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A Machine Learning Approach to Assessing Audit Quality (AQ) in Company with Non-Switching Auditors: Extra Trees Classifier (ETC) Model

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ABSTRACT

In this study, the authors utilize machine learning techniques to investigate the likelihood of a company switching auditors and examine whether the increased likelihood of switching is associated with audit quality (AQ) in Tehran stock exchange. This study aims to understand the impact of auditor switching on audit quality and employs adjusted restatements of financial statements (AudFailA, AudFailB) and a new modified report (NMR) as proxies to measure audit quality, based on the environmental conditions of the research. These findings indicate that companies with a higher likelihood of switching auditors, but ultimately deciding to stay with incumbent auditors, exhibit poor audit quality.

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1. Introduction

According to agency theory, managers have numerous incentives to present their audit reports with a favorable opinion. They are looking for auditors who will behave according to their wishes and have less professional skepticism about financial statements. This expectation can lead to "opinion shopping" and increase the possibility of fraud in financial statements (Yuejun, 2011). An auditor's opinion plays a crucial role in investors' decision-making processes, and its disregard can have detrimental effects. Consequently, companies often switch auditors to obtain favorable opinions (P. Chen et al., 2012; Gibbins et al., 2001; Ruiz-Barbadillo et al., 2006). A process known as "opinion shopping" in auditing literature undermines the auditor's independence, which is one of the fundamental concepts of auditing (DeFond & Zhang, 2014). Auditing research has shown that companies may engage in a practice known as "opinion shopping," in which they seek auditors who are likely to give them a favorable opinion of their financial statements. This practice can lead to a loss of auditor independence and a decline in audit quality (AQ). Decreasing AQ undermines the reliability of financial statements, leading to reduced confidence in their accuracy and an increased likelihood of management bias and material errors. (Krishnan, 1994; Lennox, 2000; Newton et al., 2015).

Regulators have long been concerned that auditor switching is driven by opinion shopping, which potentially harms the auditing market (Commission, 2010; Cowle et al., 2023; Securities & Exchange Commission, 1988). The concept of "opinion shopping" poses a threat to the independence of auditors, which in turn affects the quality of audits. Regulators implemented various policies to address this issue. The US Securities and Exchange Commission requires companies to disclose any differences in opinions between auditors and companies when they switch auditors. The Sarbanes-Oxley Act of 2002 gave the audit committee the responsibility for appointing an auditor previously held by management. However, recent studies indicate that despite these efforts, managers are still involved in selecting auditors and may engage in opinion shopping (Chung et al., 2019). Auditor independence is a concern for regulators, particularly when companies switch auditors. Nonetheless, a more significant concern arises when auditors accept audit work to retain clients, even when they are aware of threats to their independence. In such cases, market participants are unaware of any auditor switch and not informed about potential weaknesses in financial reporting (Hunt et al., 2021; McGrath et al., 2001). Hence, in this study, machine learning (ML) techniques are utilized to identify companies that may have the potential to switch auditors but choose not to do so. Additionally, this study investigates the correlation between this possibility and AQ.

This research aimed to identify companies that were on the verge of switching auditors but ultimately chose not to do so. The researchers then investigated whether these companies exhibited lower AQ than those that had switched auditors. By utilizing ML techniques, the researchers intended to provide insights that could assist regulators in identifying ongoing audit engagements that may be vulnerable to declining AQ. Academic literature indicates that opinion shopping, the practice of companies regarding switching auditors to obtain more favorable opinions, can undermine auditor independence and reduce AQ (Ashbaugh-Skaife et al., 2007; Lennox & Park, 2007). To the best of our knowledge, this study is the first to examine the relationship between audit quality (AQ) and companies that continue to retain auditors when they have the option to switch in Iran. This particular focus is of significant importance because, in such cases where no visible signs of auditor switching are observed, the issue of AQ becomes even more critical. It is hoped that the findings of this study will provide new insights into the factors that contribute to auditor opinion shopping and help expand our understanding of this field.

2. Literature Review and Research Question

2-1. Definition of Opinion Shopping

As there is no universally accepted definition of opinion shopping, it is important to explore how researchers interpret it. All the definitions of opinion shopping were taken from the US Securities and Exchange Commission. The commission believes that opinion shopping refers to the situation where "the company is looking for an auditor who is willing to support the company's proposed accounting procedures and help the company achieve its reporting objectives" (Securities & Exchange Commission, 1988). To this end, researchers have provided different definitions to understand and deduce this concept. F. Chen et al. (2016) stated that opinion shopping refers to the employer's willingness to consult with auditors with the intent of obtaining a favorable opinion when the current auditors issue an unfavorable opinion or when there is a disagreement on certain accounting matters that could result in receiving an adverse opinion. In such cases, a company manager may switch the current auditor to avoid publishing an unfavorable opinion, allowing them to select an auditing firm that aligns with their preference. In another argument of the Public Company Accounting Oversight Board (2013), the purchase of the auditor's opinion is related to incentives that encourage auditors to focus on the interests of the owners who pay their fees instead of paying attention to the interests of investors. In another definition, buying an auditor's opinion refers to switching the auditor to receive a favorable opinion regarding an accounting procedure or financial statements (Lennox, 2000; Lennox & Pratt, 2003; PCAOB, 2013). Xie et al. (2010) defined opinion shopping as managers' efforts to influence or manipulate auditors' decisions to obtain a more favorable audit opinion.

2-2. Opinion Shopping and Audit Quality

Audit literature suggests that if managers find auditors' services unacceptable, they may consider switching auditors as a viable strategy to achieve their objectives. This assumption is based on the condition that the new auditor has limited knowledge about the employer, leading to the belief that switching auditors impacts the likelihood of opinion shopping (Lennox, 2000; Lu, 2006). Switching auditors can influence opinion shopping and lead to achieving the desired goals. However, it is important to consider specific circumstances and regulations surrounding auditor switching and its effects on independence, AQ, and financial statement misstatements (Lu, 2006). In this regard, many studies have shown that the switch of auditor occurs through "opinion shopping" because new auditors become economically dependent on the employers and act according to the employer's wishes (Chung et al., 2019; Chung et al., 2021). According to some studies, the switch of the auditor not only achieves "opinion shopping" but also makes the new auditor's opinion more robust (e.g., Krishnan, 1994). Furthermore, "opinion shopping" probably occurs in cases where companies switch auditors for no reason and the type of opinion represents an improvement (Lennox, 2000).

AQ reflects the level of confidence that stakeholders place in the accuracy, completeness, and reliability of a company's financial statements, ensuring that the financial performance presented in the statements is free from fundamental errors or omissions. AQ is crucial for maintaining trust in financial reporting and supporting informed decision-making by various stakeholders, including investors, lenders, regulators, and the public. To improve AQ, auditors and audit firms must continuously evaluate their processes and remain updated with evolving standards and regulations. Ongoing professional development, training, and adherence to best practices are vital for auditors to maintain and enhance their AQ. Many studies have investigated factors that affect AQ (e.g., Aobdia, 2019; DeFond & Zhang, 2014; Watkins et al., 2004). Several factors are identified as significant contributors to AQ, including audit experience, auditor professionalism, time-budget pressure, audit tenure, and knowledge of error detection (Calocha & Herwiyanti, 2020).

Extensive studies have examined various factors in the audit environment that can lead to reduced audit independence and bias in audit judgments; in particular, these studies have highlighted the provision of non-audit services (Beardsley et al., 2021; DeFond et al., 2002; Kinney et al., 2004;), client importance (Li, 2009; Van Brenk et al., 2021), auditor tenure (Gul et al., 2007), and auditor "opinion shopping" (Chung et al., 2021; Lennox, 2000; Li, 2009). According to According to Taqi et al. (2024), high audit quality (AQ) serves as a significant positive signal in reducing the risk of litigation, providing confidence to stakeholders that financial statements are more reliable and less likely to contain material misstatements. Additionally, Haghighi et al. (2025) have recently found that auditor sensory processing can affect objectivity. Therefore, auditors are not objective in all situations, implying that AQ may be impaired under specific conditions. Lotfi et al. (2023) indicated that confirmation bias negatively affects AQ. Moreover, Pourheidari and Golmohammadi (2023) concluded that more management compensation and higher AQ strengthen the negative association between stakeholder management and audit fees. Similarly, Haghighi et al. (2023) found that different neuroscience factors that require more research in this area affect auditors' judgment and performance. Accordingly, studying cognitive neuroscience factors as a novel stance in audit literature can help auditors improve their professional judgments and opinions, resulting in reduced audit risk and increased AQ.

The effect of auditor switches on the AQ and financial reporting is a complex issue with no clear consensus. It is believed that these switches have implications for both AQ and financial reporting. Therefore, assessing the reasons behind these switches and their potential consequences is essential.

Companies that switch auditors because they disagree with or obtain a less conservative opinion from these professionals may be at increased risk of AQ issues. Some studies have indicated that such companies may be at risk of lower AQ. Nevertheless, there is contradictory evidence on this issue, and it is unclear whether auditor switches always lead to lower AQ.

These switches could result in a loss of independence, reduced skepticism, or compromised objectivity, all essential for high-quality audit processes (Hu et al., 2022). However, different perspectives exist regarding the effects of auditor switches on AQ and financial reporting.

Some argue that switching auditors may improve AQ by introducing new perspectives, enhancing scrutiny, and increasing attention to potential errors or irregularities. New auditors may bring different expertise or methodologies to the auditing process, potentially leading to a more thorough examination of the financial statements (Hall et al., 2023). To understand this topic thoroughly, it is important to consider reliable research and evidence. Some studies have shown that AQ can improve after an auditor switch (Lu, 2006), while others have reported that audit judgments and opinions are not significantly different after switching auditors (DeFond & Subramanyam, 1998). Lennox (2000) demonstrated that using predicted opinions rather than actual opinions reveals a tendency for audit opinions to be more favorable to management after an auditor switch. However, existing research on opinion buying concentrates mainly on the switching activities of auditors' clients and compares the AQ of previous and new auditors. This limited approach overlooks a full range of potential problems. Even if there is no switch in auditors, it is crucial to research the circumstances under which auditor independence may be jeopardized.

2-3. Audit Quality and its Relationship to Auditor Switching in Iran

AQ, an essential aspect of financial reporting, is deeply influenced by auditor characteristics, including expertise and independence. In Iran, AQ is often tied to the size and reputation of audit firms, as larger firms tend to have more resources and a higher level of expertise. Aghaei Chadegani et al. (2013) observed that the quality of audits in Iran is largely determined by the size and reputation of the audit firm, with larger firms more likely to deliver higher-quality audits due to their advanced capabilities. However, the switching of auditors may compromise AQ, particularly during the initial engagement period when new auditors face pressures related to establishing client relationships. Haghighi et al. (2024) investigated the effects of auditor sensory processing on objectivity and found that this sensory processing affected objectivity. It can be argued that auditors are not objective in all situations, highlighting that AQ may be impaired in particular conditions. This finding indicates that auditors' objectivity could be affected by different personal traits, leading to increased audit risk, which may negatively affect audit firms and professional reputations. Lotfi et al. (2023) evaluated the effect of confirmation bias on AQ and the moderating roles of client characteristics (market value and institutional shareholder's ownership) and auditors (industry specialist auditor and first-class stock exchange trusted auditor) on AQ and the relationship between them. In this study, financial restatement and the absolute value of discretionary accruals were used as AQ proxies. The results demonstrated that confirmation bias could negatively affect AQ. It was further revealed that the adverse effects of confirmation bias on AQ are less for clients with high market value, high institutional ownership percentages, and audits performed by industry-specialist auditors and first-class stock exchange trusted auditors.

2-4. The Role of Machine Learning

ML techniques can be used to identify companies more likely to switch auditors and investigate whether there is a correlation between the likelihood of switching auditors and lower AQ. Moreover, they can help regulators detect ongoing audits at risk of declining quality (Hunt et al., 2021). These techniques must be properly trained and tested to ensure accurate predictions and prevent overfitting. ML models learn from training data and are evaluated using out-of-sample data. Therefore, training and testing are essential components of ML. The training phase of ML involves exposing the algorithm to a labeled dataset, allowing it to learn the patterns and relationships within the data. Through this process, the algorithm adjusts its internal parameters to optimize its performance. Once the training is completed, the testing phase is conducted using a separate dataset that the algorithm has not observed before. This out-of-sample testing evaluates the ability of the algorithm to generalize its learning and make accurate predictions based on new, unseen data. It assists in identifying if the model has overfitted the training data, implying that it has learned the specific patterns of the training set, but fails to perform well on new data. Overfitting can lead to poor performance when applied to real-world scenarios. By following this training and testing process, ML models can learn from the data and accurately predict new, unseen instances. This ensures that the models generalize well and are reliable in real-world applications (Janiesch et al., 2021). The process described in this study was implemented for a sample from 2002 to 2021. The objective was to use auditor switch modeling as the target variable based on previous research.

This study investigates the differences in opinion between auditors and companies, particularly focusing on situations where the possibility of switching auditors exists, but no actual switch has yet been observed. ML techniques have been employed to identify cases where a switch in the auditor could occur, but the company decided to retain the current auditor. Additionally, this study examines the AQ of these companies (Hunt et al., 2021). Based on these investigations, the following hypothesis has been proposed:

> **Hypothesis 1:** Companies that retain their auditor despite the possibility of an auditor switch experience a decrease in audit quality.

3. Prediction of the Probability of Switching Auditors

A training and test dataset consisting of 1,995 observations was utilized to calculate the variable known as auditor switching probability (*PROB_SWITCH*). This variable represents the likelihood that auditors will switch within the dataset. Different variables, including LN_AT, INVT_RECT, DACC, CASH, ROA, LOSS, AT_GROW, ACQUIRE, CFEARLY, CFMATURE, MODOP, BIGN, and SWITCH, were measured for each company in the year T-1.

A company's total assets are expressed as *LN_AT*, which is the natural logarithm of its assets. *INVT_RECT* is the sum of receivables and inventory divided by total assets, and *DACC* is the estimation of discretionary accruals using the modified Jones model. In addition, *CASH* and *ROA* denote the sum of cash and cash equivalents divided by total assets and the ratio of income before extraordinary items to total assets, respectively. Another variable is *LOSS* which is set to 1 when *ROA* is less than 0; otherwise, it is set to 0. Furthermore, *AT_GROW* represents the change in total assets divided by the total assets of the previous year. *ACQUIRE* is set to 1 when the cash outflows related to acquisitions of total assets exceed 10%; otherwise, it is set to 0. *CFEARLY* is 1 if a company is in the introduction or growth stage of its lifecycle; otherwise, it is 0. The *CFMATURE* indicator is set to 1 if the company is in its mature stage, and 0 otherwise. When the independent auditor issues a modified opinion, *MODOP* is set to 1 and if not, it is set to 0. *BIGN* is an indicator variable that is set to 1 if the company is audited by a large audit organization and 0 otherwise. *SWITCH* (our target variable) is an indicator variable that equals 1 if the company switches its auditor in the current year (year t) compared to the previous year (year t-1), and 0 otherwise. Descriptive statistics for the training and testing samples are presented in Table 1.

Table 1. Descriptive Statistics

	N	Mean	SD	p25	p50	p75
SWITCH	1995	0.196	0.397	0.000	0.000	0.000
LN_AT	1995	13.418	1.489	12.330	13.270	14.370
INVT_RECT	1995	0.645	0.244	0.480	0.650	0.800
DACC	1995	0.060	0.115	-0.060	0.010	0.070
CASH	1995	0.040	0.039	0.010	0.030	0.050
ROA	1995	0.125	0.155	0.030	0.100	0.210
LOSS	1995	0.129	0.335	0.000	0.000	0.000
AT_GROW	1995	0.253	0.516	0.030	0.160	0.330
ACQUIRE	1995	0.014	0.118	0.000	0.000	0.000
CFEARLY	1995	0.535	0.499	0.000	1.000	1.000
CFMATURE	1995	0.269	0.443	0.000	0.000	1.000
MODOP	1995	0.594	0.491	0.000	1.000	1.000
BIGN	1995	0.236	0.424	0.000	0.000	0.000

3-1. Introduction to Artificial Intelligence and ML

ML algorithms play a crucial role in extracting valuable insights from diverse data types, including cybersecurity, business, and social media data. They leverage statistical techniques and models to analyze and predict potential future occurrences. ML is a potent technique that can be employed to enhance prediction tasks by learning from data and making precise forecasts (Gu et al., 2020; Sarker, 2021). To estimate parameters in accounting research, logistic regression is often used along with other traditional statistical models. However, this model may not be effective for out-of-sample predictions because they make strong assumptions about the data-generation process. However, ML methods are more flexible and require fewer assumptions, making them more suitable for out-of-sample predictions (Mullainathan & Spiess, 2017). In addition, they are more flexible and appropriate for approximating complex data-generation processes (Gu et al., 2020). ML techniques have attracted the attention of accounting and auditing researchers to investigate various issues, such as fraud detection (Cecchini et al., 2010; Jones, 2017; Maes et al., 2002; Whiting et al., 2012) and bankruptcy prediction (Bao et al., 2020; Bertomeu et al., 2020; Min & Lee, 2005; Perols et al., 2017; Perols & Lougee, 2011; Tsai & Wu, 2008). These techniques are particularly relevant to this study as they are data-driven methods for identifying rare events that can significantly affect an organization's financial standing and reputation.

Our procedure for estimating the probability of switching auditors in the current year was designed, and the train_test_split function in the scikit-learn library was used to split our dataset into training and test sets randomly. This function allows us to split arrays or matrices into random subsets, which is useful for training and evaluating ML models. The training and testing sets were allocated 75% and 25% of the data, respectively. This split ensured that the distribution of classes in both sets was representative of the entire dataset. Using the train_test_split function, it was ensured that our training and testing data were independent and unbiased, thereby enabling us to evaluate the accuracy of our estimation procedure. Additionally, a predictive model was utilized to estimate the probability of switching auditors. Likewise, the predict-proba method from the scikit-learn library was employed to calculate probability estimates (PROB_SWITCH) for each class label. This method uses a trained model and input data as inputs and produces a list of probability estimates for each class label. It is important to consider that the accuracy and reliability of the probability estimates depend on the chosen predictive model and the quality of the input data. Therefore, it is crucial to utilize appropriate evaluation techniques to assess the performance and validity of the model. Scikit-learn provides several methods for model evaluation, including score methods specific to each estimator and metric functions for assessing prediction errors.

3-2. Model Evaluation

The extremely randomized tree (ETC) model from scikit-learn, a popular Python library for ML, was used in this study. With this library, it is possible to easily analyze and model data, including classification, regression, and clustering algorithms. Moreover, receiver operating characteristic (ROC) curves were employed to investigate the performance of each classifier and determine the optimal model for our classification task. ROC curves serve as visual aids that are used to evaluate the effectiveness of binary classifiers.

3-2-1. Receiver Operating Characteristic Curve

An ROC curve is a graph that illustrates the balance between the true (sensitivity) and false (1-specificity) positive rates for different cutoff points used to classify the data. The concepts of sensitivity and specificity must be comprehended before assessing an ROC curve. Sensitivity measures how accurately a model forecasts positive results, whereas specificity evaluates how accurately a model predicts negative results. When comparing the results of a specific test between two populations, it is uncommon to find that the two groups are entirely different. As depicted in Figure 1, the test results often overlap (Metz, 1978). The ROC curve in Figure 2 is a graphical plot that shows the trade-off between the true and false positive rates of a binary classifier model.

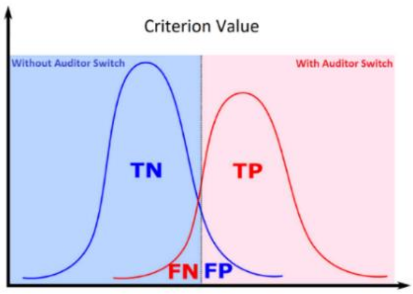

Fig. 1. ROC Curve Construction (Image Source: https://www.mdpi.com)

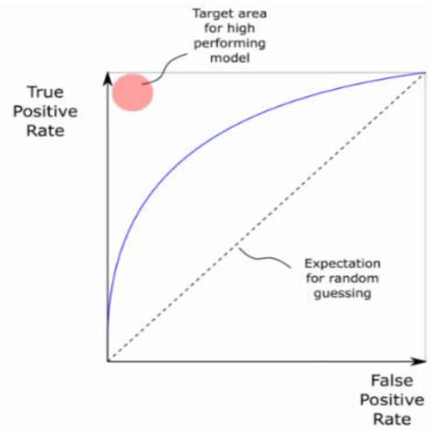

Fig. 2. ROC Curve (Source: https://deparkes.co.uk/)

ROC curves can be useful when evaluating a classifier's performance. Nonetheless, it is difficult to compare the performance of different classifiers using the ROC curve alone as it is a two-dimensional graph, and it is impossible to easily compare the curves of different classifiers visually. The area under the curve (AUC) is a common metric utilized to summarize ROC curves. Classifiers are measured by their accuracy, which is called the AUC. A classifier with an AUC of 0.5 is not better than random guessing, while a classifier with an AUC of 1 perfectly classifies all data. AUC values generally indicate the classifier's accuracy. Figure 3 displays different AUC values.

$$AUC = \int_{x=0}^{1} TPR\left(FPR^{-1}(x)\right)dx$$

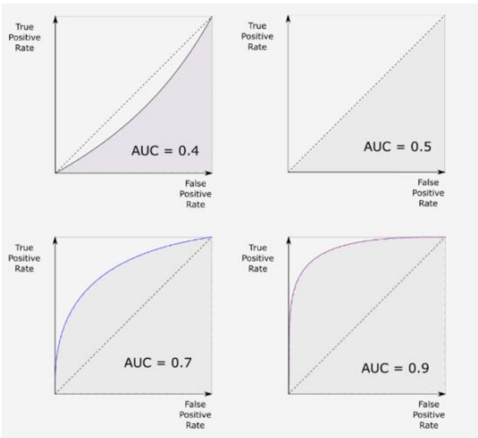

Fig. 3. AUC: Area Under the Curve (Source: https://deparkes.co.uk/)

3-1-2. Ensemble Methods

These methods are powerful ML techniques that combine the predictions of individual base models to enhance accuracy and reliability. They aim to combine weak models to create a stronger ensemble. Averaging the base model predictions or training them sequentially to focus on errors can create ensemble methods. These methods are powerful for improving the accuracy and robustness of ML models and have been successful in various ML tasks (Pedregosa et al., 2011)

The ETC is an ML method that belongs to the family of ensemble learning algorithms. The extremely randomized trees (ExtraTree) classifier is an ensemble method that consolidates multiple randomized decision trees to enhance predictive validity and control overfitting. It belongs to the family of averaging methods used in ensemble learning. The ETC model had the highest AUC level (97.7%), indicating that it is highly accurate in its predictions and has a strong ability to discriminate between positive and negative classes (Pedregosa et al., 2011). Figure 4 indicates the ROC curve of this model.

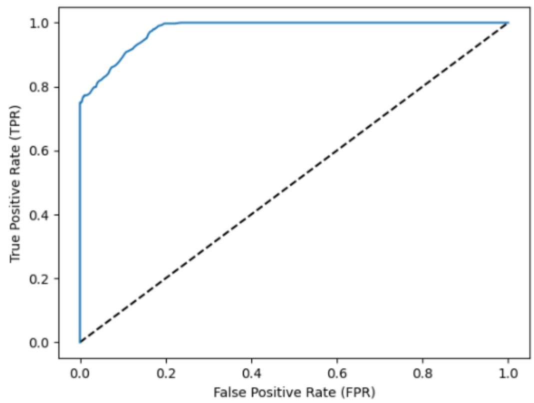

Fig. 4. ROC Curve of "ETC" Model

4. Data Collection

The following model was employed to examine the potential impact of an auditor switch on AQ.

$$AQ_{it} = \beta_0 + \beta_1 PROB\_SWITCH_{it} + \beta_2 LN\_AT_{it} + \beta_3 LEV_{it} + \beta_4 ROA_{it} + \beta_5 LOSS_{it} + \beta_6 INVT\_RECT_{it} + \beta_7 CFEARLY_{it} + \beta_8 CFMATURE_{it} + \beta_9 AT\_GROW_{it} + \beta_{10} CFO_{it} + \beta_{11} BIGN_{it} + IndustryFE + YearFE + \varepsilon_{it}$$

AQ measures have been commonly used in previous studies (e.g., Aobdia, 2016; Brown & Knechel, 2016; Mohammadrezaei & Faraji, 2019; Tan & Young, 2015). AQ, as an abstract concept (structure), should be examined from various perspectives. The various dimensions and aspects of this concept have distinct strengths and weaknesses across studies, particularly in the context of Iran. It is difficult to measure AQ, as the amount of certification and confirmation provided by the auditor is not observable (DeFond & Zhang, 2014). Three variables, namely, AudFailA, AudFailB, and 'new modified report (NMR)', are utilized to evaluate AQ.

To assess AQ, DeFond and Zheng (2014) proposed using financial statement restatements, excluding those due to tax issues, as an indicator. This indicates that the previous year's audit may have failed to detect significant distortions or errors, leading to the need for restatement in the following year. Similarly, Barnes and Renart (2013) suggested two types of audit errors (alpha and beta). Specifically, they defined the alpha error as the incorrect rejection of an acceptable report due to the problem of non-continuance of business without going bankrupt in the subsequent financial year. The beta error is the incorrect acceptance of an unacceptable report in the current financial year, leading to bankruptcy in the next fiscal year. It is noteworthy that these definitions may not be directly relevant in our country as the criteria for an acceptable or unacceptable report may vary based on local laws and regulations. Mohammad Rezaei et al. (2019) modified audit error criteria to suit Iran's research environment. They introduced a criterion with fewer errors in measuring AQ than the financial statement restatement criterion, which defines the first type of audit error (AudFailA) as the "issuance of an unacceptable audit report in the current fiscal year by auditors and the failure to restate financial statements in the following fiscal year." The second type of audit error (AudFailB) was defined as the "issuance of an acceptable audit report in the previous fiscal year and restatement of financial statements in the current year." It should be noted that the possible objections of auditing professional activists to this standard have been largely resolved with this new definition (Barnes & Renart, 2013; DeFond & Zhang, 2014; Mohammadrezaei & Faraji, 2019).

In the context of financial reporting in Iran, the variable of 'new modified report' can be utilized as a metric for assessing AQ, considering the prevailing environmental conditions. The term 'new modified report' refers to situations where the auditor is a modified report in the current year despite the entity having received a favorable opinion in the previous fiscal year. The findings of studies conducted by Mohammadrezaei et al. (2018) and Mohammadrezaei and Faraji (2019) revealed that approximately 10% of modified audit reports can be categorized as new modified reports.

5. Analysis

The primary variable in our analysis was the probability of auditor switching, denoted as PROB_SWITCH. This variable represents the likelihood that a firm will switch auditors from the year t-1 to t. LEV and CFO were other variables. LEV measures debt divided by total assets, and CFO is the cash flow from operations divided by the total assets. All other variables were previously defined.

Our sample was refined to focus on companies without auditor switching to estimate their probability of switching auditors. Consequently, 392 observations that switched auditors between years t-1 and t were removed from the analysis. Overall, 1,603 observations were obtained from this approach, the descriptive statistics of which are provided in Table 4.

Table 2. Descriptive Statistics

Stats	N	Mean	SD	p25	p50	p75
PROB_SWITCH	1603	0.046	0.109	0.000	0.000	0.000
AudFailA+ AudFailB	1603	0.273	0.446	0.000	0.000	1.000
AudFailA	1603	0.808	0.394	1.000	1.000	1.000
AudFailB	1603	0.289	0.453	0.000	0.000	1.000
NMR	1603	0.900	0.300	1.000	1.000	1.000
LN_AT	1603	13.452	1.551	12.293	13.289	14.442
LEV	1603	0.671	0.258	0.512	0.647	0.771
ROA	1603	0.997	0.122	0.030	0.088	0.168
LOSS	1603	0.124	0.329	0.000	0.000	0.000
INVT_RECT	1603	0.644	0.241	0.482	0.643	0.802
CFEARLY	1603	0.548	0.498	0.000	1.000	1.000
CFMATURE	1603	0.257	0.437	0.000	0.000	1.000
AT_GROW	1603	0.268	0.352	0.040	0.161	0.342
CFO	1603	0.033	0.109	0.018	0.080	0.147
BIGN	1603	0.284	0.451	0.000	0.000	1.000

Table 5 presents the results of Eq. (1) and supports our hypothesis. Columns 1, 2, 3, and 4 summarize the results of the logistic regression models combining AudFailA and AudFailB, AudFailA, AudFailB, and NMR, respectively. Based on the data presented in columns 1, 2, and 3, there is a negative association between the probability of switching auditors and AQ. Specifically, the coefficient on PROB_SWITCH is -1.17 ($p < 0.1$), -0.99 ($p < 0.1$), and -1.29 ($p < 0.1$) in columns 1, 2, and 3, respectively. The results in Table 5 support our hypothesis and suggest that AQ declines as companies continue to work with incumbent auditors, and they are more likely to switch auditors. In other words, companies with a high likelihood of switching auditors that choose to retain their current auditors often experience lower AQ. The persistence of lower AQ in these companies may also be influenced by the auditors 'familiarity with the client's operations, potentially leading to complacency or reduced scrutiny. Additionally, the decision to retain an auditor despite a high likelihood of switching could signal a lack of commitment to robust financial governance, further contributing to the observed decline in AQ. The importance of regular evaluations of auditor-client relationships to maintain high standards of financial reporting and oversight is highlighted in this situation.

Table 3. Results of Eq. (1)

	AudFailA+AudFailB	AudFailA	AudFailB	NMR
prob_switch	-1.17***	-0.99	-1.29***	-0.91
	(1.75)	(1.60)	(1.87)	(1.16)
LN_AT	-0.24**	0.17***	-0.28**	0.01
	(2.13)	1.76	(2.25)	0.02
LEV	-0.95**	-0.03	-0.93**	0.39
	(2.26)	(0.07)	(2.10)	0.87
ROA	1.28	1.05	1.26	-0.20
	1.17	0.94	1.13	(0.09)
LOSS	-0.78**	-0.43	-0.73***	0.00
	(2.15)	(1.60)	(1.89)	0.00
INVT_RECT	-0.10	0.49	-0.10	0.42
	(0.23)	1.22	(0.21)	0.81
CFEARLY	0.19	0.07	0.26	-0.25
	1.02	0.37	1.29	(1.10)
CFMATURE	0.03	-0.14	0.13	-0.09
	0.13	(0.60)	0.61	(0.28)
AT_GROW	-0.18	0.02	-0.20	0.46
	(0.88)	0.08	(0.93)	1.17
CFO	-0.65	0.96	-0.57	0.69
	(0.74)	0.93	(0.63)	0.61
BIGN	0.04	-0.32	-0.06	-0.18
	0.17	(1.17)	(0.21)	(0.35)

Coefficient estimates above, z-statistic below. Robust standard errors are clustered by company with year and industry fixed effects. *, **, *** indicate significance at $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

5-1. Additional Analyses for Large and Small Companies

This study investigated whether our main findings exhibit more robust patterns in larger companies, which could potentially result in lower audit fees when they choose to switch auditors. We believe that audit fees are crucial for large companies when they decide to switch auditors. A considerable increase in audit fees can prompt companies to consider alternative auditing firms. The cost of audits can be substantial, given the complexity of large companies' financial operations. Consequently, if they perceive that the current auditor fees are unreasonably high, they attempt to find cheaper alternatives. The sample consisted of larger companies whose total assets exceeded the median value and smaller companies whose total assets were below the median. Three AQ measures were used (Table 6) to present the results of our analysis (i.e., AudFailA+AudFailB, AudFailA, and AudFailB). Larger and smaller companies are represented by columns 1 and 2, as well as columns 3 and 4, respectively.

Column 4 indicates that the impact of PROB_SWITCH is not statistically significant. However, column 1 represents a significant association ($p < 0.1$). Similarly, PROB_SWITCH has an insignificant coefficient in column 2 but becomes significant in column 5 ($p < 0.1$). The coefficient of PROB_SWITCH in column 6 is not significant, while it is significant in column 3 ($p < 0.1$). For larger companies, switching auditors is associated with an increased likelihood of misstatements, but not for smaller ones. Our findings confirmed that large companies are primarily affected by more severe AQ issues related to switching probabilities.

Furthermore, the analysis revealed that the main results are concentrated among larger companies, indicating that the relationship between AQ and the probability of switching auditors is more pronounced in larger companies. This finding suggests that larger companies may have more complex financial reporting requirements and greater stakeholder scrutiny, making AQ a more critical factor in their decision-making process. Smaller companies may have less complex audit requirements or may be more constrained by cost considerations when choosing auditors. The stronger relationship between AQ and the probability of auditor switching in larger companies could also reflect their greater resources and capability to change auditors when dissatisfied with the quality of service provided.

Table 4. Additional Analyses for Large and Small Companies

	AudFailA+ AudFailB big	AudFailA big	AudFailB big	AudFailA+ AudFailB small	AudFailA small	AudFailB small
prob_switch	-1.67***	(0.15)	-1.67***	(0.89)	-1.7**	(1.02)
	(1.78)	(0.16)	(1.78)	(0.91)	(1.97)	(1.02)
LN_AT	-0.5**	0.22	-0.5**	(0.13)	0.01	(0.17)
	(2.36)	1.46	(2.36)	(0.67)	0.05	(0.81)
LEV	(0.25)	0.32	(0.25)	-1.56**	(0.89)	-1.71*
	(0.34)	0.67	(0.34)	(2.41)	(1.64)	(2.62)
ROA	2.21	1.61	2.21	1.73	0.72	1.61
	1.22	0.79	1.22	1.29	0.59	1.19
LOS	-0.98***	(0.54)	-0.98***	(0.35)	(0.39)	(0.26)
	(1.65)	(1.28)	(1.65)	(0.68)	(0.94)	(0.47)
INVT_RECT	(0.50)	0.68	(0.50)	0.49	0.66	0.66
	(0.72)	1.21	(0.72)	0.83	1.02	1.01
CFEARLY	0.41	0.71**	0.41	(0.22)	-0.52***	(0.11)
	1.19	2.57	1.19	(0.82)	(1.82)	(0.39)
CFMATURE	(0.33)	0.14	(0.33)	0.01	(0.51)	0.21
	(0.82)	0.39	(0.82)	0.03	(1.58)	0.72
AT_GROW	(0.26)	(0.13)	(0.26)	(0.01)	(0.24)	0.11
	(0.89)	(0.40)	(0.89)	(0.01)	(0.53)	0.21
CFO	(1.89)	2.11	(1.89)	0.69	0.29	0.85
	(1.30)	1.22	(1.30)	0.78	0.28	0.95
BIGN	(0.45)	-0.77**	(0.45)	0.81**	0.45	0.59***
	(1.03)	(2.22)	(1.03)	2.57	1.37	1.78

Coefficient estimates above, z-statistic below. Robust standard errors are clustered by company with year and industry fixed effects. *, **, *** indicate significance at $p<0.01$, $p<0.05$, and $p < 0.10$, respectively.

6. Conclusion

A fundamental aspect of AQ is to ensure that financial statements represent a company's financial position and performance while honestly and accurately reflecting its economic reality. Research on opinion shopping revealed that auditors' independence is undermined when clients can switch auditors at any time to more favorable audit opinions or less conservative accounting practices. However, even more concerning are situations where auditors aim to retain their current clients by creating pressure. The compromise of auditor independence without an observable auditor switch is a significant concern. It not only undermines the reliability of financial information but also threatens the integrity of financial markets. Our investigation focuses on analyzing the impact of this situation by examining the quality of audits performed by companies that are more likely to switch auditors but ultimately choose not to. Specifically, it seeks to determine whether these companies perform low-quality audits.

In this study, ML techniques were applied to forecast the probability of auditor switches. The ETC model (an ensemble learning method that combines multiple decision trees to improve prediction accuracy and reduce overfitting), also known as the extra tree classifier, from Scikit-learn (a popular Python library for ML) was utilized, and ROC analysis was employed to evaluate the performance of this model. The AUC, a widely used metric for classifier model performance, was utilized to compare the performances of our models. Moreover, hyperparameter tuning was conducted to optimize the model performance by adjusting parameters such as the number of trees, maximum depth, and minimum samples per leaf. The ETC model achieved the highest AUC level of 0.977, indicating a high level of accuracy in its predictions and a strong ability to distinguish between positive and negative classes. Additionally, the intended ETC prediction model was employed to determine the likelihood of auditor switching.

The relationship between auditor switching probability and AQ was extensively investigated in this study. The results confirmed our hypothesis, suggesting that AQ declines as companies continue to work with incumbent auditors and are more likely to switch auditors. This indicates that companies with a high likelihood of switching auditors yet choosing to retain their current auditors often experience lower AQ. AQ tends to be lower for companies whose auditors are highly likely to switch but remain with their incumbent auditors. This phenomenon may be attributed to reduced auditor effort or compromised independence as auditors seek to maintain client relationships. These situations could lead to an increase in audit risk but a decrease in financial reporting reliability for these companies. Stakeholders and regulators need to pay closer attention to firms in this category to ensure adequate oversight and maintain market confidence. In this study, adjusted restatements of financial statements (AudFailA and AudFailB) and an NMR as proxies were used for adjusting audit-quality standards.

Furthermore, the analysis revealed that the main results are concentrated among larger companies, indicating that the relationship between AQ and the probability of switching auditors is more pronounced in larger companies. Based on these findings, companies that demonstrated a higher likelihood of switching auditors but ultimately continued to work with their current auditors had poor AQ. This finding suggests that larger companies may face more scrutiny and pressure to maintain high-quality audits, making them more sensitive to audit-quality issues. This study highlights the importance of monitoring AQ, particularly in larger organizations, to ensure the integrity of financial reporting and maintain stakeholder confidence.

6-1. Practical and Managerial Implications

Using the ETC model, our research focused on auditor switching behavior and opinion shopping to gain critical insights into the auditing profession. Contrary to traditional studies that concentrated on companies that switch auditors to secure favorable opinions, this study examined companies that retain incumbent auditors despite the high likelihood of switching auditors. Retaining the same auditors can ensure continuity and consistency in the auditing process, which may be beneficial for maintaining stable financial reporting. This overlooked scenario can mask potential audit-quality impairments, thereby escaping the scrutiny of regulators and investors. According to our findings, the academic literature is enriched with an appreciation of the complexities involved in auditor-client relationships and the pressures that influence the audit results. Using the ETC model (the ML-based approach), regulators can predict audit-switching likelihood in advance, providing a proactive tool for detecting engagements in which auditors may face undue pressure. By predicting the audit-switching likelihood, this model enables regulators to identify high-risk engagements early. This allows for timely intervention and support, thereby reducing the chances of compromised AQ due to pressure. Consequently, this enhances the overall reliability and integrity of financial reporting. We advanced the audit research methodology by applying ML algorithms, particularly ETC model algorithms, to identify quality risks more effectively. This approach has the potential to revolutionize audit research by enhancing the precision and speed of risk detection. As these algorithms continue to evolve, they can lead to the development of more sophisticated tools that auditors can employ to predict and mitigate risk before escalating. Ultimately, this can result in more reliable financial reporting and increased trust in the financial systems. For audit firms, understanding why clients consider but do not switch auditors can inform strategies to preserve AQ and independence. As a result, policymakers should adopt enhanced audit oversight mechanisms and utilize technology to enhance audit integrity. Ultimately, our findings demonstrated that the ETC model is capable of revolutionizing auditing. By leveraging advanced algorithms and ML, this model can quickly and accurately analyze vast amounts of data, thereby identifying discrepancies that might be missed by traditional methods. Auditors, regulators, and audit firm decisions can be informed, potential risks can be identified, and AQ can be improved accordingly. The ETC model facilitates better decision making by providing a comprehensive framework for evaluating complex data. This enhances the accuracy and efficiency of audits by identifying potential risks early in the process.

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