
| S | | | | | | | | | |

| 2836 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.027 | 0.000 | 0.197 | 0.328 | 0.049 |
| A | | | 0.126 | 0.272 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.622 | 0.000 | 0.016 | 0.000 | 0.001 | 0.000 |
| E | | | | | 0.000 | 0.008 | 0.000 | 0.001 | 0.000 |
| S&L3 | | | | | | 0.067 | 0.325 | 0.455 | 0.745 |
| SL | | | | | | | 0.011 | 0.043 | 0.025 |
| L3 | | | | | | | | 0.904 | 0.509 |
| L | | | | | | | | | 0.550 |
| S | | | | | | | | | |

| 3845 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.049 | 0.082 | 0.690 | 0.084 | 0.088 | 0.119 | 0.148 | 0.110 |
| A | | | 0.165 | 0.472 | 0.018 | 0.035 | 0.003 | 0.000 | 0.180 |
| P | | | | 0.221 | 0.977 | 0.999 | 0.046 | 0.333 | 0.921 |
| E | | | | | 0.210 | 0.139 | 0.010 | 0.000 | 0.328 |
| S&L3 | | | | | | 0.953 | 0.334 | 0.029 | 0.919 |
| SL | | | | | | | 0.042 | 0.003 | 0.876 |
| L3 | | | | | | | | 0.366 | 0.122 |
| L | | | | | | | | | 0.778 |
| S | | | | | | | | | |

| 4931 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.010 | 0.000 | 0.131 | 0.226 |
| A | | | 0.000 | 0.992 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.002 | 0.001 |
| S&L3 | | | | | | 0.000 | 0.002 | 0.000 | 0.000 |
| SL | | | | | | | 0.000 | 0.666 | 0.426 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.533 |
| S | | | | | | | | | |

This table displays the comparison of the MAPEs of all estimation models for cost of goods sold account. Panel A depicts the comparison of the industry mean of MAPEs in estimating cost of goods sold. Panel B shows the comparison of the industry median of MAPEs in cost of goods sold account as a robustness check. Panel C is an upper triangular t-test matrix. In Panel C, the p values in the first row are generated by one-tail t-tests, indicating whether sharing models are superior to original model in prediction accuracy; the rest of p values are generated by two-tail t-tests, examining whether there is significant difference in prediction accuracy between any two models.

# Appendix C.

## The Evaluation of Error Detection in Revenue Account for The Rest of SIC Codes

1311

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 19.4 | 27.1 | 17.8 | 26.7 | 17.8 | 27.2 | 18.0 | 26.8 | 18.2 | 26.5 | 17.2 | 27.8 | 17.5 | 27.1 |
| | 0.02 | 21.2 | 27.2 | 20.6 | 26.8 | 20.4 | 27.4 | 20.9 | 27.1 | 21.2 | 26.5 | 20.2 | 27.5 | 20.8 | 27.1 |
| | 0.01 | 21.7 | 27.4 | 21.4 | 27.1 | 21.1 | 27.8 | 21.4 | 27.4 | 22.0 | 26.9 | 21.2 | 27.8 | 21.6 | 27.1 |
| 0.01 | 0.05 | 19.4 | 27.2 | 17.9 | 26.9 | 18.0 | 27.3 | 18.1 | 27.1 | 18.3 | 26.5 | 17.4 | 27.9 | 17.6 | 26.6 |
| | 0.02 | 21.2 | 27.1 | 20.8 | 26.8 | 20.5 | 27.3 | 20.9 | 27.1 | 21.3 | 26.4 | 20.5 | 27.6 | 20.9 | 26.6 |
| | 0.01 | 22.2 | 27.1 | 21.9 | 26.9 | 21.6 | 27.4 | 22.0 | 27.3 | 22.5 | 26.5 | 21.3 | 27.6 | 22.1 | 27.0 |
| 0.02 | 0.05 | 19.4 | 27.2 | 18.0 | 26.9 | 18.1 | 27.4 | 18.2 | 27.1 | 18.5 | 26.5 | 17.3 | 27.6 | 17.8 | 26.7 |
| | 0.02 | 21.7 | 27.2 | 21.1 | 26.9 | 20.8 | 27.2 | 21.3 | 27.1 | 21.7 | 26.6 | 20.4 | 27.7 | 21.2 | 26.7 |
| | 0.01 | 22.2 | 26.9 | 22.3 | 26.8 | 21.8 | 27.2 | 22.1 | 27.1 | 22.7 | 26.4 | 21.1 | 27.7 | 22.2 | 26.4 |
| 0.05 | 0.05 | 19.5 | 26.4 | 18.5 | 26.2 | 18.5 | 26.8 | 18.7 | 26.5 | 19.1 | 26.0 | 16.9 | 27.8 | 17.4 | 26.9 |
| | 0.02 | 21.9 | 26.4 | 21.7 | 26.0 | 21.3 | 26.6 | 21.7 | 26.5 | 22.0 | 25.7 | 19.9 | 27.7 | 20.8 | 26.8 |
| | 0.01 | 22.4 | 26.6 | 22.4 | 26.1 | 22.0 | 26.7 | 22.3 | 26.6 | 22.8 | 25.8 | 21.0 | 27.8 | 21.8 | 26.9 |
| 0.1 | 0.05 | 19.9 | 25.9 | 19.1 | 25.2 | 19.1 | 25.7 | 19.3 | 25.5 | 19.5 | 24.9 | 18.5 | 26.3 | 19.0 | 25.4 |
| | 0.02 | 22.7 | 25.8 | 22.4 | 24.9 | 22.1 | 25.4 | 22.1 | 25.3 | 23.1 | 24.7 | 21.7 | 26.4 | 22.5 | 25.4 |
| | 0.01 | 23.4 | 26.0 | 23.8 | 25.2 | 23.3 | 25.6 | 23.2 | 25.5 | 24.2 | 25.0 | 22.5 | 26.1 | 23.5 | 25.2 |

7370

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 16.3 | 24.4 | 12.3 | 23.9 | 12.7 | 23.7 | 12.8 | 24.3 | 12.2 | 24.0 | 12.5 | 24.2 | 14.1 | 24.2 |
| | 0.02 | 21.7 | 24.4 | 19.9 | 23.7 | 20.3 | 23.9 | 20.3 | 24.3 | 20.1 | 23.9 | 20.0 | 24.4 | 20.5 | 23.8 |
| | 0.01 | 23.4 | 24.3 | 22.4 | 23.4 | 23.2 | 23.5 | 23.0 | 24.1 | 22.4 | 23.7 | 23.4 | 24.6 | 22.9 | 23.7 |
| 0.01 | 0.05 | 16.6 | 23.7 | 12.5 | 23.4 | 12.8 | 23.3 | 13.1 | 23.9 | 12.5 | 23.3 | 13.3 | 24.7 | 14.3 | 23.6 |
| | 0.02 | 22.0 | 23.9 | 20.5 | 23.2 | 21.1 | 23.2 | 20.7 | 23.9 | 20.6 | 23.4 | 20.1 | 24.2 | 20.6 | 24.0 |
| | 0.01 | 23.5 | 23.8 | 22.7 | 23.2 | 23.6 | 23.3 | 23.4 | 23.9 | 22.9 | 23.3 | 23.6 | 24.4 | 23.4 | 23.7 |
| 0.02 | 0.05 | 16.5 | 23.9 | 12.7 | 23.5 | 13.0 | 23.6 | 13.3 | 24.1 | 12.6 | 23.7 | 13.2 | 23.9 | 14.5 | 24.0 |
| | 0.02 | 22.2 | 24.1 | 20.6 | 23.1 | 20.9 | 23.3 | 20.6 | 23.8 | 20.8 | 23.4 | 20.2 | 23.8 | 20.9 | 23.7 |
| | 0.01 | 23.7 | 24.7 | 23.0 | 23.7 | 23.7 | 23.8 | 23.2 | 24.5 | 23.1 | 24.0 | 23.7 | 24.0 | 23.6 | 23.9 |
| 0.05 | 0.05 | 17.2 | 24.0 | 13.3 | 23.2 | 13.8 | 23.2 | 13.7 | 23.9 | 13.3 | 23.2 | 13.0 | 24.6 | 14.1 | 23.7 |
| | 0.02 | 22.2 | 23.3 | 20.7 | 22.8 | 21.5 | 22.7 | 20.9 | 23.5 | 21.0 | 22.6 | 20.3 | 24.1 | 20.3 | 23.8 |
| | 0.01 | 24.3 | 23.6 | 23.8 | 22.9 | 24.2 | 22.8 | 23.8 | 23.5 | 23.7 | 22.8 | 23.5 | 24.1 | 23.3 | 24.2 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.05 | 17.3 | 22.7 | 13.5 | 22.0 | 13.8 | 21.9 | 14.1 | 22.6 | 13.4 | 21.5 | 13.8 | 23.0 | 15.3 | 22.7 |
| | 0.02 | 22.5 | 23.2 | 21.4 | 22.4 | 22.0 | 22.2 | 21.8 | 23.1 | 21.5 | 22.1 | 22.2 | 22.9 | 22.0 | 22.5 |
| | 0.01 | 25.1 | 23.0 | 24.7 | 22.2 | 25.0 | 22.0 | 24.5 | 22.8 | 24.9 | 21.9 | 24.7 | 22.8 | 24.6 | 22.5 |

2834

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 21.6 | 22.2 | 19.7 | 23.9 | 18.3 | 23.9 | 17.9 | 24.3 | 18.8 | 24.1 | 18.9 | 24.9 | 17.2 | 25.7 |
| | 0.02 | 24.6 | 23.0 | 22.7 | 24.3 | 21.4 | 24.4 | 21.5 | 24.5 | 22.1 | 24.7 | 21.9 | 25.1 | 20.7 | 26.0 |
| | 0.01 | 25.9 | 22.5 | 24.4 | 23.9 | 23.5 | 24.1 | 23.8 | 24.0 | 23.7 | 24.0 | 23.3 | 25.3 | 23.0 | 25.7 |
| 0.01 | 0.05 | 21.9 | 23.0 | 19.9 | 24.3 | 18.7 | 24.5 | 18.2 | 24.5 | 19.1 | 24.5 | 18.9 | 24.8 | 16.8 | 25.6 |
| | 0.02 | 24.9 | 22.7 | 23.1 | 24.2 | 21.9 | 24.4 | 21.7 | 24.2 | 22.3 | 24.4 | 22.5 | 24.5 | 21.0 | 26.1 |
| | 0.01 | 25.8 | 22.0 | 24.8 | 23.8 | 23.5 | 23.6 | 24.2 | 24.0 | 23.8 | 23.9 | 23.6 | 24.9 | 22.5 | 25.2 |
| 0.02 | 0.05 | 22.0 | 22.2 | 19.6 | 23.7 | 18.4 | 23.6 | 18.0 | 24.1 | 18.6 | 24.0 | 19.0 | 24.0 | 17.2 | 25.8 |
| | 0.02 | 25.6 | 22.5 | 23.5 | 24.1 | 22.2 | 23.8 | 22.0 | 23.8 | 22.7 | 24.0 | 22.9 | 24.7 | 21.4 | 25.3 |
| | 0.01 | 26.1 | 22.4 | 24.7 | 24.0 | 23.9 | 24.2 | 24.4 | 24.5 | 24.2 | 24.3 | 24.2 | 24.5 | 23.2 | 25.6 |
| 0.05 | 0.05 | 22.7 | 22.3 | 20.7 | 23.3 | 19.6 | 23.3 | 18.6 | 23.6 | 19.5 | 23.8 | 18.9 | 24.9 | 17.0 | 25.8 |
| | 0.02 | 25.6 | 22.3 | 24.2 | 23.7 | 23.2 | 23.6 | 22.4 | 23.9 | 22.9 | 24.1 | 21.8 | 25.2 | 21.0 | 25.6 |
| | 0.01 | 26.9 | 22.2 | 25.2 | 23.1 | 24.9 | 23.0 | 25.1 | 23.5 | 24.8 | 23.5 | 23.1 | 25.8 | 22.9 | 25.5 |
| 0.1 | 0.05 | 22.7 | 21.2 | 20.9 | 21.9 | 19.9 | 22.1 | 18.9 | 23.2 | 19.5 | 22.7 | 20.5 | 22.6 | 18.1 | 24.0 |
| | 0.02 | 26.5 | 21.3 | 25.2 | 22.0 | 24.2 | 22.0 | 24.0 | 22.9 | 24.0 | 22.9 | 24.2 | 23.0 | 22.4 | 23.8 |
| | 0.01 | 27.7 | 21.5 | 26.1 | 22.1 | 26.0 | 22.2 | 25.4 | 23.1 | 25.5 | 22.9 | 25.8 | 22.5 | 23.8 | 24.3 |

3674

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 16.8 | 27.5 | 13.7 | 27.7 | 14.1 | 27.3 | 14.3 | 27.0 | 13.6 | 27.3 | 13.8 | 28.1 | 13.5 | 27.4 |
| | 0.02 | 20.0 | 27.6 | 18.5 | 28.0 | 19.1 | 27.5 | 18.7 | 27.1 | 18.6 | 27.5 | 18.3 | 28.0 | 18.7 | 27.1 |
| | 0.01 | 20.8 | 27.4 | 20.1 | 27.9 | 20.6 | 27.5 | 20.5 | 27.2 | 20.3 | 27.6 | 19.9 | 27.8 | 20.3 | 27.2 |
| 0.01 | 0.05 | 16.7 | 27.2 | 13.7 | 27.5 | 14.2 | 27.0 | 14.2 | 26.5 | 13.7 | 27.1 | 13.8 | 28.0 | 13.9 | 27.0 |
| | 0.02 | 20.2 | 27.6 | 18.5 | 27.7 | 19.1 | 27.4 | 18.9 | 26.8 | 18.6 | 27.3 | 18.3 | 27.5 | 18.7 | 27.1 |
| | 0.01 | 21.2 | 27.7 | 20.3 | 27.8 | 20.8 | 27.3 | 20.6 | 26.9 | 20.4 | 27.2 | 19.8 | 27.5 | 20.5 | 27.1 |
| 0.02 | 0.05 | 17.1 | 27.0 | 14.1 | 27.2 | 14.6 | 26.8 | 14.6 | 26.3 | 14.2 | 26.8 | 13.8 | 27.4 | 13.8 | 27.1 |
| | 0.02 | 20.1 | 27.3 | 18.7 | 27.6 | 19.2 | 27.2 | 19.2 | 26.8 | 18.9 | 27.2 | 18.7 | 27.6 | 18.9 | 26.8 |
| | 0.01 | 21.4 | 27.3 | 20.8 | 27.6 | 21.2 | 27.1 | 21.2 | 26.8 | 20.9 | 27.1 | 20.1 | 27.5 | 20.6 | 27.3 |
| 0.05 | 0.05 | 17.2 | 26.7 | 14.3 | 26.7 | 15.1 | 26.5 | 15.0 | 25.9 | 14.4 | 26.4 | 13.9 | 28.6 | 13.8 | 27.3 |
| | 0.02 | 20.5 | 27.2 | 19.3 | 27.2 | 19.7 | 26.9 | 19.7 | 26.3 | 19.4 | 26.9 | 18.3 | 28.1 | 18.7 | 27.1 |
| | 0.01 | 21.6 | 27.3 | 21.0 | 27.3 | 21.5 | 27.1 | 21.5 | 26.4 | 21.3 | 27.2 | 20.3 | 28.4 | 20.5 | 27.2 |
| 0.1 | 0.05 | 17.8 | 26.1 | 15.0 | 26.0 | 15.9 | 26.0 | 15.5 | 25.1 | 15.2 | 25.9 | 15.3 | 26.3 | 15.1 | 25.7 |
| | 0.02 | 20.8 | 26.1 | 19.8 | 25.8 | 20.6 | 25.8 | 20.3 | 25.1 | 20.2 | 25.8 | 19.8 | 25.9 | 20.2 | 25.5 |
| | 0.01 | 22.1 | 26.4 | 21.8 | 26.1 | 22.1 | 26.0 | 22.4 | 25.3 | 22.0 | 26.1 | 22.0 | 26.1 | 22.2 | 25.5 |

4911

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 16.3 | 26.0 | 14.9 | 25.1 | 15.1 | 25.6 | 14.9 | 25.2 | 14.9 | 25.3 | 14.9 | 26.3 | 13.7 | 26.3 |
| | 0.02 | 20.6 | 26.1 | 20.5 | 25.3 | 20.4 | 25.7 | 20.4 | 25.4 | 20.6 | 25.5 | 20.1 | 26.3 | 19.2 | 26.4 |
| | 0.01 | 22.2 | 26.0 | 22.3 | 25.1 | 22.3 | 25.5 | 22.4 | 25.2 | 22.4 | 25.3 | 22.0 | 26.0 | 21.3 | 26.3 |
| 0.01 | 0.05 | 16.5 | 25.9 | 15.2 | 25.2 | 15.2 | 25.5 | 15.1 | 25.2 | 15.1 | 25.3 | 15.1 | 25.8 | 13.8 | 26.4 |
| | 0.02 | 20.6 | 25.9 | 20.6 | 25.1 | 20.5 | 25.5 | 20.5 | 25.2 | 20.6 | 25.2 | 20.1 | 26.0 | 19.4 | 26.4 |
| | 0.01 | 22.3 | 26.1 | 22.5 | 25.3 | 22.4 | 25.7 | 22.6 | 25.3 | 22.5 | 25.5 | 22.2 | 26.0 | 21.6 | 26.3 |
| 0.02 | 0.05 | 16.7 | 25.7 | 15.4 | 24.8 | 15.5 | 25.3 | 15.2 | 24.8 | 15.2 | 25.0 | 15.2 | 26.1 | 13.9 | 26.2 |
| | 0.02 | 20.8 | 25.8 | 20.7 | 24.9 | 20.6 | 25.3 | 20.8 | 25.1 | 20.8 | 25.1 | 20.2 | 25.9 | 19.6 | 26.2 |
| | 0.01 | 22.7 | 25.9 | 22.8 | 25.0 | 22.7 | 25.3 | 22.9 | 25.1 | 22.7 | 25.2 | 22.2 | 25.7 | 21.6 | 26.1 |
| 0.05 | 0.05 | 17.1 | 25.5 | 15.9 | 24.4 | 16.0 | 25.0 | 15.8 | 24.4 | 15.7 | 24.5 | 15.0 | 26.3 | 13.7 | 26.6 |
| | 0.02 | 21.2 | 25.3 | 21.4 | 24.3 | 21.2 | 24.8 | 21.1 | 24.4 | 21.3 | 24.5 | 20.0 | 26.2 | 19.3 | 26.5 |
| | 0.01 | 22.9 | 25.4 | 23.3 | 24.3 | 23.2 | 25.0 | 23.2 | 24.5 | 23.2 | 24.5 | 22.0 | 26.3 | 21.3 | 26.4 |
| 0.1 | 0.05 | 17.5 | 24.7 | 16.3 | 23.5 | 16.6 | 24.1 | 16.4 | 23.6 | 16.4 | 23.7 | 16.5 | 24.5 | 15.0 | 24.7 |
| | 0.02 | 22.2 | 24.7 | 22.3 | 23.7 | 22.2 | 24.2 | 22.1 | 23.7 | 22.2 | 23.9 | 21.8 | 24.2 | 20.7 | 24.7 |
| | 0.01 | 23.4 | 24.7 | 24.2 | 23.8 | 23.9 | 24.3 | 24.1 | 23.9 | 24.0 | 24.1 | 23.6 | 24.3 | 23.0 | 24.9 |

5812

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 19.3 | 22.6 | 15.6 | 22.6 | 14.8 | 21.7 | 14.8 | 22.4 | 14.7 | 23.4 | 14.5 | 23.8 | 13.7 | 23.3 |
| | 0.02 | 24.7 | 22.3 | 23.3 | 22.1 | 22.8 | 21.4 | 23.1 | 22.3 | 21.5 | 22.6 | 21.5 | 23.1 | 21.2 | 22.8 |
| | 0.01 | 25.9 | 22.6 | 25.4 | 22.7 | 24.9 | 22.1 | 25.3 | 22.6 | 24.4 | 23.4 | 24.7 | 22.7 | 23.5 | 23.5 |
| 0.01 | 0.05 | 19.4 | 21.7 | 15.3 | 21.3 | 15.3 | 21.0 | 14.4 | 21.5 | 15.0 | 22.2 | 15.0 | 22.8 | 13.7 | 23.0 |
| | 0.02 | 24.3 | 22.7 | 22.8 | 22.0 | 22.4 | 21.9 | 22.9 | 22.3 | 21.4 | 22.7 | 22.4 | 23.0 | 20.8 | 24.0 |
| | 0.01 | 26.3 | 21.9 | 26.1 | 21.7 | 25.4 | 21.2 | 25.4 | 21.8 | 24.4 | 22.4 | 25.4 | 22.8 | 23.4 | 23.1 |
| 0.02 | 0.05 | 20.2 | 22.4 | 16.2 | 21.3 | 16.0 | 21.0 | 15.3 | 21.5 | 15.5 | 22.1 | 15.3 | 22.1 | 14.3 | 23.4 |
| | 0.02 | 23.9 | 22.2 | 22.3 | 21.8 | 22.2 | 21.2 | 22.8 | 21.8 | 20.7 | 22.7 | 22.3 | 22.1 | 20.8 | 23.2 |
| | 0.01 | 26.4 | 23.0 | 25.7 | 22.5 | 25.3 | 21.8 | 25.5 | 22.7 | 24.4 | 23.2 | 25.5 | 23.1 | 23.2 | 23.1 |
| 0.05 | 0.05 | 20.2 | 22.1 | 15.7 | 21.8 | 16.1 | 20.8 | 15.4 | 21.6 | 14.8 | 22.2 | 14.9 | 23.4 | 13.7 | 23.6 |
| | 0.02 | 23.6 | 21.4 | 22.4 | 21.4 | 22.1 | 19.9 | 21.8 | 21.0 | 21.0 | 21.5 | 22.4 | 23.0 | 20.9 | 23.2 |
| | 0.01 | 26.8 | 22.2 | 26.0 | 21.5 | 26.6 | 20.8 | 26.2 | 21.2 | 25.7 | 21.8 | 24.6 | 22.7 | 23.4 | 23.0 |
| 0.1 | 0.05 | 20.6 | 21.3 | 16.5 | 20.7 | 17.2 | 19.4 | 16.1 | 21.0 | 15.8 | 20.8 | 16.2 | 21.5 | 14.6 | 22.2 |
| | 0.02 | 25.6 | 21.3 | 24.6 | 21.0 | 25.0 | 19.6 | 24.3 | 21.1 | 23.7 | 21.3 | 23.3 | 21.0 | 22.2 | 21.8 |
| | 0.01 | 27.4 | 21.7 | 27.6 | 21.3 | 28.2 | 19.8 | 27.2 | 21.2 | 27.4 | 21.2 | 26.3 | 20.8 | 25.3 | 22.4 |

2836

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 20.5 | 25.3 | 16.2 | 25.3 | 16.3 | 24.9 | 17.1 | 25.2 | 16.0 | 26.1 | 17.3 | 25.2 | 19.6 | 26.3 |
| | 0.02 | 22.1 | 24.8 | 20.4 | 25.4 | 21.5 | 25.0 | 20.4 | 25.3 | 19.8 | 26.0 | 21.2 | 24.8 | 21.7 | 26.3 |
| | 0.01 | 23.5 | 24.8 | 22.1 | 25.5 | 23.1 | 24.7 | 22.0 | 25.3 | 21.5 | 25.9 | 23.5 | 24.8 | 21.8 | 26.4 |
| 0.01 | 0.05 | 20.9 | 24.7 | 16.5 | 25.2 | 16.6 | 24.9 | 17.0 | 25.3 | 16.2 | 26.4 | 17.7 | 25.4 | 19.0 | 26.3 |
| | 0.02 | 23.1 | 25.4 | 21.1 | 25.2 | 21.9 | 24.9 | 21.2 | 25.3 | 20.3 | 25.9 | 22.2 | 25.6 | 21.6 | 26.4 |
| | 0.01 | 24.0 | 24.5 | 22.7 | 24.6 | 23.4 | 24.1 | 22.3 | 24.8 | 21.7 | 25.3 | 22.9 | 24.1 | 22.1 | 25.8 |
| 0.02 | 0.05 | 20.7 | 24.9 | 16.1 | 24.9 | 16.7 | 24.7 | 17.0 | 24.9 | 15.8 | 25.7 | 17.9 | 24.8 | 19.5 | 26.1 |
| | 0.02 | 22.3 | 25.3 | 20.3 | 25.4 | 21.8 | 25.3 | 20.8 | 25.7 | 20.1 | 26.1 | 22.4 | 24.7 | 22.1 | 25.5 |
| | 0.01 | 23.9 | 26.2 | 21.6 | 25.8 | 23.0 | 24.8 | 21.3 | 25.1 | 21.5 | 26.4 | 23.5 | 25.0 | 22.5 | 25.9 |
| 0.05 | 0.05 | 20.1 | 25.0 | 16.9 | 25.4 | 16.7 | 24.7 | 17.2 | 25.2 | 16.0 | 26.2 | 17.3 | 24.9 | 19.4 | 25.8 |
| | 0.02 | 23.2 | 24.8 | 20.9 | 24.2 | 22.5 | 24.0 | 21.3 | 24.5 | 20.3 | 24.7 | 21.0 | 25.8 | 20.8 | 25.9 |
| | 0.01 | 24.9 | 24.6 | 23.5 | 24.5 | 24.5 | 23.9 | 22.9 | 24.4 | 22.7 | 24.9 | 23.8 | 25.7 | 23.1 | 26.3 |
| 0.1 | 0.05 | 21.0 | 24.3 | 17.8 | 24.8 | 18.1 | 23.5 | 18.5 | 23.9 | 17.5 | 24.6 | 18.8 | 24.0 | 20.8 | 24.1 |
| | 0.02 | 23.9 | 23.5 | 21.9 | 24.0 | 23.4 | 22.8 | 22.2 | 23.3 | 21.8 | 23.5 | 22.2 | 23.4 | 23.3 | 24.6 |
| | 0.01 | 24.0 | 23.7 | 23.7 | 24.6 | 24.3 | 23.5 | 22.8 | 24.0 | 23.2 | 24.2 | 24.3 | 24.1 | 24.1 | 23.8 |

3845

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 20.6 | 23.8 | 16.9 | 24.8 | 16.5 | 25.6 | 17.8 | 24.9 | 16.6 | 25.5 | 17.9 | 24.4 | 14.1 | 25.1 |
| | 0.02 | 23.9 | 24.1 | 21.7 | 24.9 | 20.5 | 25.8 | 21.8 | 25.0 | 21.0 | 25.6 | 22.6 | 24.5 | 19.9 | 25.5 |
| | 0.01 | 24.6 | 25.2 | 23.4 | 25.7 | 22.3 | 26.6 | 22.5 | 25.7 | 22.5 | 26.4 | 23.3 | 24.2 | 22.2 | 25.4 |
| 0.01 | 0.05 | 20.8 | 23.8 | 17.0 | 24.2 | 16.7 | 25.4 | 17.9 | 24.4 | 16.6 | 24.9 | 17.8 | 24.8 | 13.8 | 25.4 |
| | 0.02 | 23.6 | 24.3 | 21.7 | 25.4 | 20.2 | 26.0 | 21.3 | 25.4 | 20.7 | 25.8 | 21.8 | 25.1 | 19.9 | 25.7 |
| | 0.01 | 24.1 | 25.1 | 22.9 | 25.5 | 22.0 | 26.8 | 22.7 | 25.8 | 22.0 | 26.2 | 24.1 | 24.2 | 22.3 | 25.0 |
| 0.02 | 0.05 | 20.2 | 24.1 | 17.0 | 25.0 | 16.6 | 26.2 | 17.4 | 25.6 | 16.8 | 26.3 | 18.3 | 23.7 | 14.0 | 25.8 |
| | 0.02 | 24.0 | 23.9 | 21.8 | 24.3 | 20.2 | 25.3 | 22.0 | 25.1 | 20.7 | 25.2 | 22.8 | 23.9 | 20.0 | 25.2 |
| | 0.01 | 24.8 | 24.0 | 23.5 | 24.3 | 22.8 | 25.8 | 22.9 | 24.6 | 22.8 | 25.6 | 23.8 | 23.7 | 22.5 | 25.2 |
| 0.05 | 0.05 | 20.6 | 24.1 | 17.8 | 23.8 | 17.1 | 25.2 | 18.2 | 24.9 | 16.9 | 24.9 | 16.7 | 25.1 | 14.1 | 25.4 |
| | 0.02 | 24.4 | 23.8 | 22.8 | 23.6 | 21.7 | 25.0 | 22.5 | 24.5 | 21.8 | 24.9 | 21.7 | 23.7 | 19.7 | 26.2 |
| | 0.01 | 24.7 | 24.4 | 24.2 | 24.7 | 23.0 | 25.8 | 23.8 | 25.3 | 23.3 | 25.7 | 22.8 | 25.1 | 22.1 | 25.5 |
| 0.1 | 0.05 | 21.4 | 22.5 | 18.3 | 22.1 | 17.6 | 23.6 | 18.0 | 22.8 | 17.4 | 23.3 | 18.7 | 23.6 | 15.4 | 24.0 |
| | 0.02 | 24.7 | 23.7 | 23.6 | 23.5 | 22.6 | 24.7 | 23.0 | 24.1 | 22.4 | 24.6 | 23.2 | 23.0 | 21.8 | 23.6 |
| | 0.01 | 25.3 | 23.0 | 24.8 | 22.7 | 24.0 | 23.8 | 24.1 | 23.4 | 23.8 | 23.7 | 26.0 | 23.6 | 24.3 | 24.1 |

4931

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 14.4 | 26.4 | 13.6 | 25.4 | 13.8 | 26.4 | 13.1 | 25.4 | 13.8 | 25.5 | 13.8 | 26.6 | 11.8 | 28.2 |
| | 0.02 | 19.3 | 26.1 | 20.1 | 25.4 | 19.6 | 26.3 | 19.7 | 25.2 | 20.3 | 25.3 | 18.8 | 26.7 | 16.9 | 28.5 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 21.4 | 26.6 | 22.4 | 25.6 | 21.6 | 26.5 | 22.0 | 25.6 | 22.1 | 25.4 | 20.5 | 26.9 | 19.2 | 28.4 |
| 0.01 | 0.05 | 14.4 | 25.9 | 13.7 | 25.1 | 14.0 | 25.7 | 13.4 | 25.0 | 14.0 | 25.0 | 13.9 | 26.7 | 12.3 | 28.3 |
| | 0.02 | 19.4 | 26.4 | 20.2 | 25.4 | 19.6 | 26.3 | 19.8 | 25.3 | 20.3 | 25.3 | 19.3 | 26.3 | 17.1 | 28.3 |
| | 0.01 | 21.8 | 25.9 | 22.8 | 25.0 | 22.3 | 26.0 | 22.5 | 25.1 | 22.8 | 25.0 | 20.8 | 26.5 | 19.7 | 28.1 |
| 0.02 | 0.05 | 14.7 | 26.1 | 14.0 | 24.8 | 14.4 | 25.9 | 13.6 | 25.1 | 14.3 | 24.8 | 14.2 | 26.7 | 12.0 | 28.0 |
| | 0.02 | 19.6 | 26.1 | 20.2 | 24.9 | 19.6 | 25.8 | 20.0 | 25.1 | 20.3 | 24.9 | 19.5 | 26.2 | 17.4 | 27.9 |
| | 0.01 | 21.9 | 25.9 | 22.7 | 24.7 | 22.2 | 25.9 | 22.5 | 24.9 | 22.8 | 24.9 | 20.8 | 26.3 | 19.5 | 27.8 |
| 0.05 | 0.05 | 15.1 | 25.5 | 14.8 | 24.2 | 14.9 | 25.0 | 14.4 | 24.4 | 14.8 | 24.3 | 13.9 | 26.9 | 12.0 | 28.6 |
| | 0.02 | 20.2 | 25.7 | 21.0 | 24.5 | 20.4 | 25.4 | 20.7 | 24.8 | 21.1 | 24.7 | 19.1 | 27.1 | 17.0 | 28.6 |
| | 0.01 | 22.2 | 25.4 | 23.0 | 24.2 | 22.3 | 25.0 | 22.9 | 24.7 | 23.2 | 24.3 | 20.9 | 26.8 | 19.6 | 28.2 |
| 0.1 | 0.05 | 15.7 | 24.9 | 15.3 | 23.1 | 15.5 | 24.0 | 14.7 | 23.5 | 15.3 | 23.2 | 15.1 | 24.5 | 13.5 | 26.5 |
| | 0.02 | 21.4 | 25.1 | 21.9 | 23.4 | 21.3 | 24.3 | 21.4 | 23.8 | 22.1 | 23.3 | 20.7 | 24.5 | 18.6 | 26.7 |
| | 0.01 | 23.5 | 25.1 | 24.0 | 23.3 | 23.5 | 24.3 | 23.7 | 23.8 | 24.1 | 23.4 | 22.9 | 24.3 | 21.1 | 26.7 |

## Appendix D.

### The Evaluation of Error Detection in Cost of Goods Sold Account for The Rest of SIC Codes

1311

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 22.6 | 24.5 | 20.6 | 25.4 | 20.5 | 25.4 | 21.0 | 25.0 | 20.4 | 25.5 | 20.7 | 25.4 | 21.0 | 25.6 |
| | 0.02 | 24.1 | 24.5 | 22.7 | 25.3 | 22.4 | 25.4 | 22.9 | 25.0 | 22.4 | 25.5 | 23.1 | 25.4 | 22.7 | 25.7 |
| | 0.01 | 24.8 | 24.6 | 23.7 | 25.4 | 23.4 | 25.5 | 23.9 | 25.1 | 23.1 | 25.5 | 23.9 | 25.1 | 23.5 | 25.9 |
| 0.01 | 0.05 | 22.9 | 24.4 | 21.0 | 25.3 | 21.0 | 25.1 | 21.4 | 24.9 | 20.8 | 25.3 | 21.4 | 25.2 | 21.3 | 25.3 |
| | 0.02 | 24.4 | 24.6 | 23.1 | 25.4 | 22.9 | 25.4 | 23.3 | 25.0 | 22.7 | 25.4 | 22.9 | 25.1 | 23.1 | 25.2 |
| | 0.01 | 24.9 | 24.4 | 23.9 | 25.2 | 23.7 | 25.1 | 24.3 | 24.9 | 23.6 | 25.3 | 24.2 | 25.3 | 24.1 | 25.5 |
| 0.02 | 0.05 | 22.8 | 24.3 | 21.1 | 24.9 | 21.1 | 24.9 | 21.7 | 24.7 | 20.9 | 24.9 | 21.6 | 24.8 | 21.4 | 25.1 |
| | 0.02 | 24.7 | 24.4 | 23.5 | 25.2 | 23.2 | 25.1 | 23.7 | 24.9 | 23.2 | 25.3 | 23.6 | 24.5 | 23.3 | 24.8 |
| | 0.01 | 25.0 | 24.5 | 24.2 | 25.2 | 23.8 | 25.0 | 24.3 | 24.8 | 23.9 | 25.3 | 24.0 | 24.8 | 24.4 | 24.9 |
| 0.05 | 0.05 | 23.2 | 23.8 | 21.8 | 24.1 | 22.1 | 24.0 | 22.3 | 23.8 | 21.8 | 24.3 | 20.7 | 25.1 | 20.9 | 25.6 |
| | 0.02 | 24.7 | 24.1 | 24.1 | 24.5 | 23.8 | 24.2 | 24.3 | 24.2 | 23.7 | 24.4 | 23.0 | 25.1 | 22.9 | 25.6 |
| | 0.01 | 25.6 | 24.0 | 25.1 | 24.2 | 25.0 | 24.2 | 25.3 | 23.8 | 25.1 | 24.3 | 23.6 | 25.4 | 23.6 | 25.7 |
| 0.1 | 0.05 | 23.9 | 22.9 | 23.0 | 22.8 | 23.1 | 22.7 | 23.4 | 22.8 | 23.0 | 23.0 | 23.4 | 22.9 | 23.1 | 23.3 |
| | 0.02 | 25.5 | 23.0 | 25.1 | 22.8 | 25.2 | 22.9 | 25.4 | 23.0 | 25.0 | 23.1 | 25.6 | 22.7 | 25.4 | 23.4 |
| | 0.01 | 26.5 | 22.7 | 26.4 | 22.8 | 26.3 | 22.6 | 26.5 | 22.7 | 26.3 | 22.9 | 26.5 | 22.8 | 25.9 | 23.0 |

7370

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 21.1 | 24.0 | 17.2 | 25.5 | 17.7 | 24.4 | 18.4 | 25.1 | 16.9 | 25.9 | 17.6 | 24.4 | 17.3 | 24.7 |
| | 0.02 | 23.8 | 24.2 | 21.4 | 25.6 | 21.7 | 24.6 | 22.2 | 25.4 | 20.9 | 26.1 | 21.9 | 25.2 | 22.0 | 24.5 |
| | 0.01 | 24.6 | 23.6 | 22.7 | 25.1 | 23.3 | 23.8 | 23.7 | 24.7 | 22.5 | 25.6 | 23.3 | 24.5 | 23.7 | 24.5 |
| 0.01 | 0.05 | 20.5 | 24.0 | 16.3 | 25.0 | 16.8 | 24.0 | 17.7 | 24.7 | 15.9 | 25.6 | 17.7 | 24.4 | 17.5 | 24.0 |
| | 0.02 | 23.8 | 24.2 | 21.2 | 25.2 | 21.7 | 24.3 | 22.1 | 25.0 | 20.8 | 25.8 | 22.3 | 24.3 | 21.6 | 24.2 |
| | 0.01 | 25.4 | 24.1 | 23.2 | 25.1 | 23.9 | 24.0 | 24.1 | 24.7 | 22.9 | 25.6 | 23.7 | 24.7 | 24.2 | 24.2 |
| 0.02 | 0.05 | 21.0 | 24.3 | 17.0 | 25.5 | 17.6 | 24.5 | 18.5 | 25.1 | 16.6 | 25.9 | 17.8 | 23.7 | 17.5 | 24.4 |
| | 0.02 | 23.9 | 23.9 | 21.4 | 24.9 | 21.9 | 23.9 | 22.1 | 24.3 | 21.1 | 25.3 | 22.7 | 23.9 | 22.2 | 24.3 |
| | 0.01 | 25.0 | 24.0 | 22.9 | 24.8 | 23.8 | 24.1 | 23.8 | 24.6 | 22.6 | 25.3 | 24.6 | 24.2 | 24.3 | 24.5 |
| 0.05 | 0.05 | 20.9 | 23.3 | 17.1 | 23.9 | 17.7 | 23.3 | 18.5 | 23.7 | 16.9 | 24.6 | 17.6 | 24.8 | 17.1 | 24.2 |
| | 0.02 | 24.2 | 23.8 | 22.0 | 24.5 | 22.4 | 23.7 | 22.6 | 24.2 | 21.7 | 25.0 | 21.9 | 25.0 | 21.7 | 24.4 |
| | 0.01 | 25.1 | 23.9 | 23.6 | 24.8 | 24.1 | 24.0 | 24.1 | 24.4 | 23.1 | 25.3 | 23.3 | 24.5 | 23.7 | 24.3 |
| 0.1 | 0.05 | 21.6 | 22.9 | 18.1 | 23.5 | 19.0 | 22.7 | 19.7 | 23.1 | 17.8 | 23.8 | 19.2 | 23.3 | 18.8 | 23.0 |
| | 0.02 | 25.2 | 23.1 | 22.8 | 23.7 | 23.6 | 22.8 | 23.6 | 23.1 | 22.7 | 24.1 | 23.7 | 22.5 | 23.3 | 23.0 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 26.0 | 23.1 | 24.6 | 23.7 | 25.2 | 22.7 | 24.9 | 23.1 | 24.2 | 24.0 | 25.4 | 23.6 | 25.3 | 23.1 |

| 2834 s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 22.3 | 22.7 | 19.0 | 25.1 | 20.6 | 23.0 | 19.5 | 24.8 | 18.9 | 25.1 | 19.4 | 24.1 | 19.2 | 24.9 |
| | 0.02 | 25.3 | 22.9 | 22.8 | 25.1 | 25.3 | 23.2 | 23.3 | 25.0 | 23.2 | 25.1 | 23.0 | 24.1 | 22.0 | 25.3 |
| | 0.01 | 26.4 | 22.6 | 24.0 | 24.9 | 26.4 | 22.9 | 24.5 | 24.7 | 24.5 | 24.9 | 24.2 | 24.5 | 23.1 | 24.5 |
| 0.01 | 0.05 | 22.1 | 22.0 | 18.6 | 24.1 | 20.5 | 22.2 | 19.2 | 24.2 | 18.5 | 24.0 | 19.3 | 23.3 | 19.1 | 24.9 |
| | 0.02 | 25.1 | 22.3 | 22.0 | 24.2 | 24.6 | 22.3 | 23.0 | 24.4 | 22.3 | 24.0 | 23.5 | 24.2 | 22.6 | 25.4 |
| | 0.01 | 26.0 | 23.3 | 23.5 | 25.1 | 25.9 | 23.4 | 24.0 | 25.4 | 23.7 | 25.2 | 24.3 | 23.5 | 23.7 | 24.7 |
| 0.02 | 0.05 | 22.2 | 22.4 | 18.7 | 24.0 | 20.3 | 22.5 | 19.3 | 24.2 | 18.8 | 24.1 | 19.4 | 23.9 | 19.4 | 24.7 |
| | 0.02 | 25.3 | 22.7 | 22.8 | 24.8 | 25.5 | 23.5 | 23.4 | 25.4 | 23.1 | 25.0 | 23.0 | 24.0 | 22.9 | 24.4 |
| | 0.01 | 26.0 | 22.7 | 23.7 | 24.5 | 26.1 | 22.9 | 24.3 | 25.0 | 24.2 | 24.9 | 24.8 | 24.0 | 24.1 | 24.5 |
| 0.05 | 0.05 | 22.3 | 22.3 | 19.2 | 23.8 | 21.0 | 22.3 | 19.7 | 24.1 | 19.4 | 24.1 | 19.4 | 24.3 | 18.9 | 25.0 |
| | 0.02 | 25.3 | 22.3 | 22.8 | 24.2 | 25.8 | 22.9 | 23.9 | 24.7 | 23.4 | 24.5 | 22.9 | 23.9 | 22.3 | 24.8 |
| | 0.01 | 26.4 | 22.2 | 24.5 | 23.9 | 26.8 | 22.7 | 24.9 | 24.5 | 24.8 | 24.1 | 23.9 | 23.9 | 23.8 | 25.0 |
| 0.1 | 0.05 | 23.6 | 22.3 | 20.6 | 23.3 | 22.4 | 22.3 | 20.9 | 23.7 | 20.5 | 23.3 | 20.5 | 21.9 | 20.6 | 23.1 |
| | 0.02 | 26.5 | 21.7 | 24.0 | 22.6 | 26.0 | 21.4 | 24.6 | 22.9 | 23.7 | 22.0 | 24.7 | 21.7 | 23.8 | 22.7 |
| | 0.01 | 27.4 | 21.6 | 25.7 | 22.6 | 27.3 | 21.7 | 25.4 | 22.8 | 25.4 | 22.5 | 26.3 | 22.3 | 24.5 | 22.8 |

| 3674 s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 17.2 | 26.9 | 15.1 | 27.1 | 15.7 | 26.5 | 15.4 | 26.7 | 15.2 | 27.0 | 14.7 | 28.0 | 15.2 | 27.4 |
| | 0.02 | 20.7 | 26.8 | 19.1 | 26.8 | 20.1 | 26.3 | 19.8 | 26.5 | 19.6 | 26.8 | 19.3 | 27.9 | 19.8 | 27.3 |
| | 0.01 | 21.6 | 27.3 | 21.0 | 27.4 | 21.4 | 26.7 | 21.4 | 26.9 | 21.0 | 27.4 | 20.6 | 28.0 | 20.8 | 27.0 |
| 0.01 | 0.05 | 17.4 | 27.0 | 15.3 | 27.1 | 15.9 | 26.4 | 15.7 | 26.8 | 15.5 | 27.1 | 15.1 | 27.6 | 15.5 | 26.9 |
| | 0.02 | 21.0 | 26.8 | 19.5 | 26.7 | 20.3 | 26.2 | 20.2 | 26.3 | 19.8 | 26.7 | 19.1 | 27.5 | 19.4 | 26.9 |
| | 0.01 | 22.1 | 27.0 | 21.5 | 26.8 | 22.0 | 26.3 | 21.8 | 26.4 | 21.4 | 26.8 | 20.8 | 27.5 | 21.3 | 27.0 |
| 0.02 | 0.05 | 17.5 | 26.9 | 15.2 | 26.6 | 16.0 | 26.1 | 15.6 | 26.3 | 15.4 | 26.6 | 15.0 | 27.4 | 15.7 | 27.0 |
| | 0.02 | 21.2 | 27.3 | 19.5 | 26.8 | 20.2 | 26.3 | 20.3 | 26.5 | 19.9 | 26.7 | 19.3 | 27.3 | 19.8 | 26.6 |
| | 0.01 | 21.8 | 27.0 | 21.3 | 26.9 | 21.9 | 26.4 | 21.9 | 26.6 | 21.2 | 26.8 | 20.3 | 27.5 | 21.3 | 27.2 |
| 0.05 | 0.05 | 18.1 | 26.5 | 16.0 | 26.1 | 16.8 | 25.6 | 16.2 | 25.8 | 16.2 | 26.0 | 14.5 | 28.0 | 15.2 | 27.0 |
| | 0.02 | 21.3 | 26.3 | 20.1 | 25.9 | 21.0 | 25.3 | 20.8 | 25.6 | 20.3 | 25.7 | 19.5 | 28.0 | 19.7 | 27.1 |
| | 0.01 | 22.1 | 26.3 | 22.0 | 26.2 | 22.5 | 25.6 | 22.4 | 25.8 | 21.9 | 26.0 | 20.8 | 28.1 | 21.2 | 27.2 |
| 0.1 | 0.05 | 18.2 | 26.0 | 16.4 | 25.8 | 17.4 | 25.1 | 16.7 | 25.4 | 16.6 | 25.3 | 16.2 | 25.4 | 16.9 | 25.4 |
| | 0.02 | 22.0 | 25.7 | 21.5 | 25.5 | 22.1 | 24.9 | 21.8 | 25.2 | 21.5 | 25.0 | 20.6 | 26.0 | 21.3 | 25.3 |
| | 0.01 | 22.9 | 25.9 | 22.8 | 25.7 | 23.4 | 24.9 | 23.3 | 25.4 | 22.8 | 25.2 | 22.4 | 25.9 | 23.0 | 25.3 |

4911

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 18.0 | 26.1 | 16.2 | 26.0 | 16.1 | 26.2 | 16.3 | 25.9 | 16.0 | 26.1 | 16.1 | 26.7 | 14.8 | 27.4 |
| | 0.02 | 21.3 | 26.2 | 20.6 | 26.1 | 20.3 | 26.5 | 20.6 | 26.0 | 20.5 | 26.2 | 20.4 | 26.7 | 19.4 | 27.4 |
| | 0.01 | 22.6 | 26.3 | 22.3 | 26.2 | 21.9 | 26.5 | 22.3 | 26.1 | 22.0 | 26.3 | 21.8 | 26.8 | 21.0 | 27.4 |
| 0.01 | 0.05 | 18.2 | 26.0 | 16.3 | 25.7 | 16.3 | 26.1 | 16.5 | 25.7 | 16.1 | 25.9 | 16.3 | 26.6 | 15.2 | 27.5 |
| | 0.02 | 21.3 | 26.1 | 20.7 | 26.0 | 20.2 | 26.3 | 20.7 | 26.0 | 20.5 | 26.1 | 20.4 | 26.4 | 19.4 | 27.4 |
| | 0.01 | 22.9 | 26.1 | 22.5 | 25.9 | 22.3 | 26.3 | 22.7 | 25.9 | 22.4 | 26.0 | 22.1 | 26.7 | 21.2 | 27.2 |
| 0.02 | 0.05 | 18.3 | 26.0 | 16.6 | 25.8 | 16.6 | 26.1 | 16.7 | 25.7 | 16.3 | 25.9 | 16.6 | 26.2 | 15.1 | 27.2 |
| | 0.02 | 21.5 | 26.1 | 20.9 | 25.9 | 20.6 | 26.2 | 20.9 | 25.8 | 20.8 | 26.0 | 20.8 | 26.5 | 19.6 | 27.2 |
| | 0.01 | 22.9 | 25.9 | 22.6 | 25.7 | 22.3 | 26.1 | 22.6 | 25.6 | 22.5 | 25.8 | 22.3 | 26.3 | 21.3 | 27.1 |
| 0.05 | 0.05 | 18.6 | 25.3 | 17.0 | 25.1 | 17.0 | 25.5 | 17.1 | 25.1 | 16.7 | 25.2 | 16.1 | 26.7 | 14.8 | 27.6 |
| | 0.02 | 21.8 | 25.5 | 21.2 | 25.2 | 21.0 | 25.7 | 21.4 | 25.2 | 21.1 | 25.4 | 20.3 | 26.8 | 19.4 | 27.5 |
| | 0.01 | 23.3 | 25.6 | 23.1 | 25.3 | 22.8 | 25.7 | 23.1 | 25.2 | 22.9 | 25.4 | 21.9 | 26.5 | 21.0 | 27.5 |
| 0.1 | 0.05 | 19.6 | 24.8 | 18.1 | 24.2 | 18.0 | 24.8 | 18.2 | 24.1 | 17.8 | 24.6 | 18.1 | 24.9 | 16.4 | 25.7 |
| | 0.02 | 22.8 | 24.9 | 22.3 | 24.3 | 22.1 | 24.9 | 22.5 | 24.3 | 22.1 | 24.5 | 22.1 | 25.0 | 20.9 | 25.7 |
| | 0.01 | 24.0 | 24.7 | 24.1 | 24.1 | 23.7 | 24.6 | 24.1 | 24.0 | 23.9 | 24.3 | 23.8 | 25.0 | 22.4 | 25.6 |

5812

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 17.4 | 22.4 | 14.5 | 23.5 | 15.5 | 23.0 | 14.9 | 22.4 | 14.8 | 23.5 | 13.9 | 24.4 | 13.5 | 24.8 |
| | 0.02 | 23.3 | 24.0 | 21.3 | 24.7 | 22.5 | 24.4 | 22.5 | 23.8 | 21.0 | 24.6 | 21.7 | 24.2 | 19.7 | 24.2 |
| | 0.01 | 25.6 | 23.1 | 23.8 | 23.5 | 23.8 | 23.1 | 24.4 | 22.3 | 23.3 | 23.4 | 23.9 | 24.7 | 22.1 | 24.9 |
| 0.01 | 0.05 | 17.7 | 22.8 | 14.7 | 23.4 | 15.9 | 23.3 | 15.4 | 22.9 | 14.6 | 23.9 | 14.2 | 23.4 | 13.0 | 24.6 |
| | 0.02 | 22.0 | 23.0 | 20.9 | 23.7 | 21.1 | 23.7 | 21.9 | 23.3 | 20.0 | 24.2 | 20.7 | 24.0 | 19.5 | 25.4 |
| | 0.01 | 25.7 | 22.7 | 24.2 | 23.2 | 24.3 | 23.2 | 25.1 | 22.6 | 24.0 | 23.6 | 24.1 | 24.0 | 22.1 | 24.4 |
| 0.02 | 0.05 | 17.8 | 22.4 | 14.7 | 22.9 | 16.3 | 22.9 | 15.2 | 22.0 | 14.9 | 23.3 | 14.4 | 23.2 | 13.9 | 24.6 |
| | 0.02 | 22.9 | 22.7 | 21.8 | 23.5 | 22.2 | 23.5 | 22.9 | 22.8 | 21.0 | 24.0 | 22.5 | 23.6 | 19.9 | 24.4 |
| | 0.01 | 25.6 | 23.1 | 23.8 | 23.4 | 23.7 | 23.4 | 24.4 | 22.7 | 23.5 | 23.9 | 24.5 | 23.3 | 21.8 | 24.3 |
| 0.05 | 0.05 | 18.8 | 22.4 | 15.8 | 23.2 | 16.6 | 22.8 | 16.2 | 22.1 | 15.3 | 23.3 | 14.0 | 23.4 | 13.4 | 24.8 |
| | 0.02 | 24.4 | 22.1 | 23.0 | 22.9 | 23.4 | 22.8 | 24.2 | 21.7 | 22.0 | 23.1 | 21.9 | 24.1 | 19.9 | 24.7 |
| | 0.01 | 25.6 | 22.4 | 24.2 | 23.1 | 24.4 | 23.1 | 25.0 | 22.0 | 23.7 | 23.6 | 24.2 | 24.5 | 22.1 | 24.5 |
| 0.1 | 0.05 | 19.1 | 21.3 | 16.3 | 21.9 | 16.7 | 21.6 | 17.0 | 20.8 | 15.9 | 22.7 | 14.5 | 23.2 | 14.0 | 23.1 |
| | 0.02 | 24.5 | 22.1 | 22.9 | 22.5 | 22.8 | 22.3 | 24.4 | 21.4 | 21.9 | 23.3 | 23.6 | 22.5 | 20.9 | 23.1 |
| | 0.01 | 26.8 | 21.8 | 25.4 | 22.2 | 25.4 | 21.9 | 26.8 | 21.0 | 25.2 | 22.9 | 26.0 | 22.2 | 23.7 | 23.4 |

2836

| s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0.05 | 16.4 | 27.6 | 16.6 | 25.9 | 14.4 | 26.7 | 16.5 | 26.3 | 15.4 | 26.1 | 16.3 | 28.7 | 16.5 | 26.6 |
| | 0.02 | 18.8 | 28.3 | 20.6 | 26.4 | 19.5 | 27.0 | 20.8 | 26.8 | 19.8 | 26.3 | 20.5 | 27.9 | 20.1 | 26.7 |
| | 0.01 | 19.5 | 26.2 | 21.6 | 25.1 | 20.2 | 25.3 | 21.4 | 25.5 | 20.6 | 25.3 | 21.1 | 27.9 | 21.4 | 27.0 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.01 | 0.05 | 15.3 | 27.4 | 15.9 | 26.2 | 13.7 | 26.6 | 15.8 | 26.5 | 14.6 | 26.5 | 16.1 | 27.2 | 16.6 | 27.4 |
| | 0.02 | 18.8 | 27.7 | 20.2 | 26.0 | 19.5 | 26.9 | 21.1 | 26.7 | 19.5 | 26.5 | 19.0 | 27.1 | 20.3 | 26.6 |
| | 0.01 | 20.4 | 28.1 | 22.3 | 26.6 | 21.5 | 27.5 | 22.0 | 27.2 | 21.5 | 27.1 | 20.1 | 27.8 | 21.8 | 26.6 |
| 0.02 | 0.05 | 16.2 | 27.3 | 16.6 | 25.8 | 14.6 | 26.5 | 16.3 | 26.4 | 15.3 | 26.0 | 16.9 | 27.2 | 17.4 | 27.2 |
| | 0.02 | 19.2 | 27.0 | 20.8 | 25.9 | 19.7 | 26.4 | 21.4 | 26.3 | 20.0 | 26.3 | 19.5 | 27.8 | 20.9 | 26.7 |
| | 0.01 | 20.6 | 28.6 | 22.5 | 27.0 | 21.8 | 27.8 | 22.2 | 27.7 | 22.0 | 27.5 | 21.2 | 27.7 | 21.9 | 26.7 |
| 0.05 | 0.05 | 16.3 | 27.2 | 16.8 | 25.6 | 14.9 | 25.6 | 16.4 | 26.4 | 15.3 | 25.7 | 16.1 | 27.5 | 16.8 | 26.5 |
| | 0.02 | 19.1 | 27.5 | 20.9 | 25.9 | 19.7 | 25.7 | 21.2 | 26.5 | 20.3 | 25.7 | 19.3 | 28.2 | 20.2 | 27.2 |
| | 0.01 | 21.4 | 27.3 | 23.3 | 25.6 | 22.5 | 25.5 | 22.5 | 26.1 | 22.7 | 25.7 | 20.4 | 28.2 | 22.2 | 26.3 |
| 0.1 | 0.05 | 17.1 | 26.4 | 17.9 | 25.0 | 16.3 | 24.9 | 17.9 | 25.4 | 16.8 | 25.2 | 18.4 | 27.1 | 18.5 | 24.9 |
| | 0.02 | 20.8 | 26.6 | 22.3 | 24.8 | 21.5 | 24.7 | 22.4 | 25.4 | 21.6 | 24.8 | 20.5 | 27.0 | 22.4 | 25.6 |
| | 0.01 | 22.3 | 26.4 | 24.0 | 25.0 | 23.5 | 24.6 | 23.5 | 25.4 | 23.7 | 25.0 | 21.6 | 26.2 | 24.0 | 25.0 |
| 3845 s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
| 0 | 0.05 | 21.0 | 26.5 | 18.1 | 27.2 | 18.9 | 25.4 | 18.4 | 26.3 | 18.4 | 25.9 | 18.7 | 26.7 | 15.7 | 26.5 |
| | 0.02 | 22.6 | 26.9 | 20.8 | 27.8 | 22.0 | 25.7 | 21.5 | 27.0 | 21.4 | 26.6 | 20.5 | 26.5 | 19.4 | 27.3 |
| | 0.01 | 22.5 | 26.4 | 21.4 | 27.6 | 22.9 | 25.6 | 21.7 | 26.5 | 21.9 | 26.2 | 21.8 | 26.8 | 21.0 | 26.9 |
| 0.01 | 0.05 | 21.1 | 26.5 | 18.7 | 27.5 | 19.2 | 25.6 | 18.8 | 26.8 | 18.5 | 26.4 | 18.5 | 27.0 | 15.6 | 27.3 |
| | 0.02 | 22.1 | 27.0 | 20.0 | 27.3 | 21.6 | 25.6 | 20.6 | 26.7 | 20.6 | 26.3 | 21.0 | 27.5 | 19.5 | 27.7 |
| | 0.01 | 23.1 | 26.2 | 21.9 | 27.3 | 23.4 | 25.3 | 22.2 | 26.3 | 22.7 | 26.2 | 21.9 | 26.1 | 21.1 | 27.2 |
| 0.02 | 0.05 | 21.8 | 26.7 | 19.2 | 27.4 | 19.5 | 25.6 | 19.2 | 26.6 | 19.0 | 26.6 | 19.1 | 25.9 | 15.6 | 27.7 |
| | 0.02 | 22.2 | 26.0 | 20.9 | 26.4 | 22.6 | 25.0 | 21.3 | 26.2 | 21.5 | 26.1 | 21.5 | 27.0 | 19.7 | 27.2 |
| | 0.01 | 23.1 | 26.4 | 21.0 | 26.4 | 23.3 | 25.2 | 22.1 | 26.4 | 22.6 | 26.1 | 22.7 | 26.1 | 21.2 | 26.9 |
| 0.05 | 0.05 | 21.5 | 25.9 | 19.0 | 27.0 | 19.8 | 24.5 | 19.2 | 26.2 | 19.1 | 25.9 | 18.8 | 26.4 | 15.6 | 27.2 |
| | 0.02 | 22.3 | 26.1 | 21.0 | 26.8 | 22.7 | 24.9 | 21.0 | 26.0 | 22.0 | 26.1 | 21.3 | 27.0 | 19.0 | 27.5 |
| | 0.01 | 23.6 | 25.7 | 21.8 | 26.3 | 23.4 | 23.9 | 22.7 | 25.7 | 22.9 | 25.2 | 21.4 | 26.7 | 21.2 | 27.3 |
| 0.1 | 0.05 | 21.8 | 25.1 | 19.7 | 25.9 | 20.2 | 23.9 | 20.1 | 24.9 | 20.0 | 24.8 | 20.1 | 25.3 | 16.3 | 25.1 |
| | 0.02 | 24.4 | 25.6 | 22.5 | 25.9 | 24.4 | 24.2 | 23.3 | 25.1 | 23.4 | 24.8 | 22.5 | 25.3 | 20.8 | 25.3 |
| | 0.01 | 24.0 | 24.7 | 22.8 | 25.3 | 24.5 | 23.1 | 23.8 | 24.3 | 23.5 | 24.1 | 23.9 | 25.9 | 22.8 | 25.7 |
| 4931 s | e | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_e | FP_e | FN_m | FP_m | FN_n | FP_n | FN_a | FP_a |
| 0 | 0.05 | 15.4 | 26.8 | 14.7 | 25.8 | 15.2 | 26.3 | 15.5 | 24.6 | 14.9 | 25.8 | 14.7 | 27.1 | 13.4 | 27.5 |
| | 0.02 | 19.6 | 27.2 | 20.1 | 26.0 | 20.2 | 26.4 | 21.1 | 24.7 | 20.2 | 25.9 | 19.7 | 26.7 | 18.5 | 27.7 |
| | 0.01 | 21.3 | 27.0 | 21.9 | 26.0 | 22.0 | 26.5 | 23.2 | 24.6 | 22.0 | 25.8 | 21.0 | 26.4 | 20.2 | 27.5 |
| 0.01 | 0.05 | 15.5 | 26.6 | 14.8 | 25.6 | 15.0 | 26.1 | 15.4 | 24.2 | 14.9 | 25.6 | 14.6 | 26.6 | 13.8 | 27.4 |
| | 0.02 | 19.9 | 26.9 | 20.5 | 25.7 | 20.5 | 26.2 | 21.2 | 24.3 | 20.5 | 25.7 | 19.9 | 26.9 | 18.6 | 27.6 |
| | 0.01 | 22.0 | 27.4 | 22.5 | 25.9 | 22.5 | 26.6 | 23.6 | 24.7 | 22.6 | 26.0 | 21.7 | 26.8 | 20.7 | 27.3 |
| 0.02 | 0.05 | 15.8 | 26.7 | 14.9 | 25.7 | 15.4 | 26.2 | 15.7 | 24.2 | 15.1 | 25.7 | 15.1 | 26.6 | 13.4 | 27.2 |
| | 0.02 | 19.8 | 26.3 | 20.3 | 25.3 | 20.4 | 26.0 | 21.2 | 24.0 | 20.3 | 25.2 | 19.8 | 26.5 | 19.0 | 27.4 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 21.4 | 26.8 | 22.2 | 25.6 | 22.1 | 26.2 | 23.4 | 24.4 | 22.1 | 25.6 | 21.4 | 26.6 | 20.7 | 27.2 |
| 0.05 | 0.05 | 16.2 | 25.4 | 15.4 | 24.6 | 16.1 | 25.0 | 16.2 | 23.5 | 15.7 | 24.4 | 14.3 | 26.9 | 13.6 | 27.5 |
| | 0.02 | 20.5 | 25.7 | 21.0 | 24.7 | 21.2 | 25.0 | 21.8 | 23.4 | 21.3 | 24.6 | 19.9 | 26.8 | 18.5 | 27.8 |
| | 0.01 | 22.3 | 25.7 | 23.5 | 24.7 | 23.3 | 25.2 | 24.5 | 23.5 | 23.3 | 24.5 | 21.2 | 27.1 | 20.8 | 27.7 |
| 0.1 | 0.05 | 16.9 | 25.0 | 16.6 | 23.8 | 16.9 | 24.1 | 17.0 | 22.6 | 16.6 | 23.7 | 16.2 | 25.1 | 14.9 | 25.8 |
| | 0.02 | 21.6 | 25.4 | 22.1 | 24.0 | 22.1 | 24.4 | 23.1 | 23.0 | 21.7 | 23.8 | 21.4 | 25.2 | 20.2 | 25.7 |
| | 0.01 | 23.3 | 24.9 | 24.3 | 23.6 | 23.8 | 23.8 | 25.2 | 22.4 | 24.0 | 23.5 | 23.1 | 25.2 | 22.2 | 25.8 |

This table displays (overestimating revenues & underestimating cost of goods sold) error detection performance of sharing models (sharing actual, prediction, error, either the sign of predictions and the level of deviations or both of them) and the benchmark model by percentage respectively, with different magnitudes of errors (e: from 1% to 5%) and different significance (s: determined by α) and width of prediction interval (PI) for companies with four digit SIC 7372. The term “FN” represents “False Negative” and FP represents “False Positive”. Additionally, the subscript “o” means original model, and “a”, “p”, “e”, “s”, “l” and “m” are short for “actual”, “prediction”, “error”, “the sign of prediction” “the level of deviation” and “mix” respectively (with the latter indicating sharing both the sign of predictions and the level of deviations).

## SUPPLEMENTARY MATERIALS

As we mentioned in the main body of our paper, with the respect of generality, we remove the strict peer selection criteria that forces peer companies to share common auditors in the current year, expand our sample from ten industries to twenty, and evaluate the utility our proposed privacy-preserving sharing schemes. The expansion is reasonable because of at least two possibilities. In reality, auditors can do a better job in finding peers and thus have a greater possibility to get a bigger set of peer companies for their clients. Additionally, our “sharing common auditors” constraint is based on the Audit Analytics dataset, which limits our sample size.

In section A, we show the evaluation of prediction accuracy and observe that with a larger data sample, the benefits from sharing errors (residuals) are similar to sharing predictions or real account numbers, even after converting numerical residuals to categorical dummies with suitable parameters. In section B, we present the evaluation of error detection in a similar design to Table 9 in the main body of this paper. The expanded choice of best model can be found in Section C.

**Section A.**

A.1 The Evaluation of Prediction Accuracy in Estimating Revenue Account

Panel A. The Comparison of MAPEs among Estimation Models (Industry Mean)

| SIC | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| 7372 | 0.48 | 0.31 | 0.29 | 0.29 | 0.63 | 0.42 | 0.51 | 0.44 | 0.54 |
| 1311 | 0.91 | 0.61 | 0.59 | 0.67 | 0.79 | 0.63 | 0.76 | 0.85 | 1.02 |
| 7370 | 0.42 | 0.29 | 0.28 | 0.30 | 0.56 | 0.38 | 0.29 | 0.40 | 0.28 |
| 2834 | 1.08 | 1.70 | 1.20 | 1.56 | 1.29 | 1.28 | 1.32 | 1.56 | 2.20 |
| 3674 | 0.23 | 0.15 | 0.15 | 0.15 | 0.24 | 0.17 | 0.24 | 0.26 | 0.22 |
| 4911 | 0.17 | 0.12 | 0.13 | 0.12 | 0.20 | 0.15 | 0.19 | 0.17 | 0.18 |
| 5812 | 0.10 | 0.07 | 0.07 | 0.07 | 0.10 | 0.08 | 0.10 | 0.10 | 0.10 |
| 7373 | 0.21 | 0.13 | 0.18 | 0.14 | 0.19 | 0.23 | 0.20 | 0.31 | 0.20 |
| 2836 | 1.51 | 1.09 | 1.06 | 1.20 | 1.17 | 1.11 | 2.16 | 1.79 | 1.68 |
| 3845 | 0.24 | 0.19 | 0.19 | 0.20 | 0.24 | 0.20 | 0.25 | 0.26 | 0.23 |
| 4813 | 0.10 | 0.06 | 0.06 | 0.06 | 0.10 | 0.08 | 0.10 | 0.08 | 0.10 |
| 3663 | 0.23 | 0.17 | 0.17 | 0.17 | 0.22 | 0.18 | 0.25 | 0.22 | 0.23 |
| 4931 | 0.15 | 0.10 | 0.11 | 0.11 | 0.18 | 0.13 | 0.18 | 0.15 | 0.15 |
| 3841 | 0.11 | 0.08 | 0.08 | 0.08 | 0.10 | 0.09 | 0.10 | 0.09 | 0.10 |
| 9995 | 0.84 | 0.55 | 0.45 | 0.52 | 0.73 | 0.48 | 0.71 | 0.60 | 0.63 |
| 7990 | 0.30 | 0.17 | 0.17 | 0.17 | 0.21 | 0.18 | 0.23 | 0.20 | 0.21 |
| 3714 | 0.14 | 0.09 | 0.10 | 0.09 | 0.13 | 0.11 | 0.14 | 0.12 | 0.12 |
| 6331 | 0.14 | 0.10 | 0.10 | 0.09 | 0.14 | 0.12 | 0.17 | 0.13 | 0.13 |
| 6211 | 0.73 | 0.37 | 0.22 | 0.36 | 0.31 | 0.30 | 0.53 | 0.34 | 0.56 |
| 3576 | 0.18 | 0.19 | 0.15 | 0.15 | 0.19 | 0.18 | 0.25 | 0.21 | 0.20 |

Panel B. The Comparison of MAPEs among Estimation Models (Industry Median)

| SIC | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| 7372 | 0.10 | 0.07 | 0.07 | 0.07 | 0.11 | 0.08 | 0.10 | 0.11 | 0.13 |
| 1311 | 0.18 | 0.12 | 0.13 | 0.12 | 0.16 | 0.14 | 0.18 | 0.19 | 0.23 |
| 7370 | 0.09 | 0.06 | 0.06 | 0.06 | 0.08 | 0.07 | 0.08 | 0.09 | 0.09 |
| 2834 | 0.12 | 0.08 | 0.08 | 0.08 | 0.10 | 0.09 | 0.10 | 0.11 | 0.12 |
| 3674 | 0.11 | 0.07 | 0.08 | 0.08 | 0.11 | 0.09 | 0.11 | 0.11 | 0.13 |
| 4911 | 0.09 | 0.06 | 0.07 | 0.06 | 0.11 | 0.08 | 0.10 | 0.09 | 0.11 |
| 5812 | 0.06 | 0.04 | 0.04 | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.06 |
| 7373 | 0.10 | 0.07 | 0.07 | 0.07 | 0.09 | 0.08 | 0.09 | 0.09 | 0.09 |
| 2836 | 0.15 | 0.12 | 0.12 | 0.11 | 0.14 | 0.12 | 0.15 | 0.14 | 0.15 |
| 3845 | 0.10 | 0.07 | 0.07 | 0.07 | 0.10 | 0.08 | 0.10 | 0.09 | 0.09 |
| 4813 | 0.05 | 0.03 | 0.04 | 0.04 | 0.05 | 0.04 | 0.05 | 0.05 | 0.06 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 3663 | 0.12 | 0.09 | 0.09 | 0.09 | 0.11 | 0.10 | 0.12 | 0.12 | 0.13 |
| 4931 | 0.08 | 0.06 | 0.07 | 0.06 | 0.11 | 0.08 | 0.10 | 0.09 | 0.10 |
| 3841 | 0.06 | 0.04 | 0.04 | 0.04 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| 9995 | 0.25 | 0.19 | 0.20 | 0.18 | 0.21 | 0.19 | 0.23 | 0.20 | 0.24 |
| 7990 | 0.09 | 0.07 | 0.07 | 0.07 | 0.08 | 0.07 | 0.09 | 0.08 | 0.09 |
| 3714 | 0.07 | 0.06 | 0.06 | 0.05 | 0.08 | 0.06 | 0.07 | 0.07 | 0.08 |
| 6331 | 0.07 | 0.05 | 0.05 | 0.05 | 0.07 | 0.06 | 0.07 | 0.07 | 0.07 |
| 6211 | 0.11 | 0.08 | 0.08 | 0.08 | 0.10 | 0.08 | 0.10 | 0.10 | 0.10 |
| 3576 | 0.10 | 0.10 | 0.08 | 0.08 | 0.11 | 0.10 | 0.12 | 0.11 | 0.11 |

Panel C. The t-tests of MAPEs among Estimation Models

| 7372 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.046 | 0.180 | 0.638 | 0.392 | 0.342 |
| A | | | 0.502 | 0.441 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.841 | 0.000 | 0.013 | 0.002 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.006 | 0.001 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.012 | 0.001 | 0.342 |
| SL | | | | | | | 0.074 | 0.609 | 0.089 |
| L3 | | | | | | | | 0.161 | 0.735 |
| L | | | | | | | | | 0.044 |
| S | | | | | | | | | |

| 1311 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.013 | 0.185 | 0.134 |
| A | | | 0.134 | 0.021 | 0.000 | 0.410 | 0.001 | 0.000 | 0.000 |
| P | | | | 0.007 | 0.000 | 0.127 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.008 | 0.347 | 0.060 | 0.008 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.574 | 0.165 | 0.002 |
| SL | | | | | | | 0.029 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.222 | 0.002 |
| L | | | | | | | | | 0.011 |
| S | | | | | | | | | |

| 7370 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.001 | 0.000 | 0.184 | 0.152 | 0.118 | 0.278 | 0.040 |
| A | | | 0.477 | 0.179 | 0.045 | 0.055 | 0.956 | 0.001 | 0.943 |
| P | | | | 0.124 | 0.056 | 0.089 | 0.789 | 0.007 | 0.827 |
| E | | | | | 0.058 | 0.102 | 0.809 | 0.005 | 0.672 |
| S&L3 | | | | | | 0.041 | 0.150 | 0.128 | 0.103 |
| SL | | | | | | | 0.353 | 0.277 | 0.241 |
| L3 | | | | | | | | 0.192 | 0.895 |
| L | | | | | | | | | 0.079 |
| S | | | | | | | | | |

| 2834 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.366 | 0.575 | 0.361 | 0.321 | 0.308 | 0.231 | 0.254 | 0.155 |
| A | | | 0.294 | 0.391 | 0.390 | 0.394 | 0.440 | 0.610 | 0.000 |
| P | | | | 0.257 | 0.007 | 0.020 | 0.007 | 0.096 | 0.086 |
| E | | | | | 0.396 | 0.400 | 0.467 | 0.968 | 0.018 |
| S&L3 | | | | | | 0.728 | 0.678 | 0.205 | 0.117 |
| SL | | | | | | | 0.415 | 0.221 | 0.122 |
| L3 | | | | | | | | 0.294 | 0.136 |
| L | | | | | | | | | 0.084 |
| S | | | | | | | | | |

| 3674 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.699 | 0.000 | 0.374 | 0.025 | 0.081 |
| A | | | 0.957 | 0.819 | 0.000 | 0.098 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.627 | 0.000 | 0.005 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.014 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.711 | 0.056 | 0.038 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.092 | 0.025 |
| L | | | | | | | | | 0.005 |
| S | | | | | | | | | |

| 4911 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.748 | 0.602 |
| A | | | 0.000 | 0.042 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.025 | 0.000 | 0.000 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.210 |
| S | | | | | | | | | |

| 5812 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.026 | 0.000 | 0.490 | 0.121 | 0.366 |
| A | | | 0.088 | 0.298 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.018 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.003 | 0.001 | 0.003 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.359 | 0.882 |
| L | | | | | | | | | 0.476 |
| S | | | | | | | | | |

| 7373 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.415 | 0.000 | 0.295 | 0.695 | 0.696 | 0.063 | 0.419 |
| A | | | 0.233 | 0.732 | 0.000 | 0.055 | 0.000 | 0.002 | 0.000 |
| P | | | | 0.231 | 0.612 | 0.003 | 0.370 | 0.001 | 0.461 |
| E | | | | | 0.000 | 0.053 | 0.000 | 0.003 | 0.000 |
| S&L3 | | | | | | 0.322 | 0.166 | 0.025 | 0.365 |
| SL | | | | | | | 0.578 | 0.019 | 0.433 |
| L3 | | | | | | | | 0.042 | 0.200 |
| L | | | | | | | | | 0.027 |
| S | | | | | | | | | |

| 2836 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.074 | 0.048 | 0.003 | 0.018 | 0.052 | 0.170 |
| A | | | 0.633 | 0.515 | 0.597 | 0.853 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.291 | 0.281 | 0.514 | 0.001 | 0.000 | 0.000 |
| E | | | | | 0.739 | 0.587 | 0.012 | 0.018 | 0.050 |
| S&L3 | | | | | | 0.638 | 0.007 | 0.012 | 0.022 |
| SL | | | | | | | 0.002 | 0.000 | 0.001 |
| L3 | | | | | | | | 0.067 | 0.018 |
| L | | | | | | | | | 0.434 |
| S | | | | | | | | | |

| 3845 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.592 | 0.000 | 0.887 | 0.425 | 0.000 |
| A | | | 0.433 | 0.023 | 0.017 | 0.270 | 0.010 | 0.000 | 0.000 |
| P | | | | 0.029 | 0.096 | 0.951 | 0.057 | 0.000 | 0.001 |
| E | | | | | 0.162 | 0.435 | 0.089 | 0.000 | 0.006 |
| S&L3 | | | | | | 0.014 | 0.275 | 0.429 | 0.552 |
| SL | | | | | | | 0.010 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.778 | 0.289 |
| L | | | | | | | | | 0.016 |
| S | | | | | | | | | |

| 4813 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.937 | 0.000 | 0.788 | 0.000 | 0.993 |
| A | | | 0.697 | 0.009 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.073 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.723 | 0.000 | 0.937 |
| SL | | | | | | | 0.000 | 0.431 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.818 |
| L | | | | | | | | | 0.000 |
| S | | | | | | | | | |

| 3663 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.039 | 0.053 | 0.483 |
| A | | | 0.112 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.391 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.002 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.000 | 0.296 | 0.049 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.230 |
| S | | | | | | | | | |

| 4931 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.406 | 0.956 |
| A | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.005 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.536 | 0.000 | 0.000 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.475 |
| S | | | | | | | | | |

| 3841 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| A | | | 0.002 | 0.055 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.300 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.872 | 0.062 | 0.836 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.021 | 0.958 |
| L | | | | | | | | | 0.011 |
| S | | | | | | | | | |

| 9995 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.122 | 0.000 | 0.044 | 0.000 | 0.001 |
| A | | | 0.000 | 0.278 | 0.000 | 0.009 | 0.000 | 0.093 | 0.005 |
| P | | | | 0.001 | 0.000 | 0.152 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.145 | 0.000 | 0.021 | 0.001 |
| S&L3 | | | | | | 0.000 | 0.722 | 0.013 | 0.037 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.017 | 0.066 |
| L | | | | | | | | | 0.308 |
| S | | | | | | | | | |

| 7990 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.004 | 0.000 | 0.068 | 0.012 | 0.035 |
| A | | | 0.926 | 0.161 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.201 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.005 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.205 | 0.359 | 0.732 |
| SL | | | | | | | 0.002 | 0.096 | 0.020 |
| L3 | | | | | | | | 0.001 | 0.338 |
| L | | | | | | | | | 0.189 |
| S | | | | | | | | | |

| 3714 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.055 | 0.000 | 0.308 | 0.001 | 0.000 |
| A | | | 0.000 | 0.024 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.140 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.001 | 0.003 | 0.000 |
| SL | | | | | | | 0.000 | 0.002 | 0.711 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.032 |
| S | | | | | | | | | |

| 6331 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.187 | 0.000 | 0.000 | 0.000 | 0.002 |
| A | | | 0.000 | 0.189 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.000 | 0.014 | 0.047 |
| SL | | | | | | | 0.000 | 0.000 | 0.002 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.641 |
| S | | | | | | | | | |

| 6211 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.010 | 0.008 | 0.008 | 0.023 | 0.013 | 0.035 | 0.027 | 0.056 |
| A | | | 0.006 | 0.473 | 0.247 | 0.088 | 0.046 | 0.553 | 0.010 |
| P | | | | 0.019 | 0.000 | 0.029 | 0.018 | 0.000 | 0.007 |
| E | | | | | 0.336 | 0.096 | 0.015 | 0.559 | 0.003 |
| S&L3 | | | | | | 0.726 | 0.068 | 0.187 | 0.035 |
| SL | | | | | | | 0.023 | 0.183 | 0.009 |
| L3 | | | | | | | | 0.090 | 0.158 |
| L | | | | | | | | | 0.045 |
| S | | | | | | | | | |

| 3576 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.878 | 0.000 | 0.000 | 0.190 | 0.465 | 0.000 | 0.003 | 0.037 |
| A | | | 0.001 | 0.007 | 0.521 | 0.631 | 0.000 | 0.117 | 0.290 |
| P | | | | 0.191 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.049 | 0.000 | 0.122 | 0.412 |
| SL | | | | | | | 0.000 | 0.000 | 0.033 |
| L3 | | | | | | | | 0.006 | 0.002 |
| L | | | | | | | | | 0.378 |
| S | | | | | | | | | |

This table displays the comparison of the MAPEs of all estimation models for revenue account. Panel A depicts the comparison of the industry mean of MAPEs in estimating revenue. Panel B shows the comparison of the industry median of MAPEs in revenue account as a robustness check. Panel C is an upper triangular t-test matrix. In Panel C, the p values in the first row are generated by one-tail t-tests, indicating whether sharing models are superior to original model in prediction accuracy; the rest of p values are generated by two-tail t-tests, examining whether there is significant difference in prediction accuracy between any two models.

## A.2 The Evaluation of Prediction Accuracy in Estimating Cost of Goods Sold Account

Panel A. The Comparison of MAPEs among Estimation Models (Industry Mean)

| SIC | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| 7372 | 1.57 | 0.74 | 0.73 | 0.73 | 1.57 | 0.91 | 1.44 | 1.48 | 1.77 |
| 1311 | 4.55 | 2.05 | 1.85 | 2.00 | 2.17 | 2.01 | 3.63 | 5.04 | 3.64 |
| 7370 | 0.77 | 0.36 | 0.41 | 0.45 | 0.62 | 0.58 | 1.20 | 0.56 | 1.10 |
| 2834 | 0.58 | 0.38 | 0.34 | 0.42 | 0.55 | 0.46 | 0.46 | 0.50 | 0.52 |
| 3674 | 0.39 | 0.24 | 0.23 | 0.25 | 0.36 | 0.28 | 0.37 | 0.35 | 0.40 |
| 4911 | 0.31 | 0.18 | 0.19 | 0.18 | 0.30 | 0.21 | 0.28 | 0.24 | 0.27 |
| 5812 | 0.11 | 0.08 | 0.08 | 0.08 | 0.11 | 0.09 | 0.11 | 0.11 | 0.11 |
| 7373 | 0.33 | 0.20 | 0.21 | 0.20 | 0.28 | 0.23 | 0.38 | 0.25 | 0.31 |
| 2836 | 1.92 | 0.82 | 0.85 | 0.85 | 1.17 | 1.13 | 1.04 | 1.43 | 1.56 |
| 3845 | 0.53 | 0.31 | 0.29 | 0.31 | 0.42 | 0.32 | 0.49 | 0.37 | 0.41 |
| 4813 | 0.31 | 0.21 | 0.22 | 0.21 | 0.30 | 0.25 | 0.33 | 0.34 | 0.26 |
| 3663 | 0.28 | 0.20 | 0.20 | 0.21 | 0.26 | 0.23 | 0.30 | 0.30 | 0.27 |
| 4931 | 0.25 | 0.14 | 0.15 | 0.14 | 0.23 | 0.17 | 0.25 | 0.20 | 0.22 |
| 3841 | 0.44 | 0.29 | 0.24 | 0.29 | 0.41 | 0.31 | 0.67 | 0.34 | 0.35 |
| 9995 | 0.90 | 0.55 | 0.57 | 0.60 | 0.82 | 0.61 | 0.89 | 0.73 | 0.62 |
| 7990 | 0.30 | 0.17 | 0.17 | 0.19 | 0.22 | 0.19 | 0.24 | 0.24 | 0.21 |
| 3714 | 0.20 | 0.13 | 0.13 | 0.13 | 0.16 | 0.14 | 0.17 | 0.16 | 0.15 |
| 6331 | 0.30 | 0.22 | 0.21 | 0.21 | 0.22 | 0.22 | 0.27 | 0.24 | 0.23 |
| 6211 | 0.26 | 0.17 | 0.16 | 0.17 | 0.19 | 0.17 | 0.20 | 0.20 | 0.21 |
| 3576 | 0.27 | 0.19 | 0.18 | 0.18 | 0.24 | 0.24 | 0.30 | 0.25 | 0.21 |

Panel B. The Comparison of MAPEs among Estimation Models (Industry Median)

| SIC | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| 7372 | 0.18 | 0.12 | 0.12 | 0.12 | 0.17 | 0.14 | 0.18 | 0.20 | 0.23 |
| 1311 | 0.28 | 0.20 | 0.20 | 0.20 | 0.27 | 0.22 | 0.30 | 0.31 | 0.32 |
| 7370 | 0.14 | 0.09 | 0.09 | 0.09 | 0.12 | 0.10 | 0.13 | 0.15 | 0.15 |
| 2834 | 0.16 | 0.11 | 0.11 | 0.11 | 0.14 | 0.12 | 0.16 | 0.16 | 0.17 |
| 3674 | 0.14 | 0.09 | 0.10 | 0.10 | 0.14 | 0.11 | 0.14 | 0.14 | 0.16 |
| 4911 | 0.11 | 0.08 | 0.09 | 0.08 | 0.14 | 0.10 | 0.13 | 0.13 | 0.14 |
| 5812 | 0.06 | 0.04 | 0.04 | 0.04 | 0.06 | 0.05 | 0.06 | 0.06 | 0.06 |
| 7373 | 0.11 | 0.08 | 0.08 | 0.08 | 0.11 | 0.09 | 0.11 | 0.11 | 0.12 |
| 2836 | 0.18 | 0.12 | 0.12 | 0.12 | 0.15 | 0.13 | 0.17 | 0.19 | 0.18 |
| 3845 | 0.14 | 0.10 | 0.10 | 0.10 | 0.14 | 0.11 | 0.14 | 0.13 | 0.14 |
| 4813 | 0.11 | 0.08 | 0.08 | 0.07 | 0.10 | 0.09 | 0.12 | 0.10 | 0.11 |
| 3663 | 0.15 | 0.11 | 0.11 | 0.11 | 0.15 | 0.12 | 0.15 | 0.15 | 0.15 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 4931 | 0.10 | 0.07 | 0.08 | 0.07 | 0.13 | 0.09 | 0.12 | 0.11 | 0.12 |
| 3841 | 0.11 | 0.07 | 0.07 | 0.07 | 0.09 | 0.08 | 0.09 | 0.09 | 0.10 |
| 9995 | 0.31 | 0.19 | 0.19 | 0.20 | 0.27 | 0.22 | 0.33 | 0.28 | 0.26 |
| 7990 | 0.09 | 0.07 | 0.07 | 0.07 | 0.08 | 0.08 | 0.09 | 0.09 | 0.09 |
| 3714 | 0.08 | 0.06 | 0.06 | 0.06 | 0.08 | 0.07 | 0.08 | 0.07 | 0.07 |
| 6331 | 0.10 | 0.07 | 0.07 | 0.07 | 0.09 | 0.07 | 0.09 | 0.08 | 0.09 |
| 6211 | 0.13 | 0.09 | 0.09 | 0.09 | 0.11 | 0.10 | 0.11 | 0.11 | 0.11 |
| 3576 | 0.14 | 0.10 | 0.09 | 0.11 | 0.12 | 0.12 | 0.14 | 0.13 | 0.13 |

Panel C. The t-tests of MAPEs among Estimation Models

| 7372 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.994 | 0.000 | 0.305 | 0.474 | 0.253 |
| A | | | 0.634 | 0.553 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.927 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.404 | 0.461 | 0.373 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.814 | 0.015 |
| L | | | | | | | | | 0.091 |
| S | | | | | | | | | |

| 1311 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.056 | 0.513 | 0.181 |
| A | | | 0.289 | 0.596 | 0.787 | 0.877 | 0.000 | 0.000 | 0.003 |
| P | | | | 0.174 | 0.243 | 0.366 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.628 | 0.978 | 0.000 | 0.000 | 0.001 |
| S&L3 | | | | | | 0.469 | 0.021 | 0.004 | 0.000 |
| SL | | | | | | | 0.001 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.002 | 0.977 |
| L | | | | | | | | | 0.106 |
| S | | | | | | | | | |

| 7370 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.004 | 0.002 | 0.010 | 0.214 | 0.086 | 0.168 | 0.086 | 0.070 |
| A | | | 0.087 | 0.020 | 0.000 | 0.002 | 0.020 | 0.000 | 0.012 |
| P | | | | 0.039 | 0.000 | 0.001 | 0.020 | 0.000 | 0.010 |
| E | | | | | 0.000 | 0.001 | 0.021 | 0.000 | 0.013 |
| S&L3 | | | | | | 0.123 | 0.065 | 0.023 | 0.058 |
| SL | | | | | | | 0.036 | 0.620 | 0.027 |
| L3 | | | | | | | | 0.050 | 0.592 |
| L | | | | | | | | | 0.039 |
| S | | | | | | | | | |

| 2834 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.002 | 0.000 | 0.037 | 0.000 | 0.196 | 0.215 | 0.360 |
| A | | | 0.267 | 0.239 | 0.004 | 0.000 | 0.115 | 0.000 | 0.000 |
| P | | | | 0.249 | 0.024 | 0.030 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.021 | 0.672 | 0.181 | 0.137 |
| S&L3 | | | | | | 0.020 | 0.411 | 0.541 | 0.712 |
| SL | | | | | | | 0.972 | 0.370 | 0.265 |
| L3 | | | | | | | | 0.233 | 0.031 |
| L | | | | | | | | | 0.316 |
| S | | | | | | | | | |

| 3674 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.030 | 0.000 | 0.127 | 0.002 | 0.391 |
| A | | | 0.003 | 0.023 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.488 | 0.632 | 0.000 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.024 | 0.011 |
| L | | | | | | | | | 0.000 |
| S | | | | | | | | | |

| 4911 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.736 | 0.000 | 0.237 | 0.030 | 0.175 |
| A | | | 0.437 | 0.312 | 0.000 | 0.009 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.263 | 0.000 | 0.252 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.235 | 0.006 | 0.279 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.769 |
| L | | | | | | | | | 0.019 |
| S | | | | | | | | | |

| 5812 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.606 | 0.000 | 0.000 | 0.189 | 0.000 |
| A | | | 0.240 | 0.315 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.041 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.000 | 0.082 | 0.000 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.438 |
| L | | | | | | | | | 0.009 |
| S | | | | | | | | | |

| 7373 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.006 | 0.000 | 0.078 | 0.001 | 0.430 |
| A | | | 0.276 | 0.499 | 0.000 | 0.000 | 0.000 | 0.002 | 0.000 |
| P | | | | 0.311 | 0.000 | 0.021 | 0.000 | 0.106 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.005 | 0.071 | 0.046 |
| SL | | | | | | | 0.000 | 0.418 | 0.000 |
| L3 | | | | | | | | 0.005 | 0.032 |
| L | | | | | | | | | 0.001 |
| S | | | | | | | | | |

| 2836 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.001 | 0.001 | 0.003 | 0.000 | 0.008 | 0.012 | 0.206 |
| A | | | 0.642 | 0.647 | 0.000 | 0.063 | 0.007 | 0.008 | 0.151 |
| P | | | | 0.982 | 0.002 | 0.129 | 0.014 | 0.021 | 0.185 |
| E | | | | | 0.000 | 0.101 | 0.001 | 0.012 | 0.182 |
| S&L3 | | | | | | 0.661 | 0.207 | 0.124 | 0.410 |
| SL | | | | | | | 0.637 | 0.001 | 0.251 |
| L3 | | | | | | | | 0.100 | 0.342 |
| L | | | | | | | | | 0.710 |
| S | | | | | | | | | |

| 3845 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.011 | 0.000 | 0.360 | 0.000 | 0.005 |
| A | | | 0.007 | 0.845 | 0.000 | 0.058 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.013 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.019 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.045 | 0.000 | 0.764 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.022 |
| L | | | | | | | | | 0.002 |
| S | | | | | | | | | |

| 4813 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.047 | 0.000 | 0.307 | 0.019 | 0.002 |
| A | | | 0.016 | 0.719 | 0.000 | 0.017 | 0.000 | 0.000 | 0.002 |
| P | | | | 0.040 | 0.000 | 0.035 | 0.000 | 0.000 | 0.005 |
| E | | | | | 0.000 | 0.025 | 0.000 | 0.000 | 0.003 |
| S&L3 | | | | | | 0.001 | 0.000 | 0.000 | 0.009 |
| SL | | | | | | | 0.000 | 0.000 | 0.066 |
| L3 | | | | | | | | 0.059 | 0.000 |
| L | | | | | | | | | 0.000 |
| S | | | | | | | | | |

| 3663 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.003 | 0.000 | 0.000 | 0.001 | 0.875 |
| A | | | 0.366 | 0.096 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.060 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.000 | 0.000 | 0.010 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.131 | 0.000 |
| L | | | | | | | | | 0.001 |
| S | | | | | | | | | |

| 4931 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.413 | 0.001 | 0.863 | 0.049 | 0.176 |
| A | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.066 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.000 | 0.000 | 0.112 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.148 |
| S | | | | | | | | | |

| 3841 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.079 | 0.000 | 0.001 | 0.000 | 0.002 |
| A | | | 0.102 | 0.830 | 0.000 | 0.100 | 0.000 | 0.000 | 0.003 |
| P | | | | 0.120 | 0.000 | 0.032 | 0.000 | 0.001 | 0.000 |
| E | | | | | 0.000 | 0.043 | 0.000 | 0.000 | 0.005 |
| S&L3 | | | | | | 0.000 | 0.000 | 0.000 | 0.074 |
| SL | | | | | | | 0.000 | 0.000 | 0.199 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.753 |
| S | | | | | | | | | |

| 9995 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.171 | 0.000 | 0.917 | 0.029 | 0.000 |
| A | | | 0.324 | 0.059 | 0.000 | 0.036 | 0.000 | 0.000 | 0.127 |
| P | | | | 0.257 | 0.000 | 0.031 | 0.000 | 0.000 | 0.377 |
| E | | | | | 0.000 | 0.751 | 0.000 | 0.001 | 0.722 |
| S&L3 | | | | | | 0.000 | 0.250 | 0.142 | 0.002 |
| SL | | | | | | | 0.000 | 0.001 | 0.906 |
| L3 | | | | | | | | 0.041 | 0.001 |
| L | | | | | | | | | 0.057 |
| S | | | | | | | | | |

| 7990 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.053 | 0.052 | 0.021 |
| A | | | 0.065 | 0.005 | 0.000 | 0.009 | 0.000 | 0.000 | 0.017 |
| P | | | | 0.006 | 0.000 | 0.008 | 0.000 | 0.000 | 0.001 |
| E | | | | | 0.001 | 0.411 | 0.000 | 0.000 | 0.242 |
| S&L3 | | | | | | 0.000 | 0.194 | 0.171 | 0.764 |
| SL | | | | | | | 0.011 | 0.008 | 0.493 |
| L3 | | | | | | | | 0.931 | 0.007 |
| L | | | | | | | | | 0.016 |
| S | | | | | | | | | |

| 3714 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.004 | 0.006 | 0.005 | 0.150 | 0.028 | 0.298 | 0.060 | 0.041 |
| A | | | 0.002 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.435 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.002 | 0.557 | 0.000 |
| SL | | | | | | | 0.000 | 0.001 | 0.011 |
| L3 | | | | | | | | 0.048 | 0.000 |
| L | | | | | | | | | 0.013 |
| S | | | | | | | | | |

| 6331 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.011 | 0.000 | 0.288 | 0.000 | 0.010 |
| A | | | 0.541 | 0.180 | 0.557 | 0.000 | 0.003 | 0.000 | 0.221 |
| P | | | | 0.418 | 0.157 | 0.093 | 0.000 | 0.000 | 0.006 |
| E | | | | | 0.647 | 0.021 | 0.007 | 0.000 | 0.304 |
| S&L3 | | | | | | 0.898 | 0.000 | 0.369 | 0.113 |
| SL | | | | | | | 0.010 | 0.000 | 0.490 |
| L3 | | | | | | | | 0.074 | 0.000 |
| L | | | | | | | | | 0.596 |
| S | | | | | | | | | |

| 6211 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| A | | | 0.692 | 0.564 | 0.000 | 0.824 | 0.000 | 0.000 | 0.000 |
| P | | | | 0.847 | 0.000 | 0.487 | 0.000 | 0.000 | 0.000 |
| E | | | | | 0.000 | 0.896 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.000 | 0.006 | 0.211 | 0.028 |
| SL | | | | | | | 0.000 | 0.000 | 0.000 |
| L3 | | | | | | | | 0.356 | 0.902 |
| L | | | | | | | | | 0.160 |
| S | | | | | | | | | |

| 3576 | O | A | P | E | S&L3 | SL | L3 | L | S |
|---|---|---|---|---|---|---|---|---|---|
| O | | 0.000 | 0.000 | 0.000 | 0.025 | 0.004 | 0.038 | 0.101 | 0.000 |
| A | | | 0.209 | 0.232 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |
| P | | | | 0.666 | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 |
| E | | | | | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| S&L3 | | | | | | 0.238 | 0.000 | 0.400 | 0.015 |
| SL | | | | | | | 0.000 | 0.077 | 0.062 |
| L3 | | | | | | | | 0.000 | 0.000 |
| L | | | | | | | | | 0.001 |
| S | | | | | | | | | |

This table displays the comparison of the MAPEs of all estimation models for cost of goods sold account. Panel A depicts the comparison of the industry mean of MAPEs in estimating cost of goods sold. Panel B shows the comparison of the industry median of MAPEs in cost of goods sold account as a robustness check. Panel C is an upper triangular t-test matrix. In Panel C, the p values in the first row are generated by one-tail t-tests, indicating whether sharing models are superior to original model in prediction accuracy; the rest of p values are generated by two-tail t-tests, examining whether there is significant difference in prediction accuracy between any two models.

## Section B.

### B.1 The Evaluation of Error Detection

Panel A. The Error Detection Performance in Revenue Account

SIC 7372 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 19.0 | 23.8 | 16.6 | 24.1 | 16.6 | 24.5 | 16.7 | 23.8 | 19.1 | 23.9 | 16.5 | 24.1 | 17.5 | 23.6 |
| 0.1 | 0.02 | 23.3 | 23.9 | 21.7 | 24.3 | 21.5 | 24.6 | 22.1 | 23.9 | 23.2 | 24.0 | 21.6 | 24.3 | 22.4 | 23.9 |
| | 0.01 | 24.9 | 23.7 | 23.9 | 24.0 | 23.7 | 24.3 | 24.4 | 23.8 | 24.9 | 24.0 | 23.8 | 24.2 | 24.5 | 23.8 |
| | 0.05 | 18.4 | 24.4 | 15.7 | 25.0 | 15.8 | 25.3 | 15.9 | 24.5 | 18.5 | 24.3 | 15.8 | 24.8 | 16.6 | 24.3 |
| 0.05 | 0.02 | 22.4 | 24.4 | 20.6 | 25.0 | 20.6 | 25.4 | 21.2 | 24.6 | 22.4 | 24.6 | 20.7 | 25.1 | 21.5 | 24.6 |
| | 0.01 | 23.9 | 24.4 | 22.7 | 25.1 | 22.5 | 25.4 | 23.3 | 24.6 | 24.1 | 24.3 | 23.0 | 24.9 | 23.6 | 24.4 |
| | 0.05 | 18.1 | 24.8 | 15.5 | 25.7 | 15.6 | 25.9 | 15.6 | 25.1 | 18.3 | 24.9 | 15.4 | 25.6 | 16.3 | 25.2 |
| 0.02 | 0.02 | 22.2 | 24.9 | 20.3 | 25.8 | 20.3 | 26.0 | 20.8 | 25.2 | 22.1 | 24.9 | 20.2 | 25.6 | 21.0 | 25.2 |
| | 0.01 | 23.8 | 24.9 | 22.3 | 25.8 | 22.2 | 25.9 | 23.0 | 25.2 | 23.7 | 25.0 | 22.4 | 25.7 | 23.1 | 25.2 |
| | 0.05 | 18.0 | 25.1 | 15.1 | 26.0 | 15.4 | 26.1 | 15.5 | 25.4 | 18.0 | 24.8 | 15.3 | 25.5 | 16.1 | 25.0 |
| 0.01 | 0.02 | 22.1 | 25.1 | 19.9 | 26.0 | 20.1 | 26.2 | 20.5 | 25.5 | 22.0 | 25.0 | 20.1 | 25.7 | 20.9 | 25.2 |
| | 0.01 | 23.4 | 25.1 | 21.9 | 26.1 | 21.8 | 26.1 | 22.5 | 25.4 | 23.3 | 24.9 | 22.2 | 25.7 | 22.8 | 25.3 |
| | 0.05 | 23.3 | 25.2 | 21.7 | 26.2 | 21.7 | 26.3 | 22.3 | 25.5 | 17.9 | 25.3 | 15.1 | 25.9 | 15.9 | 25.4 |
| 0 | 0.02 | 21.9 | 25.3 | 19.9 | 26.4 | 19.8 | 26.4 | 20.2 | 25.6 | 21.7 | 25.0 | 19.8 | 25.9 | 20.6 | 25.3 |
| | 0.01 | 18.1 | 25.0 | 15.3 | 26.1 | 15.5 | 26.2 | 15.5 | 25.4 | 23.3 | 25.2 | 21.8 | 25.9 | 22.5 | 25.5 |

SIC 1311 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 18.6 | 26.0 | 18.9 | 25.6 | 19.2 | 25.3 | 21.0 | 25.0 | 19.3 | 25.0 | 19.1 | 25.6 | 19.2 | 25.1 |
| 0.1 | 0.02 | 21.8 | 25.7 | 22.1 | 25.4 | 22.3 | 25.1 | 23.3 | 25.3 | 22.6 | 25.2 | 22.1 | 25.8 | 22.3 | 25.3 |
| | 0.01 | 23.0 | 25.9 | 23.3 | 25.6 | 23.6 | 25.3 | 23.9 | 25.2 | 23.7 | 25.2 | 23.3 | 25.9 | 23.5 | 25.4 |
| | 0.05 | 18.1 | 27.0 | 18.3 | 26.5 | 18.6 | 26.2 | 20.6 | 25.6 | 18.7 | 25.8 | 18.6 | 26.5 | 18.6 | 26.1 |
| 0.05 | 0.02 | 21.2 | 26.8 | 21.4 | 26.3 | 21.7 | 26.1 | 22.6 | 25.8 | 21.8 | 26.0 | 21.3 | 26.8 | 21.6 | 26.3 |
| | 0.01 | 22.2 | 26.7 | 22.4 | 26.2 | 22.6 | 25.9 | 23.4 | 25.6 | 23.0 | 25.9 | 22.4 | 26.6 | 22.8 | 26.2 |
| | 0.05 | 17.4 | 27.2 | 17.9 | 26.7 | 18.3 | 26.7 | 20.0 | 26.3 | 18.0 | 26.6 | 17.9 | 27.3 | 18.0 | 26.7 |
| 0.02 | 0.02 | 20.6 | 27.2 | 20.9 | 26.8 | 21.1 | 26.6 | 22.3 | 26.3 | 21.2 | 26.6 | 20.8 | 27.2 | 21.1 | 26.7 |
| | 0.01 | 21.6 | 27.2 | 22.1 | 26.8 | 22.3 | 26.7 | 23.0 | 26.3 | 22.2 | 26.6 | 21.8 | 27.2 | 22.1 | 26.7 |
| | 0.05 | 17.3 | 27.6 | 17.7 | 27.1 | 18.1 | 27.0 | 20.1 | 26.3 | 18.0 | 26.7 | 17.8 | 27.4 | 18.0 | 26.9 |
| 0.01 | 0.02 | 20.3 | 27.4 | 20.6 | 27.0 | 20.9 | 26.8 | 22.1 | 26.2 | 21.0 | 26.6 | 20.7 | 27.2 | 21.0 | 26.7 |
| | 0.01 | 21.4 | 27.6 | 21.8 | 27.2 | 22.0 | 27.0 | 22.9 | 26.4 | 22.1 | 26.8 | 21.6 | 27.3 | 21.9 | 26.9 |
| | 0.05 | 17.2 | 27.4 | 17.7 | 27.0 | 18.0 | 26.9 | 19.9 | 26.5 | 17.7 | 26.9 | 17.6 | 27.5 | 17.7 | 27.0 |
| 0 | 0.02 | 20.3 | 27.7 | 20.5 | 27.2 | 20.9 | 27.0 | 21.9 | 26.5 | 20.9 | 27.0 | 20.6 | 27.5 | 20.9 | 27.1 |
| | 0.01 | 21.3 | 27.7 | 21.6 | 27.2 | 21.8 | 27.1 | 22.7 | 26.3 | 21.9 | 26.8 | 21.5 | 27.4 | 21.8 | 26.9 |

SIC 7370 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 17.0 | 22.1 | 16.9 | 22.0 | 17.3 | 21.3 | 20.3 | 21.6 | 17.5 | 21.1 | 17.3 | 21.3 | 17.1 | 21.4 |
| 0.1 | 0.02 | 23.1 | 22.1 | 23.0 | 22.0 | 23.5 | 21.5 | 24.5 | 21.9 | 23.7 | 21.3 | 23.6 | 21.6 | 23.6 | 21.6 |
| | 0.01 | 25.5 | 21.7 | 25.4 | 21.6 | 26.2 | 21.2 | 26.6 | 21.7 | 26.5 | 21.4 | 26.2 | 21.6 | 26.2 | 21.7 |
| | 0.05 | 16.2 | 22.7 | 16.1 | 22.7 | 16.4 | 22.1 | 20.0 | 22.5 | 16.8 | 22.3 | 16.6 | 22.6 | 16.5 | 22.6 |
| 0.05 | 0.02 | 22.4 | 22.8 | 22.5 | 22.7 | 22.8 | 22.0 | 24.0 | 22.6 | 22.8 | 22.4 | 22.7 | 22.7 | 22.7 | 22.6 |
| | 0.01 | 24.7 | 22.7 | 24.7 | 22.7 | 25.2 | 21.9 | 25.8 | 22.6 | 25.3 | 22.4 | 25.1 | 22.6 | 25.3 | 22.6 |
| | 0.05 | 16.0 | 23.2 | 15.9 | 23.1 | 16.3 | 22.7 | 19.4 | 22.9 | 16.0 | 23.0 | 15.9 | 23.2 | 15.7 | 23.1 |
| 0.02 | 0.02 | 21.9 | 23.4 | 22.0 | 23.2 | 22.4 | 22.7 | 23.7 | 22.8 | 22.3 | 22.9 | 22.1 | 23.0 | 22.1 | 22.9 |
| | 0.01 | 24.3 | 23.1 | 24.5 | 23.1 | 25.1 | 22.6 | 25.2 | 22.7 | 24.5 | 22.8 | 24.4 | 23.0 | 24.5 | 22.9 |
| | 0.05 | 16.0 | 23.5 | 16.0 | 23.5 | 16.1 | 22.9 | 19.1 | 23.0 | 15.7 | 22.9 | 15.8 | 23.3 | 15.6 | 23.2 |
| 0.01 | 0.02 | 21.7 | 23.3 | 21.9 | 23.3 | 22.2 | 22.8 | 23.6 | 22.8 | 22.1 | 22.9 | 22.2 | 23.2 | 22.0 | 23.0 |
| | 0.01 | 24.1 | 23.3 | 24.2 | 23.4 | 24.8 | 22.9 | 25.2 | 22.8 | 24.3 | 22.8 | 24.4 | 23.3 | 24.4 | 23.0 |
| | 0.05 | 15.8 | 23.2 | 15.9 | 23.1 | 16.0 | 22.6 | 19.1 | 22.8 | 15.8 | 23.1 | 15.7 | 23.3 | 15.6 | 23.1 |
| 0 | 0.02 | 21.4 | 23.6 | 21.4 | 23.4 | 21.9 | 22.9 | 23.6 | 22.9 | 22.1 | 23.2 | 22.0 | 23.3 | 22.0 | 23.2 |
| | 0.01 | 23.9 | 23.9 | 23.9 | 23.7 | 24.5 | 23.1 | 25.1 | 22.7 | 24.2 | 23.0 | 24.3 | 23.2 | 24.3 | 23.0 |

SIC 2834 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.8 | 24.3 | 17.0 | 24.4 | 17.3 | 23.6 | 19.8 | 24.1 | 17.5 | 24.0 | 18.0 | 23.9 | 17.4 | 24.2 |
| 0.1 | 0.02 | 21.6 | 24.6 | 21.8 | 24.4 | 22.1 | 23.6 | 23.6 | 23.9 | 22.3 | 23.7 | 22.7 | 23.7 | 22.3 | 24.0 |
| | 0.01 | 23.5 | 24.3 | 24.0 | 24.5 | 24.5 | 23.7 | 24.9 | 23.8 | 24.2 | 23.8 | 24.5 | 23.8 | 24.2 | 24.0 |
| | 0.05 | 16.3 | 25.2 | 16.3 | 25.0 | 16.8 | 24.4 | 19.2 | 24.4 | 16.9 | 24.8 | 17.2 | 24.6 | 16.7 | 25.0 |
| 0.05 | 0.02 | 20.6 | 25.5 | 20.9 | 25.3 | 21.1 | 24.6 | 22.6 | 24.5 | 21.0 | 24.6 | 21.3 | 24.5 | 21.0 | 24.8 |
| | 0.01 | 22.7 | 25.5 | 23.1 | 25.3 | 23.5 | 24.7 | 24.0 | 24.4 | 23.1 | 24.5 | 23.5 | 24.5 | 23.3 | 24.8 |
| | 0.05 | 15.8 | 26.0 | 15.9 | 25.7 | 16.2 | 25.1 | 19.1 | 24.8 | 16.7 | 25.6 | 16.8 | 25.1 | 16.5 | 25.5 |
| 0.02 | 0.02 | 20.3 | 26.4 | 20.4 | 26.0 | 20.9 | 25.5 | 22.5 | 24.8 | 20.9 | 25.5 | 21.4 | 25.0 | 20.9 | 25.5 |
| | 0.01 | 22.0 | 25.9 | 22.5 | 25.5 | 22.7 | 24.9 | 24.1 | 25.0 | 22.8 | 25.4 | 23.3 | 25.1 | 23.0 | 25.4 |
| | 0.05 | 15.8 | 26.3 | 16.0 | 26.0 | 16.3 | 25.5 | 18.8 | 25.0 | 16.3 | 25.6 | 16.5 | 25.2 | 16.1 | 25.6 |
| 0.01 | 0.02 | 20.0 | 25.8 | 20.2 | 25.7 | 20.7 | 25.1 | 22.1 | 25.2 | 20.4 | 25.9 | 20.9 | 25.5 | 20.5 | 25.9 |
| | 0.01 | 22.0 | 26.0 | 22.4 | 25.7 | 22.7 | 25.2 | 23.4 | 25.2 | 22.2 | 25.8 | 22.8 | 25.4 | 22.4 | 25.8 |
| | 0.05 | 15.5 | 26.5 | 15.7 | 26.0 | 15.9 | 25.4 | 18.7 | 25.0 | 16.2 | 25.9 | 16.4 | 25.3 | 16.0 | 25.7 |
| 0 | 0.02 | 19.8 | 26.4 | 20.0 | 26.1 | 20.5 | 25.5 | 22.1 | 25.1 | 20.5 | 26.1 | 20.8 | 25.3 | 20.4 | 25.9 |
| | 0.01 | 21.8 | 26.3 | 22.1 | 25.9 | 22.5 | 25.5 | 23.4 | 25.1 | 22.1 | 26.1 | 22.6 | 25.4 | 22.5 | 25.8 |

SIC 3674 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.3 | 25.3 | 16.5 | 25.6 | 16.6 | 24.8 | 18.7 | 25.3 | 15.9 | 25.3 | 16.5 | 25.3 | 16.1 | 25.2 |
| 0.1 | 0.02 | 21.0 | 25.1 | 21.1 | 25.5 | 21.5 | 24.8 | 22.0 | 25.2 | 20.9 | 25.2 | 21.2 | 25.1 | 21.2 | 25.2 |
| | 0.01 | 23.0 | 25.3 | 22.8 | 25.6 | 23.3 | 24.8 | 23.3 | 25.4 | 22.8 | 25.4 | 23.0 | 25.3 | 22.9 | 25.3 |
| 0.05 | 0.05 | 15.5 | 26.1 | 15.8 | 26.5 | 15.9 | 25.7 | 18.1 | 26.1 | 15.4 | 26.3 | 16.0 | 26.3 | 15.6 | 26.1 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.02 | 20.1 | 25.7 | 20.3 | 26.1 | 20.7 | 25.4 | 21.5 | 26.1 | 19.9 | 26.2 | 20.5 | 26.2 | 20.3 | 26.0 |
| | 0.01 | 21.9 | 25.9 | 21.9 | 26.4 | 22.3 | 25.6 | 22.7 | 26.0 | 21.8 | 26.1 | 22.1 | 26.1 | 21.9 | 26.0 |
| | 0.05 | 14.8 | 26.7 | 15.3 | 26.9 | 15.3 | 26.2 | 17.8 | 26.5 | 14.9 | 26.8 | 15.5 | 26.7 | 15.1 | 26.7 |
| 0.02 | 0.02 | 19.5 | 26.6 | 19.8 | 26.9 | 20.2 | 26.1 | 21.2 | 26.5 | 19.5 | 26.7 | 20.1 | 26.8 | 19.9 | 26.7 |
| | 0.01 | 21.5 | 26.6 | 21.6 | 26.8 | 22.0 | 26.1 | 22.1 | 26.3 | 21.1 | 26.6 | 21.5 | 26.6 | 21.3 | 26.5 |
| | 0.05 | 15.0 | 26.9 | 15.4 | 27.2 | 15.4 | 26.5 | 17.8 | 26.5 | 14.8 | 26.7 | 15.4 | 26.7 | 15.0 | 26.7 |
| 0.01 | 0.02 | 19.6 | 26.8 | 19.7 | 26.9 | 20.3 | 26.3 | 21.2 | 26.5 | 19.4 | 26.8 | 20.0 | 26.7 | 19.6 | 26.7 |
| | 0.01 | 21.1 | 26.8 | 21.2 | 27.0 | 21.6 | 26.4 | 22.1 | 26.6 | 21.0 | 26.9 | 21.3 | 26.9 | 21.2 | 26.8 |
| | 0.05 | 14.6 | 27.0 | 15.2 | 27.1 | 15.2 | 26.5 | 17.9 | 26.4 | 14.8 | 26.8 | 15.3 | 26.8 | 14.9 | 26.8 |
| 0 | 0.02 | 19.2 | 27.3 | 19.5 | 27.4 | 19.9 | 26.8 | 20.9 | 26.7 | 19.1 | 27.1 | 19.8 | 27.0 | 19.4 | 27.0 |
| | 0.01 | 21.2 | 27.1 | 21.3 | 27.3 | 21.6 | 26.6 | 22.1 | 26.6 | 20.9 | 27.0 | 21.4 | 27.0 | 21.2 | 26.9 |

SIC 4911 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.2 | 24.9 | 15.3 | 25.9 | 16.2 | 24.0 | 17.6 | 24.6 | 16.1 | 23.8 | 16.9 | 24.1 | 16.2 | 23.7 |
| 0.1 | 0.02 | 21.3 | 24.9 | 20.2 | 25.9 | 21.7 | 24.0 | 22.1 | 24.4 | 22.0 | 23.7 | 22.1 | 23.9 | 22.1 | 23.6 |
| | 0.01 | 23.3 | 24.8 | 22.2 | 25.8 | 24.0 | 24.0 | 23.8 | 24.4 | 24.2 | 23.6 | 24.1 | 23.9 | 24.1 | 23.6 |
| | 0.05 | 15.5 | 25.7 | 14.8 | 26.7 | 15.6 | 24.8 | 16.9 | 25.2 | 15.4 | 24.6 | 16.0 | 24.7 | 15.5 | 24.6 |
| 0.05 | 0.02 | 20.6 | 25.7 | 19.6 | 26.6 | 21.0 | 24.7 | 21.3 | 25.3 | 21.1 | 24.6 | 21.2 | 24.7 | 21.1 | 24.5 |
| | 0.01 | 22.3 | 25.7 | 21.3 | 26.6 | 22.9 | 24.7 | 23.1 | 25.4 | 23.4 | 24.7 | 23.3 | 24.9 | 23.3 | 24.7 |
| | 0.05 | 14.9 | 26.4 | 14.3 | 27.2 | 15.1 | 25.4 | 16.7 | 25.7 | 15.1 | 25.0 | 15.6 | 25.2 | 15.2 | 25.0 |
| 0.02 | 0.02 | 19.9 | 26.1 | 19.1 | 27.1 | 20.4 | 25.3 | 20.7 | 25.8 | 20.6 | 25.3 | 20.6 | 25.5 | 20.5 | 25.3 |
| | 0.01 | 21.8 | 26.1 | 20.8 | 27.0 | 22.5 | 25.2 | 22.6 | 25.6 | 22.8 | 25.0 | 22.6 | 25.2 | 22.8 | 25.0 |
| | 0.05 | 14.8 | 26.5 | 14.2 | 27.4 | 14.9 | 25.6 | 16.6 | 26.0 | 15.0 | 25.3 | 15.6 | 25.6 | 15.0 | 25.3 |
| 0.01 | 0.02 | 20.0 | 26.4 | 19.0 | 27.2 | 20.3 | 25.5 | 20.7 | 26.0 | 20.5 | 25.4 | 20.5 | 25.5 | 20.4 | 25.3 |
| | 0.01 | 21.8 | 26.4 | 20.8 | 27.2 | 22.5 | 25.6 | 22.4 | 26.1 | 22.5 | 25.5 | 22.3 | 25.7 | 22.5 | 25.5 |
| | 0.05 | 14.6 | 26.5 | 14.0 | 27.3 | 14.8 | 25.7 | 16.3 | 26.3 | 14.8 | 25.7 | 15.3 | 25.9 | 14.8 | 25.7 |
| 0 | 0.02 | 19.7 | 26.5 | 18.9 | 27.4 | 20.2 | 25.6 | 20.4 | 26.2 | 20.2 | 25.6 | 20.3 | 25.8 | 20.2 | 25.6 |
| | 0.01 | 21.5 | 26.5 | 20.6 | 27.4 | 22.2 | 25.7 | 22.1 | 26.2 | 22.3 | 25.6 | 22.1 | 25.7 | 22.3 | 25.6 |

SIC 5812 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 12.8 | 22.7 | 12.5 | 23.3 | 12.4 | 23.1 | 15.5 | 22.7 | 12.4 | 22.9 | 12.8 | 22.7 | 12.4 | 22.7 |
| 0.1 | 0.02 | 20.9 | 22.5 | 20.2 | 23.0 | 20.1 | 22.8 | 22.1 | 22.9 | 20.5 | 22.9 | 20.5 | 22.8 | 20.3 | 22.8 |
| | 0.01 | 24.0 | 22.6 | 23.4 | 23.1 | 23.4 | 22.9 | 24.7 | 22.7 | 24.0 | 23.0 | 24.1 | 22.7 | 23.8 | 22.8 |
| | 0.05 | 12.4 | 23.6 | 12.0 | 24.2 | 11.9 | 24.0 | 15.0 | 23.3 | 11.8 | 23.7 | 12.3 | 23.6 | 11.7 | 23.7 |
| 0.05 | 0.02 | 19.9 | 23.5 | 19.4 | 24.1 | 19.4 | 23.9 | 21.3 | 23.4 | 19.6 | 23.7 | 19.6 | 23.7 | 19.4 | 23.6 |
| | 0.01 | 23.6 | 23.6 | 22.8 | 24.1 | 22.8 | 24.0 | 23.7 | 23.2 | 22.7 | 23.5 | 22.9 | 23.4 | 22.5 | 23.5 |
| | 0.05 | 12.0 | 23.8 | 11.5 | 24.4 | 11.5 | 24.3 | 21.2 | 27.2 | 20.9 | 26.4 | 20.8 | 26.4 | 20.6 | 26.6 |
| 0.02 | 0.02 | 19.4 | 23.8 | 18.9 | 24.4 | 18.9 | 24.3 | 21.1 | 23.7 | 19.3 | 24.4 | 19.2 | 24.1 | 19.1 | 24.2 |
| | 0.01 | 22.7 | 23.8 | 22.1 | 24.6 | 22.0 | 24.3 | 23.3 | 23.7 | 22.2 | 24.3 | 22.6 | 24.2 | 22.2 | 24.3 |
| 0.01 | 0.05 | 11.8 | 24.0 | 11.3 | 24.6 | 11.3 | 24.4 | 14.4 | 23.8 | 11.3 | 24.5 | 11.6 | 24.3 | 11.1 | 24.6 |

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.02 | 19.3 | 23.8 | 18.8 | 24.5 | 18.9 | 24.4 | 20.7 | 23.6 | 19.1 | 24.4 | 19.1 | 24.0 | 18.8 | 24.4 |
| | 0.01 | 22.5 | 24.1 | 21.9 | 24.8 | 21.9 | 24.6 | 23.5 | 23.8 | 22.4 | 24.4 | 22.6 | 24.2 | 22.2 | 24.4 |
| | 0.05 | 11.7 | 24.3 | 11.3 | 24.9 | 11.3 | 24.8 | 14.4 | 23.9 | 11.2 | 24.5 | 11.5 | 24.2 | 11.0 | 24.5 |
| 0 | 0.02 | 19.2 | 24.3 | 18.8 | 25.0 | 18.8 | 24.8 | 20.7 | 24.1 | 18.8 | 24.6 | 18.8 | 24.4 | 18.6 | 24.7 |
| | 0.01 | 22.1 | 24.0 | 21.5 | 24.7 | 21.5 | 24.6 | 23.1 | 24.0 | 21.8 | 24.6 | 22.1 | 24.3 | 21.6 | 24.6 |

SIC 7373 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 15.1 | 24.5 | 15.4 | 24.7 | 15.7 | 24.2 | 17.9 | 25.0 | 15.5 | 24.7 | 15.8 | 24.7 | 15.4 | 24.9 |
| 0.1 | 0.02 | 20.8 | 24.6 | 20.9 | 24.7 | 21.3 | 24.4 | 22.0 | 25.4 | 20.9 | 25.2 | 21.1 | 25.0 | 20.7 | 25.4 |
| | 0.01 | 23.0 | 24.7 | 23.0 | 24.8 | 23.1 | 24.3 | 23.5 | 25.0 | 22.9 | 24.6 | 23.0 | 24.5 | 22.9 | 24.8 |
| | 0.05 | 14.3 | 25.6 | 14.7 | 25.6 | 15.3 | 25.1 | 17.6 | 25.5 | 14.9 | 25.6 | 15.3 | 25.5 | 14.8 | 25.8 |
| 0.05 | 0.02 | 19.8 | 25.7 | 20.0 | 25.6 | 20.4 | 25.4 | 21.5 | 25.6 | 20.1 | 25.5 | 20.6 | 25.3 | 19.9 | 25.7 |
| | 0.01 | 22.1 | 25.9 | 22.2 | 25.8 | 22.5 | 25.5 | 23.1 | 25.9 | 22.1 | 25.7 | 22.3 | 25.6 | 22.1 | 25.9 |
| | 0.05 | 13.5 | 26.6 | 13.9 | 26.5 | 14.5 | 26.1 | 17.3 | 25.9 | 14.5 | 26.1 | 14.8 | 25.9 | 14.5 | 26.2 |
| 0.02 | 0.02 | 19.0 | 26.2 | 19.4 | 26.2 | 20.0 | 25.7 | 21.2 | 25.9 | 19.6 | 26.1 | 20.0 | 25.9 | 19.5 | 26.1 |
| | 0.01 | 21.7 | 26.3 | 21.8 | 26.2 | 22.0 | 25.7 | 22.7 | 25.7 | 21.6 | 25.9 | 22.0 | 25.7 | 21.6 | 25.9 |
| | 0.05 | 13.5 | 26.5 | 14.0 | 26.5 | 14.5 | 25.9 | 17.0 | 26.3 | 14.2 | 26.7 | 14.6 | 26.5 | 14.2 | 26.9 |
| 0.01 | 0.02 | 19.0 | 26.5 | 19.5 | 26.4 | 20.0 | 26.0 | 21.0 | 26.3 | 19.3 | 26.4 | 19.8 | 26.3 | 19.5 | 26.7 |
| | 0.01 | 21.2 | 26.4 | 21.5 | 26.4 | 21.8 | 25.9 | 22.7 | 25.9 | 21.6 | 26.2 | 22.0 | 26.1 | 21.5 | 26.3 |
| | 0.05 | 13.2 | 26.8 | 13.8 | 26.6 | 14.2 | 26.2 | 23.3 | 25.2 | 21.8 | 25.9 | 22.5 | 25.5 | 22.0 | 25.8 |
| 0 | 0.02 | 18.5 | 26.5 | 19.2 | 26.1 | 19.5 | 25.7 | 21.7 | 25.2 | 19.8 | 26.0 | 20.5 | 25.5 | 19.9 | 25.8 |
| | 0.01 | 20.8 | 26.7 | 21.2 | 26.4 | 21.3 | 26.0 | 23.4 | 25.4 | 21.8 | 26.1 | 22.5 | 25.6 | 22.0 | 26.0 |

SIC 2836 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 19.0 | 23.0 | 18.4 | 23.9 | 19.4 | 22.6 | 22.0 | 22.1 | 19.2 | 22.7 | 19.5 | 22.5 | 19.2 | 22.5 |
| 0.1 | 0.02 | 23.4 | 23.0 | 22.9 | 23.9 | 23.7 | 22.4 | 24.8 | 22.1 | 23.3 | 22.8 | 23.5 | 22.4 | 23.6 | 22.4 |
| | 0.01 | 25.3 | 22.8 | 24.5 | 23.7 | 25.7 | 22.3 | 26.4 | 21.9 | 25.4 | 22.7 | 25.8 | 22.4 | 25.5 | 22.3 |
| | 0.05 | 18.7 | 23.7 | 17.9 | 24.7 | 19.2 | 23.7 | 21.3 | 22.3 | 18.3 | 23.2 | 18.7 | 23.1 | 18.3 | 23.3 |
| 0.05 | 0.02 | 22.7 | 24.0 | 22.2 | 25.0 | 22.9 | 23.8 | 24.3 | 22.6 | 22.6 | 23.5 | 23.0 | 23.5 | 22.5 | 23.8 |
| | 0.01 | 24.1 | 23.3 | 23.5 | 24.3 | 24.6 | 23.3 | 25.9 | 22.4 | 25.0 | 23.4 | 25.3 | 23.3 | 24.9 | 23.4 |
| | 0.05 | 18.5 | 23.8 | 17.9 | 24.7 | 18.8 | 23.5 | 21.3 | 23.0 | 18.1 | 24.0 | 18.5 | 23.9 | 18.0 | 24.4 |
| 0.02 | 0.02 | 22.3 | 24.2 | 21.6 | 24.9 | 22.5 | 24.0 | 23.8 | 23.1 | 21.6 | 23.9 | 22.2 | 23.7 | 21.7 | 24.2 |
| | 0.01 | 23.7 | 23.9 | 23.3 | 24.9 | 24.2 | 23.7 | 25.5 | 22.5 | 24.4 | 23.7 | 24.8 | 23.6 | 24.6 | 24.1 |
| | 0.05 | 18.2 | 24.3 | 17.5 | 24.8 | 18.7 | 24.0 | 21.0 | 23.0 | 18.0 | 24.3 | 18.4 | 24.2 | 18.1 | 24.4 |
| 0.01 | 0.02 | 22.5 | 24.5 | 21.6 | 25.3 | 22.7 | 24.4 | 24.2 | 23.1 | 22.2 | 24.6 | 22.7 | 24.3 | 22.1 | 24.6 |
| | 0.01 | 23.9 | 24.5 | 23.4 | 25.3 | 24.3 | 24.3 | 25.3 | 22.8 | 24.2 | 24.2 | 24.5 | 24.1 | 24.5 | 24.5 |
| | 0.05 | 18.1 | 24.6 | 17.4 | 25.4 | 18.6 | 24.4 | 20.7 | 23.5 | 17.4 | 24.6 | 17.9 | 24.4 | 17.4 | 24.6 |
| 0 | 0.02 | 22.0 | 25.1 | 21.0 | 25.8 | 22.2 | 24.6 | 24.1 | 23.3 | 21.8 | 24.4 | 22.2 | 24.2 | 21.7 | 24.4 |
| | 0.01 | 23.6 | 24.7 | 23.1 | 25.5 | 24.1 | 24.5 | 25.4 | 22.9 | 24.0 | 24.1 | 24.2 | 23.9 | 24.1 | 24.1 |

SIC 3845 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.1 | 24.2 | 15.5 | 24.4 | 16.5 | 23.5 | 19.1 | 23.6 | 16.2 | 23.3 | 16.3 | 23.5 | 16.3 | 23.8 |
| 0.1 | 0.02 | 21.4 | 24.2 | 21.4 | 24.5 | 21.9 | 23.5 | 23.3 | 23.6 | 22.1 | 23.4 | 21.9 | 23.8 | 21.8 | 23.9 |
| | 0.01 | 23.9 | 24.0 | 23.7 | 24.3 | 24.6 | 23.5 | 24.6 | 23.6 | 24.2 | 23.4 | 23.8 | 23.8 | 23.7 | 23.9 |
| | 0.05 | 15.3 | 25.1 | 14.7 | 25.2 | 15.5 | 24.2 | 18.4 | 24.6 | 15.5 | 24.6 | 15.3 | 25.0 | 15.5 | 25.0 |
| 0.05 | 0.02 | 20.6 | 25.2 | 20.6 | 25.4 | 21.1 | 24.5 | 22.7 | 24.7 | 21.2 | 24.8 | 21.1 | 25.2 | 21.0 | 25.2 |
| | 0.01 | 22.7 | 25.1 | 22.7 | 25.2 | 23.4 | 24.3 | 23.9 | 24.6 | 23.2 | 24.7 | 22.5 | 25.1 | 22.5 | 25.0 |
| | 0.05 | 14.9 | 25.6 | 14.4 | 25.6 | 15.2 | 25.0 | 18.1 | 25.1 | 14.8 | 25.2 | 14.8 | 25.9 | 14.9 | 25.7 |
| 0.02 | 0.02 | 20.0 | 25.7 | 19.9 | 25.6 | 20.7 | 25.2 | 22.1 | 24.9 | 20.7 | 25.1 | 20.4 | 25.7 | 20.4 | 25.6 |
| | 0.01 | 22.1 | 25.8 | 22.2 | 25.8 | 22.8 | 25.3 | 23.7 | 24.8 | 22.7 | 25.0 | 22.3 | 25.6 | 22.3 | 25.4 |
| | 0.05 | 14.7 | 26.0 | 14.1 | 25.9 | 15.0 | 25.2 | 17.8 | 24.8 | 14.6 | 25.0 | 14.5 | 25.7 | 14.5 | 25.5 |
| 0.01 | 0.02 | 20.1 | 25.8 | 19.8 | 25.8 | 20.5 | 25.1 | 21.9 | 25.2 | 20.4 | 25.3 | 20.2 | 26.0 | 20.1 | 25.8 |
| | 0.01 | 22.0 | 25.7 | 21.9 | 25.7 | 22.7 | 25.2 | 23.8 | 25.1 | 22.7 | 25.3 | 22.4 | 26.1 | 22.3 | 25.9 |
| | 0.05 | 14.5 | 26.1 | 14.1 | 26.1 | 14.7 | 25.4 | 17.7 | 24.9 | 14.5 | 25.4 | 14.6 | 25.9 | 14.5 | 25.8 |
| 0 | 0.02 | 19.9 | 26.1 | 19.7 | 26.2 | 20.5 | 25.4 | 22.0 | 25.4 | 20.3 | 25.7 | 20.1 | 26.2 | 20.0 | 26.1 |
| | 0.01 | 21.7 | 26.2 | 21.6 | 26.2 | 22.5 | 25.6 | 23.5 | 25.0 | 22.5 | 25.4 | 22.1 | 25.9 | 22.0 | 25.8 |

SIC 4813 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 10.4 | 23.8 | 10.8 | 23.7 | 11.2 | 23.6 | 13.7 | 25.2 | 10.0 | 23.8 | 11.2 | 23.1 | 9.7 | 23.9 |
| 0.1 | 0.02 | 18.7 | 24.1 | 19.2 | 24.1 | 19.0 | 23.8 | 20.4 | 25.7 | 18.3 | 24.1 | 19.2 | 23.3 | 17.8 | 24.2 |
| | 0.01 | 22.0 | 23.6 | 22.5 | 23.7 | 22.7 | 23.0 | 22.4 | 25.1 | 22.0 | 23.6 | 22.9 | 22.8 | 22.0 | 23.6 |
| | 0.05 | 9.6 | 24.4 | 10.2 | 24.1 | 10.6 | 23.9 | 13.4 | 26.1 | 9.5 | 25.1 | 10.8 | 24.4 | 9.3 | 25.6 |
| 0.05 | 0.02 | 17.6 | 24.6 | 18.2 | 24.4 | 18.4 | 24.4 | 19.3 | 25.8 | 17.7 | 24.5 | 18.6 | 23.9 | 17.2 | 25.0 |
| | 0.01 | 21.0 | 24.4 | 21.3 | 24.1 | 21.4 | 23.9 | 21.5 | 26.0 | 20.7 | 24.8 | 21.5 | 24.1 | 20.5 | 25.4 |
| | 0.05 | 9.2 | 25.6 | 9.8 | 25.3 | 10.3 | 25.3 | 13.2 | 26.7 | 9.1 | 25.9 | 10.4 | 25.0 | 8.8 | 26.0 |
| 0.02 | 0.02 | 17.1 | 25.4 | 17.6 | 25.0 | 17.5 | 25.0 | 19.0 | 26.0 | 16.7 | 25.2 | 17.7 | 24.5 | 16.3 | 25.4 |
| | 0.01 | 20.7 | 25.4 | 21.0 | 25.2 | 21.2 | 25.1 | 21.7 | 26.1 | 20.6 | 25.4 | 21.4 | 24.6 | 20.4 | 25.7 |
| | 0.05 | 8.8 | 25.6 | 9.5 | 25.3 | 10.1 | 25.4 | 13.3 | 26.5 | 9.1 | 25.6 | 10.3 | 25.2 | 8.8 | 26.0 |
| 0.01 | 0.02 | 17.0 | 25.7 | 17.8 | 25.4 | 17.6 | 25.1 | 19.0 | 26.5 | 16.8 | 25.8 | 17.7 | 25.1 | 16.4 | 26.0 |
| | 0.01 | 20.4 | 25.6 | 20.6 | 25.3 | 21.0 | 25.2 | 21.3 | 26.6 | 20.2 | 26.1 | 21.0 | 25.4 | 19.9 | 26.4 |
| | 0.05 | 9.1 | 25.9 | 9.6 | 25.5 | 9.9 | 25.3 | 12.8 | 26.5 | 8.9 | 26.0 | 9.9 | 25.1 | 8.5 | 26.1 |
| 0 | 0.02 | 16.5 | 25.6 | 16.9 | 25.4 | 17.2 | 24.9 | 18.8 | 26.9 | 16.4 | 26.3 | 17.4 | 25.4 | 15.9 | 26.4 |
| | 0.01 | 19.9 | 25.9 | 20.2 | 25.3 | 20.2 | 25.2 | 21.3 | 26.1 | 19.9 | 25.7 | 20.8 | 24.9 | 19.7 | 25.9 |

SIC 3663 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.8 | 25.3 | 18.1 | 24.4 | 17.6 | 25.1 | 20.4 | 23.8 | 17.7 | 24.7 | 17.1 | 25.3 | 17.4 | 25.0 |
| 0.1 | 0.02 | 20.9 | 25.0 | 22.3 | 24.1 | 21.7 | 24.8 | 23.7 | 23.6 | 22.0 | 24.5 | 21.3 | 25.1 | 21.8 | 24.8 |
| | 0.01 | 22.5 | 25.1 | 23.8 | 24.2 | 23.1 | 24.8 | 24.9 | 24.2 | 23.7 | 25.1 | 23.0 | 25.9 | 23.5 | 25.5 |
| | 0.05 | 16.3 | 26.5 | 17.4 | 25.5 | 17.0 | 26.1 | 19.8 | 24.8 | 16.6 | 25.8 | 16.2 | 26.3 | 16.4 | 26.0 |
| 0.05 | 0.02 | 20.4 | 26.3 | 21.6 | 25.4 | 21.1 | 25.9 | 23.1 | 24.6 | 21.1 | 25.8 | 20.5 | 26.1 | 21.0 | 25.9 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 21.8 | 26.5 | 23.0 | 25.4 | 22.5 | 26.0 | 24.2 | 24.8 | 22.7 | 26.0 | 22.1 | 26.4 | 22.5 | 26.0 |
| | 0.05 | 16.0 | 27.2 | 17.0 | 26.1 | 16.6 | 26.6 | 19.5 | 24.8 | 16.1 | 26.4 | 15.8 | 26.9 | 15.9 | 26.5 |
| 0.02 | 0.02 | 19.6 | 27.1 | 21.0 | 26.2 | 20.3 | 26.6 | 22.6 | 25.0 | 20.3 | 26.5 | 20.0 | 27.1 | 20.5 | 26.6 |
| | 0.01 | 21.2 | 27.5 | 22.6 | 26.3 | 22.1 | 26.9 | 23.8 | 25.0 | 22.0 | 26.5 | 21.5 | 26.9 | 21.8 | 26.3 |
| | 0.05 | 15.8 | 27.4 | 16.5 | 26.1 | 16.4 | 26.7 | 19.7 | 25.3 | 16.4 | 26.9 | 15.8 | 27.5 | 16.1 | 26.9 |
| 0.01 | 0.02 | 19.1 | 27.3 | 20.3 | 26.3 | 19.9 | 26.8 | 22.3 | 25.3 | 20.4 | 27.0 | 19.9 | 27.5 | 20.5 | 27.1 |
| | 0.01 | 21.2 | 27.4 | 22.4 | 26.2 | 21.9 | 26.7 | 23.5 | 24.8 | 21.7 | 26.4 | 21.4 | 26.9 | 21.5 | 26.4 |
| | 0.05 | 15.6 | 27.2 | 16.6 | 26.0 | 16.2 | 26.5 | 19.1 | 25.1 | 15.7 | 26.7 | 15.2 | 27.1 | 15.3 | 26.6 |
| 0 | 0.02 | 19.2 | 27.5 | 20.3 | 26.1 | 19.8 | 26.7 | 22.5 | 25.1 | 20.3 | 26.7 | 19.8 | 27.2 | 20.4 | 26.8 |
| | 0.01 | 20.9 | 27.7 | 22.2 | 26.5 | 21.8 | 27.1 | 23.8 | 25.2 | 21.7 | 26.8 | 21.2 | 27.3 | 21.5 | 26.7 |

<u>SIC 4931 (%)</u>

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.2 | 24.5 | 15.1 | 26.1 | 16.2 | 23.5 | 17.4 | 24.5 | 16.0 | 23.2 | 17.1 | 23.2 | 16.2 | 23.0 |
| 0.1 | 0.02 | 21.6 | 24.5 | 20.3 | 26.0 | 21.9 | 23.4 | 22.2 | 24.7 | 22.2 | 23.5 | 22.7 | 23.5 | 22.5 | 23.2 |
| | 0.01 | 23.4 | 24.2 | 22.0 | 25.9 | 24.1 | 23.4 | 23.8 | 24.8 | 24.1 | 23.5 | 24.7 | 23.5 | 24.6 | 23.3 |
| | 0.05 | 15.4 | 25.3 | 14.5 | 26.6 | 15.7 | 24.3 | 16.7 | 25.3 | 15.4 | 24.3 | 16.2 | 24.2 | 15.4 | 23.9 |
| 0.05 | 0.02 | 20.6 | 25.4 | 19.5 | 26.7 | 21.4 | 24.4 | 21.3 | 25.4 | 21.2 | 24.4 | 21.5 | 24.3 | 21.5 | 24.1 |
| | 0.01 | 22.6 | 25.3 | 21.3 | 26.7 | 23.3 | 24.3 | 23.1 | 25.2 | 23.3 | 24.1 | 24.0 | 24.2 | 23.8 | 23.8 |
| | 0.05 | 15.1 | 26.1 | 14.3 | 27.4 | 15.5 | 25.0 | 16.2 | 25.7 | 14.9 | 24.8 | 15.5 | 24.6 | 14.9 | 24.4 |
| 0.02 | 0.02 | 19.9 | 26.0 | 19.1 | 27.3 | 20.8 | 25.0 | 20.7 | 25.6 | 20.7 | 24.8 | 21.0 | 24.6 | 21.0 | 24.4 |
| | 0.01 | 22.2 | 25.8 | 21.0 | 27.0 | 22.8 | 24.7 | 22.5 | 25.9 | 22.6 | 24.9 | 23.2 | 24.8 | 23.1 | 24.6 |
| | 0.05 | 14.9 | 26.3 | 14.0 | 27.5 | 15.1 | 25.1 | 16.3 | 26.0 | 14.7 | 25.1 | 15.4 | 25.0 | 14.7 | 24.7 |
| 0.01 | 0.02 | 20.0 | 26.1 | 19.1 | 27.2 | 20.8 | 25.0 | 20.7 | 25.9 | 20.6 | 25.0 | 21.0 | 24.8 | 20.8 | 24.6 |
| | 0.01 | 22.0 | 25.9 | 20.8 | 27.0 | 22.8 | 24.9 | 22.3 | 26.0 | 22.3 | 25.0 | 22.9 | 25.0 | 22.8 | 24.7 |
| | 0.05 | 14.8 | 26.2 | 14.0 | 27.4 | 15.1 | 25.1 | 16.4 | 25.8 | 14.8 | 24.9 | 15.5 | 24.9 | 14.9 | 24.4 |
| 0 | 0.02 | 19.9 | 26.2 | 19.1 | 27.4 | 20.8 | 25.1 | 20.7 | 26.1 | 20.7 | 25.2 | 21.0 | 25.1 | 20.9 | 24.8 |
| | 0.01 | 22.0 | 26.2 | 20.9 | 27.4 | 22.8 | 25.1 | 22.2 | 26.1 | 22.4 | 25.3 | 22.8 | 25.1 | 22.7 | 24.8 |

<u>SIC 3841 (%)</u>

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 11.1 | 26.1 | 11.5 | 25.9 | 11.6 | 24.9 | 14.2 | 25.9 | 11.6 | 24.9 | 11.6 | 25.4 | 11.4 | 25.2 |
| 0.1 | 0.02 | 18.1 | 26.3 | 18.4 | 26.2 | 18.4 | 25.2 | 19.6 | 25.7 | 18.9 | 25.0 | 18.3 | 25.5 | 18.3 | 25.4 |
| | 0.01 | 20.8 | 25.8 | 21.0 | 25.7 | 21.4 | 24.8 | 22.1 | 25.1 | 22.2 | 24.2 | 21.1 | 24.6 | 22.0 | 24.6 |
| | 0.05 | 10.8 | 26.3 | 11.2 | 26.4 | 11.6 | 25.7 | 13.3 | 25.8 | 11.0 | 24.9 | 10.9 | 25.4 | 10.8 | 25.4 |
| 0.05 | 0.02 | 16.9 | 26.5 | 17.5 | 26.4 | 17.7 | 25.8 | 19.0 | 26.0 | 18.0 | 25.4 | 17.6 | 25.9 | 17.7 | 26.0 |
| | 0.01 | 20.4 | 26.6 | 20.5 | 26.5 | 20.9 | 26.0 | 21.1 | 26.1 | 20.7 | 25.3 | 20.0 | 26.0 | 20.5 | 25.8 |
| | 0.05 | 10.4 | 27.4 | 10.7 | 27.4 | 10.9 | 26.5 | 13.2 | 26.5 | 10.6 | 26.0 | 10.4 | 26.9 | 10.3 | 26.4 |
| 0.02 | 0.02 | 16.5 | 26.8 | 17.1 | 26.8 | 17.3 | 26.1 | 18.3 | 26.2 | 17.2 | 26.0 | 17.2 | 26.6 | 17.0 | 26.4 |
| | 0.01 | 20.0 | 27.2 | 20.1 | 27.1 | 20.2 | 26.3 | 20.8 | 26.3 | 20.6 | 25.6 | 19.7 | 26.5 | 20.1 | 26.2 |
| | 0.05 | 10.0 | 27.3 | 10.4 | 27.4 | 10.5 | 26.5 | 13.1 | 26.2 | 10.6 | 26.1 | 10.6 | 26.7 | 10.3 | 26.4 |
| 0.01 | 0.02 | 16.4 | 27.1 | 17.0 | 27.0 | 17.0 | 26.2 | 18.4 | 26.2 | 17.4 | 25.8 | 17.2 | 26.7 | 17.2 | 26.3 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 19.9 | 27.4 | 19.9 | 27.3 | 20.0 | 26.4 | 20.8 | 26.4 | 20.8 | 26.4 | 19.6 | 26.9 | 20.2 | 26.8 |
| | 0.05 | 9.9 | 27.5 | 10.3 | 27.5 | 10.5 | 26.7 | 13.1 | 26.9 | 10.6 | 26.3 | 10.5 | 27.1 | 10.3 | 26.7 |
| 0 | 0.02 | 16.1 | 27.8 | 16.6 | 27.5 | 16.9 | 26.8 | 18.2 | 26.4 | 17.1 | 26.2 | 17.0 | 27.0 | 16.9 | 26.6 |
| | 0.01 | 19.6 | 27.4 | 19.7 | 27.4 | 19.8 | 26.7 | 20.2 | 26.4 | 20.2 | 26.3 | 19.4 | 26.8 | 19.7 | 26.4 |

SIC 9995 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 23.7 | 21.9 | 24.2 | 22.6 | 26.8 | 19.0 | 28.1 | 16.4 | 26.1 | 17.9 | 26.8 | 17.7 | 27.3 | 16.6 |
| 0.1 | 0.02 | 26.4 | 21.7 | 26.5 | 22.4 | 29.1 | 18.9 | 31.8 | 16.9 | 30.0 | 18.3 | 29.1 | 18.3 | 29.8 | 16.9 |
| | 0.01 | 26.9 | 22.1 | 26.3 | 21.8 | 29.2 | 19.0 | 31.0 | 16.8 | 29.2 | 18.2 | 28.7 | 18.1 | 29.8 | 16.8 |
| | 0.05 | 23.6 | 22.5 | 23.7 | 23.5 | 26.5 | 19.8 | 27.9 | 18.4 | 24.9 | 19.9 | 25.7 | 20.7 | 26.4 | 19.0 |
| 0.05 | 0.02 | 25.2 | 22.2 | 24.5 | 23.0 | 27.8 | 18.9 | 30.4 | 18.3 | 28.2 | 18.9 | 27.2 | 20.2 | 28.9 | 18.6 |
| | 0.01 | 28.2 | 22.1 | 27.4 | 22.9 | 30.5 | 19.3 | 30.7 | 17.4 | 29.6 | 18.9 | 29.0 | 19.7 | 30.9 | 18.3 |
| | 0.05 | 23.5 | 22.1 | 23.0 | 23.0 | 26.5 | 19.3 | 26.5 | 18.6 | 24.0 | 19.9 | 25.0 | 20.8 | 26.0 | 19.2 |
| 0.02 | 0.02 | 25.3 | 23.4 | 24.6 | 24.3 | 27.5 | 20.0 | 29.2 | 17.6 | 27.9 | 19.3 | 26.6 | 20.0 | 28.7 | 18.1 |
| | 0.01 | 26.9 | 22.3 | 26.6 | 23.5 | 29.1 | 19.6 | 30.4 | 18.2 | 29.0 | 19.6 | 28.1 | 20.9 | 30.5 | 18.8 |
| | 0.05 | 23.6 | 21.9 | 23.6 | 22.8 | 26.8 | 19.3 | 28.3 | 18.5 | 25.4 | 20.1 | 25.8 | 20.6 | 27.1 | 19.0 |
| 0.01 | 0.02 | 25.9 | 22.3 | 25.4 | 23.0 | 28.5 | 19.7 | 29.7 | 19.0 | 28.1 | 20.7 | 26.7 | 21.6 | 28.9 | 19.6 |
| | 0.01 | 26.3 | 22.8 | 26.1 | 23.9 | 28.2 | 19.9 | 30.5 | 19.1 | 28.2 | 20.3 | 26.9 | 20.9 | 29.5 | 18.6 |
| | 0.05 | 23.0 | 23.5 | 23.0 | 24.3 | 25.5 | 20.2 | 27.0 | 17.9 | 24.1 | 19.3 | 25.1 | 21.0 | 26.0 | 18.3 |
| 0 | 0.02 | 24.8 | 23.8 | 24.6 | 24.7 | 27.1 | 21.0 | 29.9 | 18.1 | 28.1 | 19.8 | 27.4 | 21.2 | 29.0 | 18.6 |
| | 0.01 | 26.6 | 23.9 | 25.9 | 24.5 | 28.6 | 20.8 | 31.0 | 18.5 | 29.1 | 19.9 | 27.8 | 21.0 | 30.2 | 18.9 |

SIC 7990 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.7 | 23.2 | 16.7 | 22.8 | 16.6 | 23.3 | 19.0 | 23.0 | 16.7 | 22.9 | 17.0 | 22.3 | 16.6 | 22.8 |
| 0.1 | 0.02 | 22.3 | 23.2 | 23.0 | 23.2 | 22.1 | 23.4 | 24.0 | 23.1 | 22.8 | 23.0 | 23.1 | 22.5 | 22.3 | 23.0 |
| | 0.01 | 24.2 | 22.9 | 24.9 | 22.8 | 24.1 | 23.2 | 25.0 | 23.4 | 24.6 | 23.4 | 24.7 | 22.8 | 24.3 | 23.2 |
| | 0.05 | 15.9 | 23.7 | 16.0 | 22.9 | 15.8 | 23.9 | 18.5 | 23.7 | 16.1 | 23.6 | 16.2 | 23.4 | 15.9 | 23.6 |
| 0.05 | 0.02 | 21.2 | 24.2 | 21.8 | 23.7 | 20.5 | 24.5 | 23.1 | 23.9 | 21.6 | 23.8 | 21.7 | 23.7 | 21.1 | 23.9 |
| | 0.01 | 23.3 | 24.6 | 23.8 | 23.9 | 23.0 | 24.9 | 24.6 | 24.0 | 23.9 | 24.2 | 24.3 | 24.1 | 23.7 | 24.2 |
| | 0.05 | 15.5 | 24.7 | 15.6 | 24.4 | 15.5 | 25.2 | 18.4 | 25.2 | 15.9 | 25.4 | 16.1 | 25.0 | 15.7 | 25.3 |
| 0.02 | 0.02 | 20.7 | 25.0 | 21.2 | 24.5 | 20.2 | 25.5 | 22.3 | 24.6 | 20.8 | 24.7 | 21.0 | 24.4 | 20.6 | 24.7 |
| | 0.01 | 22.9 | 24.9 | 23.4 | 24.5 | 22.8 | 25.5 | 24.1 | 24.3 | 23.2 | 24.5 | 23.7 | 24.2 | 23.0 | 24.4 |
| | 0.05 | 15.5 | 24.7 | 15.7 | 24.2 | 15.6 | 25.2 | 18.1 | 24.8 | 15.5 | 24.8 | 15.5 | 24.6 | 15.2 | 24.9 |
| 0.01 | 0.02 | 21.0 | 24.6 | 21.7 | 24.3 | 20.5 | 25.1 | 22.3 | 24.4 | 21.0 | 24.8 | 21.2 | 24.4 | 20.6 | 24.8 |
| | 0.01 | 22.9 | 24.8 | 23.6 | 24.5 | 22.5 | 25.1 | 24.2 | 24.5 | 23.1 | 24.6 | 23.6 | 24.4 | 22.8 | 24.7 |
| | 0.05 | 15.0 | 25.1 | 15.2 | 24.8 | 15.1 | 25.7 | 17.8 | 24.5 | 15.2 | 24.6 | 15.2 | 24.3 | 14.9 | 24.7 |
| 0 | 0.02 | 20.4 | 25.5 | 20.9 | 25.0 | 19.7 | 25.8 | 22.2 | 24.8 | 20.5 | 24.9 | 20.9 | 24.4 | 20.3 | 25.0 |
| | 0.01 | 22.7 | 25.2 | 23.3 | 24.9 | 22.2 | 25.7 | 23.8 | 25.0 | 22.6 | 25.0 | 22.9 | 24.6 | 22.3 | 25.1 |

SIC 3714 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 15.8 | 22.8 | 15.9 | 23.1 | 14.9 | 23.4 | 17.1 | 23.5 | 15.1 | 22.2 | 15.5 | 22.6 | 15.2 | 22.4 |
| 0.1 | 0.02 | 22.3 | 22.6 | 22.3 | 23.1 | 21.4 | 23.3 | 22.1 | 23.9 | 22.0 | 22.7 | 22.1 | 23.1 | 21.8 | 23.1 |
| | 0.01 | 24.7 | 22.6 | 24.8 | 23.1 | 23.8 | 23.3 | 24.1 | 23.9 | 24.5 | 22.4 | 24.7 | 22.7 | 24.4 | 22.7 |
| | 0.05 | 15.2 | 23.9 | 15.1 | 24.1 | 14.3 | 24.5 | 16.7 | 24.9 | 14.4 | 23.9 | 14.8 | 24.0 | 14.4 | 23.9 |
| 0.05 | 0.02 | 21.8 | 23.4 | 21.4 | 23.8 | 20.6 | 24.3 | 21.6 | 24.6 | 21.1 | 23.5 | 21.0 | 23.6 | 20.8 | 23.6 |
| | 0.01 | 24.1 | 23.8 | 24.3 | 24.1 | 23.1 | 24.6 | 23.0 | 24.9 | 23.8 | 23.9 | 23.5 | 24.2 | 23.5 | 24.1 |
| | 0.05 | 14.3 | 24.2 | 14.3 | 24.1 | 13.6 | 24.7 | 21.0 | 24.9 | 20.2 | 23.8 | 20.4 | 24.2 | 20.2 | 24.1 |
| 0.02 | 0.02 | 21.3 | 24.4 | 20.8 | 24.3 | 20.0 | 25.3 | 21.0 | 24.9 | 20.2 | 23.8 | 20.4 | 24.2 | 20.2 | 24.1 |
| | 0.01 | 22.9 | 24.1 | 23.1 | 24.2 | 21.8 | 24.9 | 23.1 | 24.9 | 23.5 | 24.1 | 23.4 | 24.4 | 23.6 | 24.2 |
| | 0.05 | 14.5 | 24.3 | 14.4 | 24.3 | 13.7 | 24.8 | 16.3 | 25.4 | 14.0 | 24.5 | 14.3 | 24.7 | 14.0 | 24.6 |
| 0.01 | 0.02 | 20.8 | 24.5 | 20.5 | 24.4 | 19.4 | 25.1 | 21.3 | 24.8 | 20.7 | 24.0 | 20.8 | 24.3 | 20.4 | 24.0 |
| | 0.01 | 23.0 | 24.3 | 23.2 | 24.4 | 22.0 | 25.0 | 22.9 | 25.6 | 23.0 | 24.7 | 23.0 | 24.9 | 23.1 | 24.7 |
| | 0.05 | 14.3 | 24.8 | 14.4 | 24.7 | 13.5 | 25.4 | 16.5 | 25.5 | 14.1 | 24.6 | 14.5 | 24.7 | 14.2 | 24.6 |
| 0 | 0.02 | 20.5 | 25.1 | 20.2 | 25.0 | 19.1 | 25.6 | 21.1 | 25.7 | 20.4 | 24.9 | 20.6 | 25.0 | 20.2 | 24.9 |
| | 0.01 | 23.0 | 24.6 | 23.0 | 24.5 | 22.0 | 25.2 | 22.8 | 25.8 | 22.7 | 24.8 | 22.9 | 25.0 | 23.0 | 24.8 |

<u>SIC 6331 (%)</u>

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 13.1 | 24.6 | 13.1 | 24.8 | 13.1 | 24.1 | 14.8 | 25.9 | 12.9 | 24.9 | 13.3 | 24.9 | 13.3 | 25.3 |
| 0.1 | 0.02 | 18.9 | 24.7 | 19.3 | 24.9 | 19.4 | 24.5 | 20.0 | 25.7 | 19.6 | 24.8 | 19.3 | 24.7 | 19.4 | 25.1 |
| | 0.01 | 21.7 | 25.1 | 21.9 | 25.3 | 22.1 | 24.6 | 22.2 | 25.7 | 22.1 | 24.8 | 22.2 | 24.8 | 22.0 | 25.2 |
| | 0.05 | 12.2 | 26.2 | 12.5 | 26.3 | 12.5 | 25.6 | 14.2 | 26.3 | 12.5 | 26.1 | 12.7 | 25.6 | 12.5 | 26.1 |
| 0.05 | 0.02 | 18.1 | 25.9 | 18.3 | 25.8 | 18.7 | 25.3 | 19.5 | 26.4 | 18.5 | 25.8 | 18.7 | 25.6 | 18.8 | 26.1 |
| | 0.01 | 20.9 | 26.4 | 21.2 | 26.6 | 21.4 | 25.7 | 21.4 | 26.5 | 21.4 | 25.9 | 21.3 | 25.6 | 21.3 | 26.1 |
| | 0.05 | 11.6 | 26.4 | 11.9 | 26.4 | 11.8 | 26.0 | 25.2 | 22.7 | 24.5 | 22.8 | 24.4 | 23.0 | 24.5 | 22.9 |
| 0.02 | 0.02 | 18.1 | 26.7 | 18.2 | 26.6 | 18.5 | 26.0 | 18.9 | 27.2 | 17.9 | 26.5 | 18.1 | 26.7 | 17.8 | 26.7 |
| | 0.01 | 20.4 | 26.9 | 20.5 | 27.1 | 20.7 | 26.3 | 21.2 | 27.2 | 20.9 | 26.4 | 20.8 | 26.4 | 20.6 | 26.6 |
| | 0.05 | 11.8 | 27.0 | 11.9 | 27.0 | 11.8 | 26.4 | 13.5 | 26.8 | 11.6 | 26.3 | 11.9 | 26.3 | 11.7 | 26.6 |
| 0.01 | 0.02 | 18.2 | 27.0 | 18.6 | 27.2 | 18.7 | 26.4 | 18.8 | 27.1 | 17.9 | 26.7 | 18.1 | 26.9 | 17.7 | 27.0 |
| | 0.01 | 20.6 | 26.6 | 20.6 | 26.8 | 20.9 | 26.1 | 20.7 | 26.7 | 20.8 | 26.4 | 20.4 | 26.4 | 20.5 | 26.7 |
| | 0.05 | 11.6 | 26.8 | 11.9 | 27.0 | 11.8 | 26.3 | 13.8 | 27.4 | 11.7 | 26.9 | 12.0 | 26.9 | 11.8 | 27.2 |
| 0 | 0.02 | 17.6 | 27.2 | 17.7 | 27.1 | 18.1 | 26.6 | 18.7 | 27.7 | 17.3 | 27.2 | 17.7 | 27.0 | 17.2 | 27.4 |
| | 0.01 | 20.0 | 27.1 | 20.3 | 27.3 | 20.5 | 26.5 | 21.0 | 27.6 | 20.7 | 26.9 | 20.5 | 26.9 | 20.4 | 27.2 |

<u>SIC 6211 (%)</u>

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 18.0 | 24.5 | 17.2 | 24.5 | 18.0 | 24.5 | 20.7 | 23.3 | 18.5 | 24.4 | 18.9 | 22.1 | 18.6 | 22.8 |
| 0.1 | 0.02 | 22.8 | 24.3 | 22.0 | 24.5 | 22.5 | 24.2 | 24.0 | 23.6 | 22.2 | 24.6 | 24.3 | 22.8 | 23.7 | 23.3 |
| | 0.01 | 24.1 | 23.7 | 23.8 | 24.3 | 24.0 | 23.9 | 25.2 | 23.0 | 24.2 | 24.2 | 25.6 | 22.0 | 25.3 | 22.6 |
| | 0.05 | 17.4 | 25.5 | 16.5 | 25.8 | 16.9 | 24.9 | 19.8 | 24.7 | 17.7 | 25.7 | 18.6 | 24.1 | 18.2 | 24.5 |
| 0.05 | 0.02 | 22.0 | 24.6 | 21.1 | 25.2 | 21.6 | 24.4 | 23.8 | 24.6 | 22.1 | 25.3 | 22.6 | 23.6 | 23.0 | 24.0 |
| | 0.01 | 23.7 | 24.7 | 22.5 | 25.3 | 23.4 | 24.5 | 24.1 | 24.3 | 23.1 | 25.5 | 24.3 | 23.8 | 24.2 | 24.2 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 16.8 | 25.4 | 16.4 | 26.8 | 17.1 | 25.6 | 24.1 | 24.2 | 22.7 | 25.3 | 23.7 | 23.9 | 23.8 | 24.3 |
| 0.02 | 0.02 | 22.3 | 25.1 | 21.3 | 26.0 | 21.5 | 24.9 | 22.9 | 24.9 | 21.5 | 26.0 | 22.5 | 24.7 | 22.3 | 25.0 |
| | 0.01 | 23.0 | 26.1 | 22.2 | 27.0 | 23.0 | 26.0 | 24.2 | 24.7 | 22.9 | 25.7 | 23.9 | 24.0 | 23.8 | 24.5 |
| | 0.05 | 16.2 | 25.2 | 16.0 | 26.3 | 16.3 | 25.1 | 19.2 | 25.2 | 17.1 | 26.2 | 17.7 | 25.0 | 17.7 | 25.3 |
| 0.01 | 0.02 | 20.9 | 25.4 | 20.5 | 26.8 | 20.6 | 25.4 | 23.0 | 25.0 | 21.7 | 25.8 | 21.6 | 24.4 | 21.9 | 24.6 |
| | 0.01 | 23.5 | 25.2 | 22.3 | 26.1 | 23.1 | 24.9 | 23.7 | 24.9 | 22.5 | 26.1 | 23.4 | 24.5 | 23.5 | 25.0 |
| | 0.05 | 16.4 | 25.9 | 16.0 | 26.6 | 16.3 | 25.6 | 19.5 | 24.7 | 17.1 | 25.7 | 17.8 | 24.2 | 17.9 | 24.7 |
| 0 | 0.02 | 21.3 | 25.8 | 20.4 | 26.6 | 20.9 | 25.7 | 23.3 | 25.7 | 21.6 | 26.2 | 21.9 | 24.8 | 22.0 | 25.3 |
| | 0.01 | 22.0 | 25.3 | 21.4 | 26.7 | 22.0 | 25.2 | 23.7 | 26.1 | 22.3 | 26.9 | 23.4 | 25.8 | 22.9 | 25.9 |

SIC 3576 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 21.3 | 20.6 | 24.1 | 18.5 | 22.0 | 19.1 | 25.1 | 18.5 | 22.9 | 19.9 | 22.7 | 19.9 | 22.7 | 20.2 |
| 0.1 | 0.02 | 26.5 | 20.4 | 28.8 | 18.4 | 27.0 | 19.3 | 29.7 | 18.2 | 27.7 | 19.1 | 28.2 | 19.5 | 26.9 | 19.4 |
| | 0.01 | 27.7 | 21.6 | 30.0 | 19.5 | 28.9 | 20.3 | 31.3 | 19.1 | 30.0 | 20.1 | 29.8 | 20.0 | 29.5 | 20.2 |
| | 0.05 | 19.8 | 21.5 | 22.5 | 19.3 | 20.5 | 20.2 | 23.7 | 19.1 | 21.5 | 20.4 | 21.1 | 20.8 | 21.2 | 21.0 |
| 0.05 | 0.02 | 25.7 | 21.5 | 27.8 | 19.1 | 26.5 | 20.3 | 29.1 | 19.1 | 27.1 | 20.6 | 27.5 | 20.9 | 27.1 | 21.0 |
| | 0.01 | 26.3 | 22.0 | 28.7 | 19.5 | 27.7 | 20.6 | 29.8 | 19.1 | 28.2 | 19.7 | 28.3 | 20.4 | 27.5 | 20.8 |
| | 0.05 | 20.0 | 21.6 | 22.8 | 19.4 | 20.5 | 20.6 | 23.6 | 19.3 | 20.7 | 20.3 | 20.8 | 21.0 | 20.5 | 20.9 |
| 0.02 | 0.02 | 25.1 | 23.0 | 27.9 | 20.5 | 25.7 | 21.7 | 28.4 | 20.0 | 26.5 | 21.5 | 25.9 | 21.9 | 26.0 | 22.2 |
| | 0.01 | 27.1 | 21.4 | 29.8 | 18.8 | 28.0 | 20.3 | 30.3 | 18.8 | 28.3 | 19.8 | 28.9 | 20.3 | 27.9 | 20.4 |
| | 0.05 | 19.3 | 22.8 | 22.0 | 20.0 | 20.4 | 21.8 | 23.3 | 19.2 | 20.8 | 20.7 | 20.6 | 20.8 | 20.8 | 21.4 |
| 0.01 | 0.02 | 24.6 | 22.2 | 27.5 | 19.7 | 25.4 | 21.2 | 28.4 | 19.6 | 26.3 | 21.4 | 26.1 | 21.5 | 25.7 | 22.0 |
| | 0.01 | 25.2 | 21.8 | 27.9 | 19.0 | 26.5 | 20.9 | 29.7 | 18.8 | 27.5 | 20.3 | 28.5 | 20.6 | 27.4 | 20.8 |
| | 0.05 | 19.8 | 23.0 | 22.0 | 20.1 | 20.6 | 21.9 | 23.6 | 19.4 | 20.8 | 21.5 | 21.0 | 21.5 | 21.1 | 22.0 |
| 0 | 0.02 | 23.9 | 22.7 | 27.1 | 20.5 | 25.1 | 21.7 | 28.2 | 20.0 | 25.7 | 21.5 | 24.9 | 21.3 | 24.8 | 21.9 |
| | 0.01 | 26.2 | 22.5 | 28.6 | 19.7 | 27.1 | 21.3 | 29.8 | 19.0 | 27.8 | 20.8 | 28.8 | 21.2 | 27.7 | 21.6 |

Panel B. The Error Detection Performance in Cost of Goods Sold Account

SIC 7372 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 21.6 | 22.2 | 21.6 | 22.1 | 21.7 | 22.1 | 20.8 | 25.0 | 17.9 | 25.9 | 18.5 | 25.6 | 17.8 | 25.8 |
| 0.1 | 0.02 | 25.5 | 21.9 | 25.5 | 21.8 | 25.6 | 21.9 | 23.4 | 25.0 | 21.9 | 25.8 | 22.0 | 25.6 | 21.8 | 25.8 |
| | 0.01 | 26.5 | 22.2 | 26.6 | 22.1 | 26.6 | 22.1 | 24.2 | 25.1 | 23.0 | 25.9 | 23.2 | 25.6 | 23.0 | 25.8 |
| | 0.05 | 20.8 | 23.2 | 20.6 | 23.0 | 20.6 | 23.0 | 21.4 | 24.5 | 18.8 | 24.9 | 19.3 | 24.7 | 18.8 | 24.8 |
| 0.05 | 0.02 | 24.4 | 23.1 | 24.5 | 23.0 | 24.6 | 22.9 | 23.9 | 24.4 | 22.6 | 24.8 | 22.9 | 24.7 | 22.8 | 24.8 |
| | 0.01 | 25.7 | 23.0 | 25.7 | 22.8 | 25.7 | 22.9 | 24.8 | 24.4 | 23.9 | 24.8 | 24.1 | 24.6 | 23.9 | 24.7 |
| | 0.05 | 20.3 | 23.5 | 20.1 | 23.6 | 20.2 | 23.5 | 22.0 | 24.0 | 19.6 | 24.1 | 20.1 | 24.1 | 19.6 | 24.0 |
| 0.02 | 0.02 | 24.0 | 23.5 | 23.9 | 23.6 | 24.1 | 23.6 | 24.2 | 24.1 | 23.2 | 24.2 | 23.3 | 24.2 | 23.3 | 24.1 |
| | 0.01 | 25.0 | 23.5 | 25.0 | 23.5 | 25.1 | 23.5 | 25.1 | 24.0 | 24.5 | 24.1 | 24.6 | 24.0 | 24.5 | 24.0 |
| 0.01 | 0.05 | 20.1 | 23.7 | 20.0 | 23.7 | 20.0 | 23.7 | 22.0 | 23.9 | 19.7 | 24.0 | 20.0 | 23.9 | 19.6 | 24.0 |
| | 0.02 | 23.9 | 23.9 | 23.7 | 23.9 | 23.9 | 23.9 | 24.1 | 24.0 | 23.2 | 24.0 | 23.3 | 23.9 | 23.4 | 24.0 |

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 24.9 | 23.9 | 25.0 | 23.9 | 25.1 | 23.8 | 25.2 | 24.1 | 24.7 | 24.2 | 24.8 | 24.1 | 24.7 | 24.0 |
| | 0.05 | 19.8 | 23.7 | 19.9 | 23.9 | 19.8 | 23.9 | 22.0 | 23.9 | 19.7 | 23.9 | 20.1 | 23.9 | 19.8 | 23.8 |
| 0 | 0.02 | 23.1 | 23.9 | 23.5 | 23.6 | 23.6 | 23.7 | 24.5 | 23.8 | 23.6 | 23.9 | 23.7 | 23.7 | 23.6 | 23.7 |
| | 0.01 | 24.8 | 23.9 | 23.9 | 23.5 | 24.5 | 24.0 | 25.4 | 23.8 | 25.0 | 23.8 | 25.0 | 23.7 | 25.0 | 23.6 |
| | | | | | | | | SIC 1311 (%) | | | | | | | |
| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
| | 0.05 | 18.9 | 22.9 | 20.0 | 22.1 | 19.7 | 22.0 | 19.9 | 27.2 | 18.8 | 27.1 | 19.3 | 26.5 | 19.3 | 26.4 |
| 0.1 | 0.02 | 22.9 | 22.8 | 24.1 | 22.2 | 23.8 | 22.0 | 21.7 | 27.3 | 21.2 | 27.2 | 21.7 | 26.6 | 21.7 | 26.5 |
| | 0.01 | 25.6 | 22.7 | 26.5 | 22.0 | 26.5 | 21.8 | 22.4 | 27.1 | 22.1 | 27.0 | 22.7 | 26.4 | 22.7 | 26.3 |
| | 0.05 | 18.0 | 23.8 | 19.1 | 23.0 | 18.9 | 22.9 | 20.8 | 26.5 | 20.1 | 26.2 | 20.7 | 25.5 | 20.6 | 25.6 |
| 0.05 | 0.02 | 21.9 | 24.1 | 23.1 | 23.2 | 22.8 | 23.1 | 22.4 | 26.5 | 22.1 | 26.0 | 22.9 | 25.4 | 22.9 | 25.5 |
| | 0.01 | 24.3 | 24.0 | 25.3 | 23.1 | 25.2 | 22.9 | 23.2 | 26.5 | 23.3 | 26.1 | 24.0 | 25.5 | 24.1 | 25.5 |
| | 0.05 | 17.2 | 24.8 | 18.2 | 23.8 | 18.0 | 23.8 | 21.1 | 26.1 | 20.6 | 25.4 | 21.2 | 24.6 | 21.0 | 24.8 |
| 0.02 | 0.02 | 21.2 | 24.6 | 22.3 | 23.6 | 22.2 | 23.7 | 22.9 | 26.3 | 22.9 | 25.5 | 23.7 | 24.7 | 23.5 | 24.9 |
| | 0.01 | 23.7 | 24.8 | 24.6 | 23.7 | 24.6 | 23.7 | 23.3 | 26.1 | 23.9 | 25.5 | 24.7 | 24.8 | 24.5 | 25.0 |
| | 0.05 | 17.1 | 24.8 | 18.2 | 23.8 | 18.0 | 23.8 | 21.1 | 26.0 | 20.8 | 25.3 | 21.4 | 24.4 | 21.2 | 24.7 |
| 0.01 | 0.02 | 21.0 | 24.9 | 22.0 | 23.8 | 21.9 | 24.0 | 22.9 | 26.0 | 23.3 | 25.3 | 23.9 | 24.3 | 23.9 | 24.7 |
| | 0.01 | 23.4 | 24.7 | 24.4 | 23.8 | 24.4 | 23.8 | 23.4 | 25.9 | 24.0 | 25.3 | 24.8 | 24.5 | 24.7 | 24.8 |
| | 0.05 | 16.8 | 25.2 | 17.7 | 24.3 | 17.6 | 24.3 | 21.3 | 25.7 | 21.0 | 24.7 | 21.7 | 23.9 | 21.6 | 24.2 |
| 0 | 0.02 | 20.7 | 25.1 | 21.8 | 24.2 | 21.6 | 24.2 | 23.1 | 25.8 | 23.6 | 24.9 | 24.3 | 24.1 | 24.2 | 24.4 |
| | 0.01 | 23.3 | 25.2 | 24.2 | 24.2 | 24.2 | 24.3 | 23.6 | 25.8 | 24.1 | 24.8 | 25.1 | 24.1 | 24.8 | 24.4 |
| | | | | | | | | SIC 7370 (%) | | | | | | | |
| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
| | 0.05 | 18.3 | 23.2 | 18.2 | 23.4 | 18.1 | 23.6 | 17.9 | 26.7 | 15.2 | 26.6 | 15.1 | 26.3 | 15.4 | 25.8 |
| 0.1 | 0.02 | 23.3 | 23.0 | 23.5 | 23.2 | 23.4 | 23.4 | 21.1 | 27.1 | 19.8 | 27.0 | 19.9 | 26.7 | 20.1 | 26.1 |
| | 0.01 | 25.4 | 23.2 | 25.2 | 23.3 | 25.1 | 23.5 | 22.1 | 26.7 | 21.4 | 26.5 | 21.5 | 26.3 | 22.1 | 25.7 |
| | 0.05 | 17.5 | 24.1 | 17.4 | 24.2 | 17.2 | 24.3 | 18.6 | 26.2 | 16.2 | 25.8 | 16.0 | 25.6 | 16.4 | 24.9 |
| 0.05 | 0.02 | 22.8 | 24.1 | 22.8 | 24.2 | 22.8 | 24.3 | 21.6 | 26.4 | 20.8 | 26.0 | 20.9 | 26.0 | 21.2 | 25.2 |
| | 0.01 | 24.2 | 24.0 | 24.3 | 24.1 | 24.0 | 24.1 | 22.7 | 26.4 | 22.6 | 26.0 | 22.6 | 25.8 | 23.3 | 25.1 |
| | 0.05 | 17.2 | 24.4 | 16.9 | 24.4 | 16.7 | 24.6 | 18.8 | 26.2 | 16.5 | 25.5 | 16.4 | 25.5 | 16.7 | 24.8 |
| 0.02 | 0.02 | 22.1 | 24.3 | 22.1 | 24.4 | 22.1 | 24.7 | 21.8 | 26.2 | 21.1 | 25.5 | 21.4 | 25.4 | 21.7 | 24.8 |
| | 0.01 | 23.6 | 24.6 | 23.6 | 24.7 | 23.8 | 25.0 | 23.0 | 26.0 | 23.1 | 25.3 | 23.2 | 25.3 | 23.7 | 24.5 |
| | 0.05 | 17.0 | 24.6 | 16.8 | 24.6 | 16.5 | 24.9 | 18.9 | 26.2 | 16.8 | 25.3 | 16.6 | 25.5 | 16.8 | 24.6 |
| 0.01 | 0.02 | 22.0 | 24.6 | 22.0 | 24.8 | 21.8 | 25.0 | 22.1 | 26.1 | 21.4 | 25.2 | 21.7 | 25.2 | 22.1 | 24.5 |
| | 0.01 | 23.6 | 24.4 | 23.4 | 24.3 | 23.6 | 24.6 | 23.2 | 26.1 | 23.4 | 25.3 | 23.3 | 25.2 | 24.0 | 24.5 |
| | 0.05 | 16.7 | 24.8 | 16.7 | 24.9 | 16.2 | 25.0 | 19.1 | 25.7 | 17.0 | 24.8 | 16.8 | 24.7 | 17.1 | 24.0 |
| 0 | 0.02 | 21.6 | 24.9 | 21.5 | 25.1 | 21.3 | 25.2 | 22.2 | 25.7 | 21.4 | 24.6 | 21.9 | 24.7 | 22.1 | 23.9 |
| | 0.01 | 23.5 | 24.9 | 23.3 | 25.0 | 23.5 | 25.2 | 23.4 | 25.7 | 23.6 | 24.8 | 23.8 | 24.9 | 24.4 | 24.1 |
| | | | | | | | | SIC 2834 (%) | | | | | | | |
| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.05 | 21.6 | 22.1 | 21.8 | 21.9 | 21.5 | 22.1 | 19.2 | 26.5 | 17.9 | 26.4 | 17.7 | 26.4 | 17.8 | 26.2 |
| | 0.02 | 25.6 | 22.0 | 26.1 | 21.8 | 25.5 | 21.9 | 22.3 | 26.2 | 21.6 | 26.1 | 21.7 | 26.2 | 21.7 | 25.8 |
| | 0.01 | 26.6 | 21.9 | 27.0 | 21.8 | 26.7 | 21.8 | 22.9 | 26.4 | 22.5 | 26.3 | 22.7 | 26.4 | 22.7 | 26.1 |
| 0.05 | 0.05 | 20.6 | 23.1 | 20.8 | 22.9 | 20.5 | 23.1 | 19.9 | 25.8 | 18.6 | 25.4 | 18.6 | 25.4 | 18.7 | 25.1 |
| | 0.02 | 24.4 | 23.2 | 24.8 | 23.0 | 24.2 | 23.0 | 22.8 | 25.9 | 22.2 | 25.3 | 22.4 | 25.3 | 22.4 | 25.1 |
| | 0.01 | 25.8 | 23.5 | 26.3 | 23.3 | 25.7 | 23.3 | 23.5 | 26.0 | 23.4 | 25.6 | 23.6 | 25.5 | 23.8 | 25.3 |
| 0.02 | 0.05 | 19.7 | 23.8 | 20.1 | 23.5 | 19.6 | 23.8 | 20.2 | 25.4 | 19.1 | 24.9 | 19.1 | 24.9 | 19.3 | 24.7 |
| | 0.02 | 24.0 | 23.7 | 24.5 | 23.5 | 23.9 | 23.7 | 22.9 | 25.5 | 22.5 | 24.8 | 22.9 | 24.9 | 22.7 | 24.6 |
| | 0.01 | 25.2 | 23.6 | 25.6 | 23.3 | 25.2 | 23.6 | 23.8 | 25.4 | 24.0 | 24.8 | 24.1 | 24.7 | 24.3 | 24.6 |
| 0.01 | 0.05 | 19.9 | 23.8 | 20.0 | 23.4 | 19.7 | 23.8 | 20.3 | 25.1 | 19.2 | 24.6 | 19.1 | 24.5 | 19.3 | 24.4 |
| | 0.02 | 23.8 | 23.4 | 24.3 | 23.2 | 23.5 | 23.4 | 23.1 | 25.1 | 22.9 | 24.6 | 23.1 | 24.4 | 23.0 | 24.4 |
| | 0.01 | 25.0 | 23.5 | 25.4 | 23.3 | 24.9 | 23.5 | 24.0 | 25.3 | 24.1 | 24.4 | 24.3 | 24.4 | 24.2 | 24.2 |
| 0 | 0.05 | 19.7 | 23.6 | 19.9 | 23.5 | 19.6 | 23.8 | 20.3 | 25.4 | 19.2 | 24.7 | 19.3 | 24.6 | 19.3 | 24.7 |
| | 0.02 | 23.8 | 23.8 | 24.0 | 23.7 | 23.6 | 24.0 | 23.1 | 25.2 | 22.8 | 24.6 | 23.2 | 24.6 | 23.1 | 24.5 |
| | 0.01 | 24.5 | 23.6 | 25.1 | 23.6 | 24.5 | 23.8 | 24.0 | 25.3 | 24.2 | 24.5 | 24.3 | 24.3 | 24.4 | 24.4 |

SIC 3674 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.05 | 20.3 | 22.2 | 21.3 | 21.2 | 20.7 | 21.5 | 19.4 | 25.3 | 17.2 | 25.5 | 17.3 | 25.5 | 17.4 | 25.4 |
| | 0.02 | 24.6 | 22.3 | 25.8 | 21.1 | 25.4 | 21.5 | 22.5 | 25.5 | 21.5 | 25.7 | 21.6 | 25.7 | 21.7 | 25.5 |
| | 0.01 | 26.4 | 22.4 | 27.5 | 21.3 | 27.0 | 21.7 | 23.7 | 25.3 | 23.2 | 25.4 | 23.0 | 25.5 | 23.2 | 25.2 |
| 0.05 | 0.05 | 19.7 | 23.1 | 20.6 | 22.0 | 20.1 | 22.4 | 20.0 | 24.8 | 18.0 | 24.8 | 18.1 | 24.8 | 18.2 | 24.7 |
| | 0.02 | 23.9 | 23.2 | 25.0 | 22.1 | 24.3 | 22.5 | 23.1 | 24.6 | 22.5 | 24.7 | 22.4 | 24.6 | 22.6 | 24.6 |
| | 0.01 | 25.4 | 23.1 | 26.5 | 21.9 | 26.1 | 22.4 | 24.2 | 24.5 | 23.9 | 24.5 | 23.8 | 24.5 | 24.1 | 24.4 |
| 0.02 | 0.05 | 19.0 | 23.8 | 20.0 | 22.6 | 19.4 | 22.9 | 20.5 | 24.4 | 18.6 | 24.1 | 19.0 | 24.1 | 18.9 | 24.1 |
| | 0.02 | 23.5 | 23.5 | 24.5 | 22.3 | 24.0 | 22.7 | 23.4 | 24.4 | 22.9 | 24.1 | 22.8 | 24.2 | 23.0 | 24.1 |
| | 0.01 | 25.0 | 23.6 | 25.9 | 22.4 | 25.6 | 22.7 | 24.4 | 24.6 | 24.1 | 24.2 | 24.0 | 24.3 | 24.3 | 24.1 |
| 0.01 | 0.05 | 18.8 | 23.6 | 19.8 | 22.7 | 19.3 | 23.0 | 20.4 | 24.3 | 18.7 | 24.1 | 19.0 | 24.1 | 19.0 | 24.0 |
| | 0.02 | 23.3 | 23.7 | 24.3 | 22.7 | 23.9 | 23.1 | 23.5 | 24.2 | 23.1 | 24.0 | 23.0 | 24.0 | 23.2 | 23.9 |
| | 0.01 | 24.9 | 23.7 | 25.9 | 22.7 | 25.6 | 23.0 | 24.9 | 24.2 | 24.8 | 23.9 | 24.7 | 23.9 | 24.9 | 23.8 |
| 0 | 0.05 | 18.9 | 23.9 | 19.6 | 22.9 | 19.2 | 23.1 | 20.6 | 24.0 | 18.8 | 23.7 | 19.1 | 23.7 | 19.0 | 23.7 |
| | 0.02 | 23.1 | 23.8 | 24.1 | 22.9 | 23.4 | 23.1 | 23.7 | 24.1 | 23.2 | 23.6 | 23.1 | 23.7 | 23.3 | 23.5 |
| | 0.01 | 24.4 | 23.8 | 25.3 | 22.7 | 25.0 | 23.1 | 24.7 | 23.9 | 24.6 | 23.4 | 24.6 | 23.5 | 24.7 | 23.4 |

SIC 4911 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.05 | 19.0 | 22.6 | 20.5 | 21.5 | 20.1 | 20.9 | 17.8 | 25.5 | 15.5 | 25.9 | 16.4 | 25.7 | 16.0 | 25.8 |
| | 0.02 | 23.9 | 22.7 | 25.1 | 21.6 | 25.4 | 20.9 | 22.0 | 25.4 | 20.5 | 25.6 | 21.2 | 25.5 | 20.8 | 25.5 |
| | 0.01 | 25.6 | 22.6 | 26.6 | 21.4 | 27.2 | 20.7 | 23.1 | 25.6 | 22.2 | 26.0 | 22.8 | 25.8 | 22.5 | 25.8 |
| 0.05 | 0.05 | 18.2 | 23.4 | 19.7 | 22.5 | 19.3 | 21.7 | 18.4 | 24.9 | 16.3 | 25.1 | 17.2 | 24.8 | 16.6 | 25.0 |
| | 0.02 | 23.2 | 23.7 | 24.5 | 22.7 | 24.5 | 21.9 | 22.3 | 24.8 | 21.1 | 24.9 | 21.8 | 24.7 | 21.4 | 24.8 |
| | 0.01 | 24.8 | 23.5 | 25.7 | 22.6 | 26.4 | 21.7 | 23.8 | 25.0 | 23.1 | 25.1 | 23.7 | 24.9 | 23.3 | 25.0 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 17.5 | 24.0 | 18.9 | 23.1 | 18.8 | 22.2 | 19.1 | 24.4 | 16.9 | 24.4 | 17.9 | 24.2 | 17.2 | 24.3 |
| 0.02 | 0.02 | 22.4 | 23.9 | 23.7 | 23.0 | 23.9 | 22.3 | 23.0 | 24.6 | 21.9 | 24.6 | 22.6 | 24.3 | 22.2 | 24.5 |
| | 0.01 | 24.3 | 24.0 | 25.3 | 23.1 | 25.7 | 22.3 | 24.3 | 24.4 | 23.8 | 24.5 | 24.2 | 24.1 | 23.9 | 24.4 |
| | 0.05 | 17.2 | 24.1 | 18.7 | 23.2 | 18.6 | 22.5 | 19.3 | 24.3 | 17.0 | 24.2 | 18.1 | 24.0 | 17.3 | 24.1 |
| 0.01 | 0.02 | 22.4 | 24.4 | 23.5 | 23.3 | 23.8 | 22.5 | 23.2 | 24.3 | 22.2 | 24.3 | 22.9 | 24.1 | 22.5 | 24.3 |
| | 0.01 | 24.1 | 24.3 | 25.1 | 23.4 | 25.5 | 22.6 | 24.4 | 24.3 | 23.8 | 24.2 | 24.3 | 24.0 | 23.9 | 24.2 |
| | 0.05 | 17.2 | 24.3 | 18.6 | 23.4 | 18.4 | 22.6 | 19.3 | 24.1 | 17.2 | 24.2 | 18.2 | 23.8 | 17.5 | 24.0 |
| 0 | 0.02 | 22.2 | 24.3 | 23.4 | 23.5 | 23.7 | 22.6 | 23.3 | 24.2 | 22.4 | 24.2 | 23.0 | 23.9 | 22.6 | 24.1 |
| | 0.01 | 24.1 | 24.3 | 25.1 | 23.3 | 25.4 | 22.5 | 24.6 | 24.1 | 24.2 | 24.0 | 24.6 | 23.7 | 24.3 | 24.0 |

SIC 5812 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 11.2 | 24.8 | 11.5 | 24.7 | 11.6 | 24.2 | 13.3 | 26.0 | 10.4 | 26.2 | 10.1 | 26.7 | 10.4 | 26.0 |
| 0.1 | 0.02 | 18.5 | 25.0 | 18.9 | 24.8 | 19.4 | 24.2 | 19.5 | 26.1 | 17.4 | 26.3 | 17.2 | 26.8 | 17.5 | 26.1 |
| | 0.01 | 21.7 | 25.2 | 22.2 | 24.9 | 22.6 | 24.4 | 21.7 | 26.1 | 20.4 | 26.2 | 20.4 | 26.8 | 20.6 | 26.0 |
| | 0.05 | 11.7 | 24.2 | 12.0 | 23.9 | 12.2 | 23.3 | 13.9 | 25.3 | 11.1 | 25.3 | 10.8 | 25.8 | 11.1 | 25.2 |
| 0.05 | 0.02 | 19.3 | 24.1 | 19.7 | 23.8 | 20.2 | 23.2 | 20.1 | 25.2 | 18.4 | 25.2 | 18.1 | 25.7 | 18.5 | 25.1 |
| | 0.01 | 22.5 | 24.2 | 22.9 | 24.0 | 23.5 | 23.3 | 22.3 | 25.2 | 21.4 | 25.3 | 21.3 | 25.7 | 21.6 | 25.2 |
| | 0.05 | 11.2 | 24.6 | 11.6 | 24.6 | 11.8 | 24.1 | 14.1 | 25.0 | 11.4 | 24.7 | 11.1 | 25.2 | 11.3 | 24.6 |
| 0.02 | 0.02 | 18.7 | 24.5 | 19.1 | 24.3 | 19.7 | 23.8 | 20.2 | 24.9 | 18.8 | 24.9 | 18.5 | 25.3 | 18.8 | 24.7 |
| | 0.01 | 22.2 | 24.4 | 22.9 | 24.4 | 23.1 | 23.7 | 22.6 | 24.6 | 21.7 | 24.5 | 21.6 | 24.8 | 21.8 | 24.3 |
| | 0.05 | 11.3 | 24.8 | 11.6 | 24.5 | 11.8 | 24.0 | 14.2 | 24.7 | 11.5 | 24.5 | 11.2 | 25.0 | 11.4 | 24.4 |
| 0.01 | 0.02 | 18.5 | 24.8 | 18.9 | 24.6 | 19.4 | 24.0 | 20.5 | 24.9 | 18.9 | 24.6 | 18.6 | 24.9 | 18.9 | 24.3 |
| | 0.01 | 22.0 | 24.4 | 22.6 | 24.3 | 23.0 | 23.8 | 23.1 | 24.8 | 22.3 | 24.7 | 22.2 | 25.0 | 22.4 | 24.5 |
| | 0.05 | 11.0 | 25.1 | 11.3 | 24.9 | 11.3 | 24.4 | 14.4 | 24.6 | 11.7 | 24.5 | 11.2 | 24.7 | 11.6 | 24.3 |
| 0 | 0.02 | 18.6 | 24.8 | 18.9 | 24.5 | 19.5 | 23.9 | 20.4 | 24.6 | 19.1 | 24.4 | 18.9 | 24.9 | 19.1 | 24.4 |
| | 0.01 | 21.5 | 25.2 | 22.1 | 25.0 | 22.5 | 24.3 | 22.8 | 24.8 | 22.0 | 24.6 | 21.8 | 24.9 | 22.1 | 24.4 |

SIC 7373 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 17.3 | 23.5 | 17.1 | 23.1 | 17.1 | 23.4 | 18.0 | 25.4 | 16.1 | 25.3 | 15.5 | 25.9 | 15.8 | 25.5 |
| 0.1 | 0.02 | 22.8 | 23.7 | 22.9 | 23.4 | 23.0 | 23.7 | 21.8 | 25.7 | 20.9 | 25.3 | 20.3 | 26.3 | 20.7 | 25.6 |
| | 0.01 | 24.4 | 23.8 | 24.9 | 23.4 | 24.8 | 23.6 | 23.2 | 25.7 | 22.6 | 25.4 | 22.2 | 26.3 | 22.6 | 25.7 |
| | 0.05 | 17.8 | 23.7 | 17.7 | 23.4 | 17.7 | 23.9 | 18.5 | 25.0 | 16.8 | 24.5 | 15.9 | 25.1 | 16.4 | 24.8 |
| 0.05 | 0.02 | 23.1 | 23.4 | 23.2 | 23.1 | 23.3 | 23.5 | 22.6 | 25.2 | 21.8 | 24.8 | 21.4 | 25.4 | 21.8 | 24.9 |
| | 0.01 | 24.4 | 23.8 | 24.8 | 23.5 | 24.8 | 23.9 | 24.0 | 25.0 | 23.6 | 24.5 | 23.1 | 25.0 | 23.4 | 24.6 |
| | 0.05 | 17.8 | 23.3 | 17.6 | 23.0 | 17.5 | 23.4 | 18.9 | 25.0 | 17.0 | 24.3 | 16.4 | 24.4 | 16.7 | 24.4 |
| 0.02 | 0.02 | 23.3 | 23.4 | 23.5 | 23.3 | 23.4 | 23.6 | 22.9 | 25.0 | 22.1 | 24.4 | 21.7 | 24.6 | 22.1 | 24.5 |
| | 0.01 | 24.5 | 23.2 | 25.0 | 23.0 | 24.8 | 23.4 | 24.4 | 24.6 | 24.3 | 24.1 | 23.9 | 24.4 | 24.2 | 24.2 |
| | 0.05 | 18.4 | 22.9 | 18.2 | 22.5 | 18.5 | 23.1 | 19.2 | 24.6 | 17.6 | 23.7 | 16.9 | 24.0 | 17.2 | 23.8 |
| 0.01 | 0.02 | 23.6 | 22.7 | 23.7 | 22.5 | 23.7 | 22.9 | 23.0 | 24.4 | 22.2 | 23.7 | 21.9 | 24.0 | 22.1 | 23.7 |
| | 0.01 | 25.4 | 23.1 | 26.0 | 22.7 | 25.5 | 23.1 | 24.2 | 24.4 | 24.1 | 23.7 | 23.6 | 23.9 | 24.1 | 23.8 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 19.0 | 21.8 | 19.2 | 21.7 | 19.2 | 21.7 | 19.5 | 24.2 | 17.9 | 23.5 | 17.1 | 23.7 | 17.4 | 23.5 |
| 0 | 0.02 | 24.3 | 22.1 | 24.9 | 22.0 | 24.4 | 22.1 | 23.4 | 23.9 | 22.7 | 23.3 | 22.5 | 23.5 | 22.7 | 23.4 |
| | 0.01 | 26.1 | 22.0 | 26.8 | 21.8 | 26.3 | 22.0 | 24.3 | 24.3 | 24.3 | 23.7 | 23.9 | 23.7 | 24.3 | 23.7 |

SIC 2836 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 22.5 | 21.4 | 23.0 | 20.7 | 22.6 | 21.0 | 21.3 | 24.9 | 19.3 | 24.7 | 19.2 | 25.1 | 19.0 | 24.6 |
| 0.1 | 0.02 | 26.2 | 21.3 | 26.5 | 20.8 | 26.7 | 21.1 | 23.6 | 25.1 | 22.8 | 25.0 | 22.5 | 25.1 | 22.7 | 24.8 |
| | 0.01 | 27.2 | 21.6 | 27.5 | 21.0 | 27.4 | 21.1 | 24.9 | 24.4 | 24.7 | 24.8 | 24.4 | 24.9 | 24.7 | 24.4 |
| | 0.05 | 21.8 | 22.6 | 22.0 | 22.0 | 21.6 | 22.0 | 22.0 | 24.2 | 20.4 | 23.8 | 20.2 | 23.8 | 20.1 | 23.9 |
| 0.05 | 0.02 | 25.1 | 22.5 | 25.6 | 22.1 | 25.6 | 22.0 | 24.5 | 23.5 | 24.0 | 23.4 | 23.8 | 23.2 | 23.8 | 23.4 |
| | 0.01 | 26.7 | 22.4 | 27.1 | 22.1 | 27.1 | 21.7 | 25.4 | 24.0 | 25.1 | 23.6 | 25.2 | 23.6 | 25.1 | 23.7 |
| | 0.05 | 21.8 | 22.7 | 21.6 | 22.1 | 21.7 | 22.3 | 22.3 | 23.6 | 20.8 | 23.2 | 20.7 | 23.4 | 20.7 | 23.3 |
| 0.02 | 0.02 | 24.7 | 23.0 | 24.9 | 22.3 | 25.1 | 22.4 | 24.9 | 23.4 | 24.7 | 23.3 | 24.6 | 23.8 | 24.7 | 23.6 |
| | 0.01 | 25.5 | 23.1 | 25.9 | 22.3 | 26.0 | 22.5 | 25.6 | 23.2 | 25.7 | 23.1 | 25.8 | 23.2 | 25.8 | 23.4 |
| | 0.05 | 21.2 | 22.9 | 21.1 | 22.6 | 21.1 | 22.4 | 22.1 | 23.1 | 20.8 | 22.9 | 20.9 | 23.1 | 20.6 | 23.2 |
| 0.01 | 0.02 | 25.0 | 23.1 | 25.3 | 22.7 | 25.4 | 22.6 | 24.6 | 23.2 | 24.4 | 23.1 | 24.1 | 23.2 | 24.3 | 23.2 |
| | 0.01 | 25.7 | 23.0 | 26.0 | 22.4 | 26.4 | 22.5 | 25.8 | 23.3 | 25.9 | 23.0 | 25.9 | 23.2 | 26.0 | 23.3 |
| | 0.05 | 20.8 | 23.0 | 20.8 | 22.4 | 20.7 | 22.4 | 22.4 | 23.4 | 20.9 | 23.0 | 21.0 | 23.2 | 20.9 | 23.3 |
| 0 | 0.02 | 24.7 | 23.5 | 24.7 | 22.9 | 24.7 | 22.8 | 25.2 | 23.0 | 25.1 | 22.9 | 24.8 | 22.9 | 24.9 | 23.0 |
| | 0.01 | 26.0 | 23.6 | 26.2 | 23.0 | 26.1 | 22.8 | 25.7 | 23.3 | 25.6 | 22.9 | 25.7 | 23.2 | 25.8 | 23.3 |

SIC 3845 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 20.8 | 22.1 | 21.5 | 20.9 | 21.4 | 21.2 | 19.3 | 24.8 | 17.3 | 25.1 | 17.9 | 24.7 | 17.6 | 24.8 |
| 0.1 | 0.02 | 25.3 | 22.2 | 26.2 | 21.0 | 26.1 | 21.3 | 22.9 | 24.8 | 21.9 | 25.1 | 22.5 | 24.6 | 22.5 | 24.8 |
| | 0.01 | 26.6 | 21.9 | 27.8 | 20.8 | 27.4 | 21.1 | 24.3 | 24.9 | 23.4 | 25.0 | 24.0 | 24.6 | 24.0 | 24.7 |
| | 0.05 | 19.9 | 23.0 | 20.4 | 21.7 | 20.3 | 22.3 | 20.1 | 24.1 | 18.5 | 23.9 | 18.9 | 23.5 | 18.7 | 23.6 |
| 0.05 | 0.02 | 24.1 | 22.9 | 25.0 | 21.6 | 24.9 | 22.2 | 23.4 | 24.5 | 22.7 | 24.5 | 23.2 | 23.9 | 23.4 | 24.2 |
| | 0.01 | 25.8 | 23.0 | 26.8 | 21.8 | 26.4 | 22.2 | 24.2 | 24.2 | 23.9 | 24.2 | 24.5 | 23.8 | 24.4 | 23.9 |
| | 0.05 | 19.6 | 23.7 | 20.1 | 22.5 | 19.8 | 22.9 | 20.4 | 24.0 | 18.9 | 23.8 | 19.2 | 23.5 | 19.0 | 23.5 |
| 0.02 | 0.02 | 23.6 | 23.4 | 24.5 | 22.3 | 24.3 | 22.7 | 23.7 | 23.8 | 23.3 | 23.7 | 23.7 | 23.4 | 23.8 | 23.4 |
| | 0.01 | 25.0 | 23.5 | 25.9 | 22.3 | 25.7 | 22.8 | 25.1 | 24.1 | 24.9 | 23.8 | 25.3 | 23.6 | 25.2 | 23.6 |
| | 0.05 | 19.4 | 23.5 | 19.7 | 22.5 | 19.6 | 22.9 | 20.4 | 23.9 | 18.9 | 23.6 | 19.2 | 23.3 | 19.1 | 23.3 |
| 0.01 | 0.02 | 23.5 | 23.7 | 24.2 | 22.5 | 24.0 | 22.9 | 23.7 | 23.7 | 23.3 | 23.4 | 23.7 | 23.2 | 23.7 | 23.1 |
| | 0.01 | 25.1 | 23.7 | 26.0 | 22.7 | 25.7 | 23.0 | 25.1 | 23.5 | 25.1 | 23.3 | 25.6 | 23.0 | 25.4 | 23.0 |
| | 0.05 | 19.3 | 23.6 | 19.8 | 22.5 | 19.5 | 22.9 | 20.6 | 23.6 | 19.1 | 23.1 | 19.5 | 23.1 | 19.4 | 23.2 |
| 0 | 0.02 | 23.4 | 23.9 | 24.3 | 22.9 | 23.9 | 23.2 | 24.1 | 24.0 | 23.6 | 23.6 | 24.1 | 23.4 | 24.2 | 23.5 |
| | 0.01 | 24.8 | 23.9 | 25.7 | 22.8 | 25.4 | 23.2 | 25.2 | 23.8 | 25.1 | 23.3 | 25.7 | 23.3 | 25.5 | 23.3 |

SIC 4813 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.05 | 19.0 | 20.5 | 18.9 | 20.8 | 20.8 | 18.8 | 17.2 | 25.2 | 14.6 | 26.0 | 15.1 | 25.6 | 14.6 | 26.0 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.02 | 23.9 | 21.1 | 23.8 | 21.3 | 21.3 | 23.5 | 21.9 | 25.1 | 19.5 | 25.8 | 20.3 | 25.3 | 19.9 | 25.7 |
| | 0.01 | 26.9 | 21.1 | 26.6 | 21.5 | 21.5 | 26.4 | 23.5 | 25.0 | 21.4 | 25.8 | 22.3 | 25.4 | 21.9 | 25.9 |
| | 0.05 | 18.2 | 21.9 | 18.0 | 22.2 | 22.2 | 18.2 | 18.2 | 24.7 | 15.5 | 25.1 | 15.9 | 24.7 | 15.4 | 24.6 |
| 0.05 | 0.02 | 23.7 | 22.0 | 23.8 | 22.4 | 22.4 | 23.6 | 22.9 | 24.5 | 20.6 | 25.1 | 21.5 | 24.5 | 21.1 | 24.6 |
| | 0.01 | 25.9 | 22.2 | 25.8 | 22.5 | 22.5 | 25.7 | 24.3 | 24.4 | 23.0 | 24.7 | 23.6 | 24.3 | 23.2 | 24.3 |
| | 0.05 | 17.2 | 22.4 | 17.1 | 22.8 | 22.8 | 17.1 | 18.5 | 23.7 | 15.5 | 23.8 | 16.4 | 23.3 | 15.7 | 23.5 |
| 0.02 | 0.02 | 22.6 | 22.7 | 22.7 | 22.9 | 22.9 | 22.5 | 23.2 | 24.3 | 21.6 | 24.5 | 22.3 | 24.2 | 22.1 | 24.3 |
| | 0.01 | 25.1 | 22.6 | 25.0 | 22.8 | 22.8 | 25.0 | 24.5 | 23.6 | 23.7 | 23.9 | 24.1 | 23.4 | 24.0 | 23.7 |
| | 0.05 | 17.5 | 22.9 | 17.0 | 22.8 | 22.8 | 17.2 | 18.5 | 24.1 | 15.8 | 24.2 | 16.4 | 23.9 | 15.9 | 24.0 |
| 0.01 | 0.02 | 22.7 | 22.8 | 22.8 | 23.0 | 23.0 | 22.6 | 23.5 | 23.9 | 22.0 | 24.2 | 22.7 | 23.7 | 22.2 | 23.8 |
| | 0.01 | 24.4 | 22.9 | 24.8 | 23.2 | 23.2 | 24.5 | 24.5 | 23.9 | 23.9 | 24.2 | 24.3 | 23.6 | 23.9 | 23.8 |
| | 0.05 | 17.2 | 23.4 | 16.7 | 23.3 | 23.3 | 17.3 | 18.7 | 23.7 | 16.2 | 23.9 | 16.7 | 23.5 | 16.2 | 23.4 |
| 0 | 0.02 | 22.2 | 22.9 | 22.1 | 23.0 | 23.0 | 22.0 | 23.3 | 23.5 | 21.5 | 23.6 | 22.1 | 23.1 | 21.9 | 22.9 |
| | 0.01 | 24.6 | 23.3 | 24.8 | 23.3 | 23.3 | 24.8 | 24.3 | 23.9 | 23.9 | 24.1 | 23.9 | 23.4 | 24.0 | 23.5 |

SIC 3663 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 14.5 | 22.9 | 14.7 | 22.3 | 14.4 | 22.3 | 17.8 | 27.6 | 17.1 | 26.0 | 17.2 | 26.7 | 17.4 | 25.8 |
| 0.1 | 0.02 | 20.4 | 22.8 | 21.0 | 22.1 | 20.8 | 22.3 | 20.4 | 27.8 | 20.9 | 26.2 | 20.7 | 26.8 | 21.2 | 25.9 |
| | 0.01 | 24.5 | 22.8 | 24.9 | 22.0 | 24.9 | 22.1 | 21.4 | 27.6 | 22.2 | 26.1 | 21.9 | 26.7 | 22.8 | 25.9 |
| | 0.05 | 13.5 | 23.3 | 13.7 | 23.0 | 13.4 | 22.8 | 18.5 | 27.1 | 18.0 | 25.2 | 17.9 | 25.9 | 18.5 | 24.8 |
| 0.05 | 0.02 | 19.7 | 23.9 | 20.3 | 23.3 | 20.3 | 23.3 | 21.1 | 27.3 | 21.9 | 25.5 | 21.6 | 26.2 | 22.2 | 25.1 |
| | 0.01 | 23.7 | 23.8 | 24.2 | 23.3 | 24.1 | 23.4 | 22.1 | 27.1 | 23.4 | 25.2 | 22.9 | 25.8 | 23.8 | 24.7 |
| | 0.05 | 13.1 | 24.1 | 13.1 | 23.5 | 12.9 | 23.5 | 18.5 | 26.1 | 18.3 | 24.4 | 18.2 | 24.8 | 18.7 | 24.0 |
| 0.02 | 0.02 | 19.1 | 24.2 | 19.5 | 23.8 | 19.4 | 23.5 | 21.7 | 26.8 | 22.6 | 24.8 | 22.1 | 25.3 | 23.1 | 24.5 |
| | 0.01 | 23.1 | 24.2 | 23.9 | 23.9 | 23.7 | 23.7 | 22.5 | 26.5 | 24.1 | 24.6 | 23.3 | 24.8 | 24.3 | 24.1 |
| | 0.05 | 12.9 | 24.4 | 13.1 | 23.9 | 12.9 | 23.9 | 18.7 | 26.1 | 18.5 | 24.3 | 18.3 | 24.5 | 18.9 | 23.9 |
| 0.01 | 0.02 | 18.9 | 24.5 | 19.4 | 23.9 | 19.4 | 23.9 | 21.9 | 26.6 | 23.1 | 24.8 | 22.5 | 25.1 | 23.4 | 24.3 |
| | 0.01 | 22.5 | 24.4 | 23.0 | 23.7 | 23.1 | 23.8 | 22.4 | 26.6 | 24.0 | 24.8 | 23.5 | 25.2 | 24.3 | 24.4 |
| | 0.05 | 13.1 | 24.9 | 13.2 | 24.4 | 12.8 | 24.4 | 19.1 | 26.1 | 18.8 | 24.2 | 18.7 | 24.7 | 19.2 | 23.9 |
| 0 | 0.02 | 18.6 | 24.4 | 19.1 | 23.8 | 19.0 | 23.8 | 21.9 | 26.2 | 22.9 | 24.3 | 22.5 | 24.8 | 23.4 | 23.9 |
| | 0.01 | 22.5 | 24.7 | 23.1 | 24.1 | 23.0 | 24.2 | 22.9 | 26.4 | 24.4 | 24.3 | 23.8 | 24.9 | 24.7 | 24.1 |

SIC 4931 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 17.3 | 23.5 | 19.6 | 22.1 | 19.3 | 20.5 | 17.6 | 25.3 | 14.8 | 26.0 | 15.5 | 26.1 | 14.9 | 26.0 |
| 0.1 | 0.02 | 22.4 | 23.6 | 24.7 | 22.2 | 25.4 | 20.7 | 21.8 | 25.5 | 19.9 | 26.3 | 20.2 | 26.2 | 19.9 | 26.2 |
| | 0.01 | 24.6 | 23.7 | 26.4 | 22.3 | 27.6 | 20.7 | 23.2 | 25.2 | 22.0 | 26.1 | 22.1 | 25.9 | 22.1 | 26.1 |
| | 0.05 | 16.4 | 24.8 | 18.6 | 23.2 | 18.3 | 21.5 | 18.4 | 24.9 | 15.8 | 25.4 | 16.4 | 25.5 | 15.8 | 25.2 |
| 0.05 | 0.02 | 21.5 | 24.6 | 23.6 | 23.0 | 24.2 | 21.3 | 22.7 | 24.8 | 20.8 | 25.3 | 21.3 | 25.4 | 20.9 | 25.2 |
| | 0.01 | 23.5 | 24.6 | 25.4 | 23.2 | 26.5 | 21.4 | 23.9 | 24.9 | 22.9 | 25.5 | 22.9 | 25.4 | 22.8 | 25.2 |
| 0.02 | 0.05 | 15.7 | 25.2 | 18.0 | 23.6 | 17.8 | 21.9 | 18.6 | 24.4 | 16.0 | 24.8 | 16.6 | 24.9 | 15.9 | 24.7 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.02 | 21.1 | 25.1 | 23.2 | 23.6 | 23.8 | 21.9 | 23.0 | 24.2 | 21.4 | 24.7 | 22.0 | 24.8 | 21.7 | 24.7 |
| | 0.01 | 23.0 | 25.1 | 24.9 | 23.7 | 25.9 | 21.9 | 24.2 | 24.1 | 23.3 | 24.7 | 23.5 | 24.6 | 23.5 | 24.6 |
| | 0.05 | 15.6 | 25.4 | 17.7 | 23.8 | 17.5 | 22.2 | 18.8 | 24.2 | 16.2 | 24.7 | 16.8 | 24.7 | 16.2 | 24.5 |
| 0.01 | 0.02 | 21.0 | 25.2 | 23.1 | 23.6 | 23.6 | 22.0 | 23.4 | 24.3 | 21.9 | 24.7 | 22.4 | 24.8 | 22.0 | 24.6 |
| | 0.01 | 23.0 | 25.4 | 24.9 | 23.7 | 25.8 | 22.2 | 24.7 | 23.8 | 23.7 | 24.3 | 24.0 | 24.3 | 23.9 | 24.2 |
| | 0.05 | 15.5 | 25.4 | 17.8 | 23.8 | 17.6 | 22.4 | 19.0 | 23.8 | 16.3 | 24.2 | 17.2 | 24.3 | 16.3 | 24.2 |
| 0 | 0.02 | 20.6 | 25.3 | 22.7 | 23.9 | 23.4 | 22.4 | 23.3 | 23.9 | 22.0 | 24.3 | 22.3 | 24.3 | 21.9 | 24.2 |
| | 0.01 | 22.8 | 25.3 | 24.7 | 23.8 | 25.7 | 22.2 | 24.8 | 24.1 | 23.8 | 24.6 | 24.0 | 24.5 | 24.0 | 24.4 |

SIC 3841 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 18.8 | 20.6 | 19.1 | 19.8 | 19.0 | 20.4 | 17.8 | 25.0 | 15.6 | 23.8 | 15.5 | 23.8 | 16.0 | 23.7 |
| 0.1 | 0.02 | 25.0 | 20.4 | 25.5 | 19.5 | 25.0 | 20.0 | 22.1 | 24.7 | 21.9 | 23.4 | 21.7 | 23.6 | 21.9 | 23.5 |
| | 0.01 | 27.4 | 21.0 | 27.9 | 20.1 | 27.2 | 20.6 | 23.4 | 25.1 | 24.0 | 23.7 | 23.7 | 23.9 | 23.8 | 23.7 |
| | 0.05 | 17.8 | 21.2 | 18.2 | 20.6 | 17.7 | 21.5 | 18.2 | 24.6 | 16.7 | 22.9 | 16.5 | 23.2 | 16.9 | 22.9 |
| 0.05 | 0.02 | 23.8 | 21.0 | 24.2 | 20.1 | 23.9 | 21.2 | 22.5 | 24.2 | 22.8 | 22.5 | 22.6 | 22.5 | 22.8 | 22.4 |
| | 0.01 | 26.5 | 21.0 | 27.5 | 20.3 | 26.5 | 21.0 | 24.4 | 24.6 | 25.0 | 22.7 | 24.9 | 22.8 | 25.1 | 22.6 |
| | 0.05 | 17.9 | 21.6 | 18.1 | 20.9 | 17.7 | 21.6 | 18.9 | 24.3 | 17.2 | 22.1 | 17.3 | 22.0 | 17.6 | 22.0 |
| 0.02 | 0.02 | 23.0 | 21.8 | 23.8 | 21.0 | 23.3 | 21.7 | 20.6 | 25.6 | 18.7 | 25.9 | 19.5 | 25.8 | 18.7 | 26.2 |
| | 0.01 | 26.2 | 22.2 | 26.9 | 21.3 | 26.4 | 22.1 | 22.7 | 26.0 | 21.4 | 26.4 | 22.1 | 25.9 | 21.5 | 26.4 |
| | 0.05 | 17.6 | 22.1 | 17.9 | 21.4 | 17.6 | 22.0 | 18.7 | 24.3 | 17.1 | 22.0 | 17.3 | 22.1 | 17.4 | 22.1 |
| 0.01 | 0.02 | 23.1 | 22.2 | 24.1 | 21.4 | 23.3 | 22.1 | 23.3 | 23.8 | 23.5 | 21.6 | 23.5 | 21.5 | 23.4 | 21.5 |
| | 0.01 | 25.5 | 22.7 | 26.3 | 21.7 | 25.6 | 22.6 | 25.1 | 24.3 | 26.0 | 21.8 | 25.9 | 22.0 | 26.0 | 22.0 |
| | 0.05 | 16.8 | 22.5 | 17.3 | 21.7 | 17.1 | 22.4 | 18.7 | 24.0 | 17.1 | 21.9 | 17.3 | 21.7 | 17.4 | 21.8 |
| 0 | 0.02 | 22.8 | 22.3 | 23.9 | 21.7 | 23.2 | 22.1 | 23.3 | 24.2 | 23.7 | 21.7 | 23.6 | 22.0 | 23.7 | 22.0 |
| | 0.01 | 25.5 | 22.3 | 26.5 | 21.6 | 25.8 | 22.3 | 24.5 | 23.5 | 25.9 | 21.5 | 25.7 | 21.4 | 25.8 | 21.6 |

SIC 9995 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 15.1 | 28.3 | 12.6 | 28.5 | 14.7 | 26.4 | 14.5 | 33.8 | 16.1 | 30.6 | 13.5 | 32.2 | 15.8 | 30.6 |
| 0.1 | 0.02 | 18.7 | 28.5 | 18.0 | 28.6 | 20.5 | 26.8 | 16.2 | 33.7 | 17.3 | 29.8 | 15.5 | 31.8 | 17.3 | 30.2 |
| | 0.01 | 20.8 | 29.0 | 20.1 | 29.0 | 22.0 | 26.6 | 16.3 | 33.0 | 19.0 | 29.7 | 17.2 | 31.6 | 18.8 | 30.0 |
| | 0.05 | 14.6 | 28.2 | 11.9 | 29.2 | 14.2 | 26.9 | 15.6 | 32.6 | 17.0 | 28.6 | 14.3 | 30.6 | 16.0 | 29.6 |
| 0.05 | 0.02 | 18.5 | 29.1 | 16.5 | 29.7 | 19.7 | 28.0 | 16.4 | 31.8 | 18.4 | 28.1 | 16.4 | 29.6 | 17.9 | 29.0 |
| | 0.01 | 18.8 | 29.4 | 18.9 | 30.3 | 20.1 | 28.1 | 17.2 | 32.6 | 20.8 | 28.9 | 18.5 | 31.1 | 20.2 | 30.3 |
| | 0.05 | 14.6 | 30.1 | 11.8 | 30.3 | 13.6 | 28.4 | 16.2 | 31.2 | 16.8 | 27.3 | 15.3 | 29.4 | 16.4 | 27.8 |
| 0.02 | 0.02 | 17.4 | 29.1 | 15.9 | 30.4 | 18.7 | 28.1 | 16.6 | 32.1 | 19.0 | 28.1 | 17.3 | 30.5 | 18.8 | 28.7 |
| | 0.01 | 18.6 | 29.7 | 17.8 | 30.5 | 19.7 | 28.1 | 16.7 | 32.5 | 20.6 | 29.1 | 18.4 | 31.0 | 20.3 | 29.7 |
| | 0.05 | 13.8 | 29.5 | 11.4 | 30.4 | 13.3 | 27.7 | 16.3 | 33.4 | 17.3 | 29.3 | 15.6 | 31.1 | 17.1 | 29.3 |
| 0.01 | 0.02 | 17.4 | 29.3 | 15.2 | 29.9 | 18.3 | 27.7 | 16.9 | 32.4 | 19.8 | 28.3 | 17.6 | 30.5 | 19.2 | 28.6 |
| | 0.01 | 19.3 | 30.2 | 18.1 | 30.7 | 20.2 | 28.4 | 17.8 | 31.5 | 21.1 | 27.3 | 18.5 | 29.0 | 20.6 | 27.4 |
| 0 | 0.05 | 13.7 | 31.2 | 12.1 | 31.9 | 13.5 | 29.2 | 15.5 | 32.7 | 17.4 | 28.9 | 15.2 | 30.4 | 16.8 | 28.9 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.02 | 16.5 | 30.8 | 14.5 | 31.3 | 17.5 | 28.8 | 17.1 | 31.9 | 20.2 | 28.1 | 17.6 | 29.7 | 19.9 | 28.3 |
| | 0.01 | 18.3 | 29.7 | 17.7 | 30.5 | 19.9 | 28.3 | 16.8 | 32.5 | 20.9 | 28.7 | 18.8 | 30.7 | 20.5 | 29.1 |

SIC 7990 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 15.5 | 23.9 | 15.9 | 23.5 | 14.9 | 24.2 | 14.1 | 29.0 | 12.3 | 28.2 | 13.0 | 27.6 | 12.5 | 27.9 |
| 0.1 | 0.02 | 21.7 | 24.4 | 21.6 | 23.9 | 21.6 | 24.6 | 18.0 | 28.9 | 17.7 | 28.4 | 18.1 | 27.6 | 17.7 | 27.9 |
| | 0.01 | 24.0 | 23.8 | 24.0 | 23.4 | 24.0 | 24.0 | 20.0 | 28.5 | 20.1 | 27.9 | 20.8 | 27.3 | 20.4 | 27.5 |
| | 0.05 | 15.2 | 24.8 | 14.8 | 24.3 | 14.0 | 24.9 | 14.6 | 27.9 | 13.0 | 26.7 | 13.7 | 26.3 | 13.5 | 26.2 |
| 0.05 | 0.02 | 20.7 | 24.6 | 21.0 | 24.3 | 20.1 | 24.9 | 18.6 | 28.4 | 18.4 | 27.4 | 19.0 | 26.9 | 18.5 | 27.0 |
| | 0.01 | 22.6 | 24.8 | 22.9 | 24.5 | 22.5 | 24.8 | 20.2 | 28.0 | 20.5 | 26.9 | 21.2 | 26.4 | 20.9 | 26.4 |
| | 0.05 | 14.6 | 24.9 | 14.2 | 24.6 | 13.4 | 25.1 | 14.4 | 27.5 | 13.3 | 26.6 | 13.7 | 26.2 | 13.7 | 26.5 |
| 0.02 | 0.02 | 20.5 | 25.7 | 20.6 | 25.3 | 19.7 | 25.7 | 19.1 | 27.5 | 18.9 | 26.4 | 19.5 | 26.0 | 18.9 | 26.2 |
| | 0.01 | 22.4 | 24.9 | 22.6 | 25.0 | 22.3 | 25.1 | 20.9 | 27.3 | 21.2 | 26.1 | 21.8 | 25.5 | 21.7 | 25.9 |
| | 0.05 | 14.7 | 25.7 | 14.2 | 25.8 | 13.4 | 25.9 | 14.5 | 27.4 | 13.2 | 26.2 | 13.4 | 25.8 | 13.4 | 25.9 |
| 0.01 | 0.02 | 20.4 | 25.7 | 20.3 | 25.5 | 19.7 | 25.7 | 19.7 | 27.5 | 19.1 | 26.0 | 19.9 | 25.8 | 19.3 | 25.9 |
| | 0.01 | 22.2 | 25.7 | 22.2 | 25.6 | 21.9 | 25.8 | 21.1 | 27.0 | 21.5 | 25.8 | 22.0 | 25.3 | 21.8 | 25.6 |
| | 0.05 | 14.6 | 25.9 | 13.9 | 25.5 | 13.3 | 25.9 | 15.1 | 27.4 | 13.7 | 26.1 | 14.2 | 25.8 | 14.1 | 25.9 |
| 0 | 0.02 | 20.0 | 25.6 | 20.1 | 25.7 | 19.3 | 26.0 | 19.5 | 27.3 | 19.1 | 26.0 | 19.8 | 25.6 | 19.3 | 26.0 |
| | 0.01 | 22.2 | 25.9 | 22.3 | 25.8 | 21.8 | 25.9 | 21.1 | 27.4 | 21.7 | 26.2 | 22.2 | 26.0 | 21.9 | 25.9 |

SIC 3714 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 14.9 | 23.8 | 15.4 | 22.6 | 15.3 | 23.4 | 14.9 | 26.9 | 11.6 | 28.0 | 11.9 | 27.4 | 11.6 | 28.1 |
| 0.1 | 0.02 | 22.0 | 24.2 | 22.5 | 23.1 | 22.2 | 23.9 | 19.5 | 26.9 | 17.3 | 27.7 | 18.3 | 27.4 | 17.5 | 27.9 |
| | 0.01 | 24.2 | 23.7 | 25.0 | 22.7 | 24.3 | 23.6 | 21.5 | 26.8 | 19.7 | 27.5 | 20.5 | 27.1 | 19.8 | 27.7 |
| | 0.05 | 14.0 | 24.9 | 14.0 | 23.8 | 14.1 | 24.6 | 15.5 | 26.1 | 12.5 | 26.6 | 12.9 | 26.1 | 12.6 | 26.7 |
| 0.05 | 0.02 | 20.8 | 24.5 | 21.1 | 23.6 | 20.9 | 24.5 | 20.2 | 26.1 | 18.2 | 27.0 | 19.0 | 26.4 | 18.5 | 27.0 |
| | 0.01 | 23.2 | 24.2 | 23.9 | 23.5 | 23.1 | 24.2 | 22.0 | 26.1 | 20.6 | 26.9 | 21.3 | 26.3 | 20.7 | 26.9 |
| | 0.05 | 13.8 | 24.8 | 13.9 | 24.3 | 13.8 | 25.2 | 15.7 | 26.1 | 13.0 | 26.7 | 13.3 | 26.2 | 12.9 | 26.9 |
| 0.02 | 0.02 | 20.3 | 25.0 | 20.9 | 24.5 | 20.3 | 25.1 | 20.6 | 26.1 | 19.0 | 26.4 | 19.6 | 26.0 | 18.9 | 26.5 |
| | 0.01 | 22.8 | 25.0 | 23.2 | 24.3 | 22.5 | 24.9 | 21.7 | 25.8 | 20.6 | 26.2 | 21.5 | 25.9 | 21.0 | 26.5 |
| | 0.05 | 13.6 | 24.8 | 13.5 | 24.2 | 13.6 | 24.8 | 15.7 | 25.9 | 13.0 | 26.5 | 13.1 | 25.7 | 12.9 | 26.4 |
| 0.01 | 0.02 | 20.5 | 24.8 | 20.7 | 24.3 | 20.3 | 24.9 | 20.9 | 25.6 | 19.1 | 26.1 | 19.7 | 25.5 | 19.0 | 26.1 |
| | 0.01 | 22.7 | 25.2 | 23.1 | 24.7 | 22.3 | 25.2 | 22.4 | 25.4 | 21.4 | 26.0 | 22.3 | 25.5 | 21.5 | 26.1 |
| | 0.05 | 13.3 | 25.1 | 13.4 | 24.4 | 13.3 | 24.9 | 16.0 | 25.7 | 13.3 | 26.2 | 13.3 | 25.6 | 13.2 | 26.3 |
| 0 | 0.02 | 20.1 | 25.3 | 20.3 | 24.8 | 19.8 | 25.4 | 20.9 | 25.7 | 19.3 | 26.2 | 20.1 | 25.8 | 19.2 | 26.3 |
| | 0.01 | 22.0 | 25.3 | 22.5 | 24.9 | 21.6 | 25.1 | 22.5 | 26.1 | 21.3 | 26.3 | 22.4 | 26.1 | 21.3 | 26.6 |

SIC 6331 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.05 | 17.0 | 22.7 | 17.1 | 21.6 | 17.0 | 22.0 | 16.9 | 25.8 | 14.1 | 26.0 | 14.4 | 26.3 | 14.3 | 25.5 |
| | 0.02 | 23.3 | 22.8 | 23.7 | 21.7 | 23.8 | 22.1 | 21.2 | 25.6 | 19.5 | 26.1 | 19.9 | 26.3 | 20.1 | 25.6 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 25.4 | 22.5 | 25.7 | 21.6 | 25.9 | 21.8 | 22.4 | 25.8 | 21.7 | 26.1 | 21.6 | 26.4 | 22.0 | 25.7 |
| | 0.05 | 16.2 | 23.2 | 16.3 | 22.6 | 16.4 | 22.8 | 17.4 | 25.4 | 14.5 | 25.4 | 14.7 | 25.4 | 14.8 | 24.4 |
| 0.05 | 0.02 | 22.1 | 23.3 | 22.4 | 23.1 | 22.7 | 23.1 | 21.6 | 25.3 | 20.2 | 25.2 | 20.3 | 25.4 | 20.6 | 24.4 |
| | 0.01 | 24.3 | 23.8 | 24.6 | 23.4 | 24.9 | 23.3 | 22.9 | 25.4 | 22.4 | 25.4 | 22.4 | 25.7 | 22.9 | 24.5 |
| | 0.05 | 15.6 | 24.2 | 15.9 | 23.6 | 15.8 | 23.6 | 17.7 | 25.3 | 15.1 | 24.8 | 15.4 | 25.1 | 15.3 | 24.0 |
| 0.02 | 0.02 | 21.5 | 23.9 | 21.8 | 23.3 | 22.0 | 23.0 | 21.3 | 25.3 | 20.4 | 24.8 | 20.3 | 25.3 | 20.9 | 24.0 |
| | 0.01 | 23.4 | 24.3 | 23.7 | 23.7 | 24.2 | 23.7 | 23.9 | 24.9 | 23.3 | 24.5 | 23.2 | 24.8 | 24.1 | 23.7 |
| | 0.05 | 15.7 | 24.6 | 15.8 | 24.0 | 16.0 | 23.9 | 18.0 | 25.3 | 15.4 | 24.9 | 15.5 | 25.2 | 15.7 | 24.2 |
| 0.01 | 0.02 | 21.1 | 24.2 | 21.3 | 23.8 | 21.5 | 23.6 | 22.0 | 25.3 | 21.2 | 24.8 | 21.0 | 25.0 | 21.9 | 24.1 |
| | 0.01 | 23.5 | 24.5 | 23.7 | 24.1 | 24.2 | 23.9 | 23.6 | 25.3 | 23.2 | 25.0 | 23.0 | 25.2 | 23.8 | 24.2 |
| | 0.05 | 15.3 | 24.3 | 15.6 | 24.1 | 15.6 | 23.7 | 18.0 | 24.8 | 15.5 | 24.3 | 15.8 | 24.5 | 15.9 | 23.5 |
| 0 | 0.02 | 21.1 | 24.5 | 21.3 | 24.2 | 21.6 | 24.0 | 22.2 | 25.0 | 21.3 | 24.5 | 21.2 | 24.7 | 22.1 | 23.8 |
| | 0.01 | 23.3 | 24.4 | 23.7 | 24.3 | 24.0 | 23.9 | 23.8 | 25.2 | 23.7 | 24.7 | 23.3 | 24.8 | 24.2 | 23.9 |

SIC 6211 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 18.4 | 22.7 | 18.0 | 23.4 | 19.9 | 22.5 | 21.8 | 23.1 | 18.0 | 23.4 | 19.5 | 23.1 | 19.1 | 23.2 |
| 0.1 | 0.02 | 23.8 | 22.0 | 22.6 | 22.7 | 24.1 | 21.8 | 25.4 | 22.4 | 23.1 | 23.0 | 23.9 | 22.5 | 23.9 | 22.9 |
| | 0.01 | 26.4 | 22.2 | 25.2 | 22.6 | 26.7 | 21.7 | 25.9 | 22.9 | 23.9 | 23.5 | 24.9 | 23.2 | 24.5 | 23.5 |
| | 0.05 | 16.6 | 23.7 | 16.4 | 24.4 | 18.5 | 23.3 | 20.9 | 22.9 | 17.1 | 24.7 | 18.4 | 24.1 | 17.9 | 24.4 |
| 0.05 | 0.02 | 23.3 | 23.0 | 22.1 | 23.8 | 23.9 | 22.9 | 24.0 | 23.0 | 22.2 | 24.5 | 22.4 | 24.1 | 22.7 | 24.2 |
| | 0.01 | 25.7 | 22.7 | 24.7 | 23.3 | 26.2 | 22.4 | 25.8 | 23.0 | 24.1 | 25.0 | 24.7 | 24.5 | 24.6 | 24.6 |
| | 0.05 | 16.9 | 23.9 | 16.2 | 24.6 | 18.3 | 23.5 | 20.3 | 23.6 | 16.4 | 25.9 | 18.0 | 24.7 | 17.7 | 25.3 |
| 0.02 | 0.02 | 22.8 | 23.2 | 21.7 | 24.1 | 23.4 | 23.0 | 23.8 | 23.8 | 21.3 | 25.9 | 21.7 | 24.5 | 21.9 | 25.1 |
| | 0.01 | 24.0 | 23.7 | 23.4 | 24.9 | 24.3 | 23.5 | 24.6 | 23.6 | 22.5 | 25.7 | 23.2 | 24.7 | 23.2 | 25.1 |
| | 0.05 | 16.7 | 24.0 | 16.3 | 25.2 | 18.3 | 23.8 | 20.4 | 23.7 | 16.1 | 25.8 | 18.1 | 24.7 | 17.5 | 25.1 |
| 0.01 | 0.02 | 22.4 | 23.9 | 21.4 | 25.0 | 23.3 | 23.9 | 23.7 | 23.7 | 21.3 | 25.8 | 21.6 | 24.7 | 22.0 | 25.0 |
| | 0.01 | 24.8 | 23.8 | 23.8 | 25.1 | 24.9 | 23.7 | 24.7 | 23.6 | 22.8 | 26.0 | 23.1 | 24.7 | 23.3 | 25.2 |
| | 0.05 | 16.7 | 23.7 | 16.1 | 24.3 | 18.1 | 23.5 | 20.0 | 24.5 | 16.2 | 26.9 | 17.7 | 25.6 | 17.1 | 26.0 |
| 0 | 0.02 | 22.5 | 24.8 | 21.4 | 25.3 | 23.1 | 24.6 | 24.3 | 23.9 | 21.4 | 25.7 | 22.3 | 25.0 | 22.3 | 25.1 |
| | 0.01 | 24.4 | 24.5 | 23.1 | 25.1 | 24.6 | 24.0 | 24.6 | 24.0 | 22.4 | 26.1 | 22.7 | 25.0 | 22.8 | 25.3 |

SIC 3576 (%)

| s | e | FN_e | FP_e | FN_p | FP_p | FN_a | FP_a | FN_o | FP_o | FN_s | FP_s | FN_l | FP_l | FN_m | FP_m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.05 | 9.5 | 26.6 | 10.4 | 25.6 | 10.4 | 27.0 | 11.8 | 30.6 | 14.0 | 30.5 | 12.3 | 30.9 | 13.5 | 29.9 |
| 0.1 | 0.02 | 15.1 | 26.7 | 16.8 | 26.0 | 15.8 | 27.0 | 17.6 | 30.4 | 17.9 | 30.6 | 16.8 | 30.6 | 17.3 | 29.5 |
| | 0.01 | 20.0 | 26.8 | 20.6 | 25.9 | 20.6 | 27.1 | 19.1 | 30.6 | 18.4 | 30.0 | 18.0 | 30.2 | 18.2 | 29.3 |
| | 0.05 | 14.5 | 28.8 | 15.7 | 27.8 | 15.1 | 28.4 | 13.1 | 30.1 | 14.9 | 29.5 | 13.1 | 29.9 | 14.5 | 28.7 |
| 0.05 | 0.02 | 18.8 | 28.1 | 19.8 | 27.5 | 18.9 | 27.9 | 17.1 | 30.1 | 17.5 | 29.6 | 17.0 | 30.2 | 17.5 | 28.9 |
| | 0.01 | 21.5 | 27.6 | 21.4 | 26.2 | 21.7 | 27.2 | 19.4 | 30.6 | 19.0 | 29.6 | 18.8 | 30.5 | 19.6 | 28.9 |
| 0.02 | 0.05 | 14.1 | 28.7 | 15.3 | 27.6 | 14.6 | 28.2 | 14.3 | 31.3 | 15.6 | 29.4 | 14.0 | 30.2 | 15.4 | 28.9 |
| | 0.02 | 18.5 | 28.9 | 19.5 | 28.7 | 18.3 | 28.6 | 18.4 | 30.7 | 18.2 | 29.3 | 18.3 | 30.3 | 18.5 | 29.0 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 0.01 | 20.2 | 28.9 | 21.1 | 28.6 | 20.4 | 28.5 | 19.0 | 30.2 | 19.2 | 28.6 | 18.4 | 29.6 | 19.6 | 28.3 |
| | 0.05 | 14.0 | 28.5 | 16.0 | 27.9 | 14.8 | 27.9 | 14.0 | 30.6 | 15.7 | 29.1 | 14.0 | 30.1 | 15.4 | 29.2 |
| 0.01 | 0.02 | 18.5 | 27.7 | 19.0 | 27.0 | 18.3 | 27.0 | 18.7 | 29.9 | 18.2 | 27.9 | 18.0 | 28.8 | 18.8 | 27.7 |
| | 0.01 | 19.9 | 28.9 | 20.5 | 28.3 | 20.4 | 28.7 | 19.8 | 30.0 | 20.3 | 28.3 | 19.4 | 29.2 | 20.8 | 28.3 |
| | 0.05 | 13.9 | 28.5 | 15.5 | 28.1 | 14.8 | 28.0 | 13.8 | 30.2 | 15.4 | 28.5 | 14.0 | 29.7 | 15.0 | 28.5 |
| 0 | 0.02 | 18.3 | 28.3 | 19.4 | 28.4 | 18.6 | 28.1 | 19.1 | 30.2 | 18.4 | 28.0 | 18.4 | 29.2 | 18.9 | 28.0 |
| | 0.01 | 20.1 | 29.1 | 20.7 | 28.6 | 20.5 | 28.7 | 19.3 | 30.1 | 19.9 | 28.3 | 19.3 | 29.3 | 20.0 | 28.1 |

This table displays (overestimating revenues & underestimating cost of goods sold) error detection performance of sharing models (sharing actual, prediction, error, either the sign of predictions and the level of deviations or both of them) and the benchmark model by percentage respectively, with different magnitudes of errors (e: from 1% to 5%) and different significance (s: determined by α) and width of prediction interval (PI) for. The term "FN" represents "False Negative" and FP represents "False Positive". Additionally, the subscript "o" means original model, and "a", "p", "e", "s", "l" and "m" are short for "actual", "prediction", "error", "the sign of prediction" "the level of deviation" and "mix" respectively (with the latter indicating sharing both the sign of predictions and the level of deviations).

## Section C.

**C.1 The Change of Best Models According to Different Magnitudes of Errors**

| | ***Panel A. Overestimated Revenue*** | | | ***Panel B. Underestimated cost of goods sold*** | | |
|---|---|---|---|---|---|---|
| SIC | 0.01 | 0.02 | 0.05 | 0.01 | 0.02 | 0.05 |
| 1311 | M | M | A | O | O | E |
| 2834 | M | M | M | O | S | A |
| 2836 | M | M | M | S/L | S/L | L |
| 3576 | M | M | M | S | A | S |
| 3663 | M | M | M | O | O | P |
| 3674 | M | M | M | O | L | E |
| 3714 | M | M | L | S | A | A |
| 3841 | M | M | M | O | E | P |
| 3845 | M | M | M | E/S/O | E | S |
| 4813 | M | M | L | A | S | S |
| 4911 | M | A | A | S | S | E |
| 4931 | M | A | A | E | E | E |
| 5812 | M | M | A | E | S | L |
| 6211 | M | M | P | L | O | L |
| 6331 | M | M | S | P | L/P | P |

| | | | | | | |
|---|---|---|---|---|---|---|
| 7370 | M | M | M | O | A | P |
| 7372 | M | M | M | S | P | P |
| 7373 | M | M | A | L | L | P |
| 7990 | M | M | M/P | O | L | L |
| 9995 | M | M | M | M | M | P |

**The Change of Best Models According to Different Cost Ratios**

***Panel C.***

***Overestimated Revenue***

| SIC | 1:1 | 1:10 | 1:20 | 1:50 | 1:100 |
|---|---|---|---|---|---|
| 1311 | A | M | M | M | M |
| 2834 | E | M | M | M | M |
| 2836 | L/S | M | M | M | M |
| 3576 | S | M | M | M | M |
| 3663 | P | M | M | M | M |
| 3674 | P | M | M | M | M |
| 3714 | E | M | M | M | M |
| 3841 | A/L | M | M | M | M |
| 3845 | S | M | M | M | M |
| 4813 | A | M | M | M | M |
| 4911 | E | M | M | M | M |
| 4931 | A/S | M | M | M | M |
| 5812 | S | M | M | M | M |
| 6211 | L | M | M | M | M |
| 6331 | A | M | M | M | M |
| 7370 | S | M | M | M | M |
| 7372 | S | M | M | M | M |
| 7373 | A | M | M | M | M |
| 7990 | L | M | M | M | M |
| 9995 | E | M | M | M | M |

***Panel D.***

***Underestimated cost of goods sold***

| SIC | 1:1 | 1:10 | 1:20 | 1:50 | 1:100 |
|---|---|---|---|---|---|
| 1311 | L | O | O | O | O |
| 2834 | A | S | O | O | O |
| 2836 | S | /S/P | S | S | S |
| 3576 | A | A/E | A/E | A/E | A/E |
| 3663 | A/S/E/P | O | O | O | O |
| 3674 | P | L | L/O | O | O |

| | | | | | |
|---|---|---|---|---|---|
| 3714 | L | S | A/S | S | S |
| 3841 | L | E | E | E | E |
| 3845 | P | S/E/P | E | E | E |
| 4813 | S | A | S/O | S/O | S/O |
| 4911 | A | S | S | S | S |
| 4931 | A | E | E | E | E |
| 5812 | E | E | E | E | E |
| 6211 | P | O | O | O | O |
| 6331 | P | P | P | P | P |
| 7370 | E | P | P/A | P/A | A |
| 7372 | S | S | S | P | P |
| 7373 | P | L | L | L | L |
| 7990 | S | S | S | S | S |
| 9995 | M | M | M | M | M |

This table illustrates the change of best models according to the different magnitudes of errors and cost ratios between false positives and false negatives. The column titles 1:1, 1:10, 1:20, 1:50 and 1:100 represents the cost ratio. “O” is short for “Original”, “E” means the “Error” sharing model, “P” represents the “Prediction” model, “A” is the “Actual” sharing model, “S” stands for the “Sign” of and “L” stands for the “Level” of deviations of prediction errors. At last, “M” represents the combined sharing model containing both the sign and the level of deviations of prediction errors.