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DRIVERS OF UTILITY VIABILITY AND SUSTAINABILITY: DO NONFINANCIAL PERFORMANCE MEASURES MAKE A DIFFERENCE?

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ABSTRACT

The study reviews the growth trend for investor-owned utilities (water and wastewater), adopts the National Regulatory Research Institute's financial viability ratios modified by Acheampong et al., and identifies four categories of nonfinancial performance instruments that drive utility abandonments and transfers. The study observed a downward trend in investor-owned utilities from the sample state (Florida). Prior research has concentrated on financial performance measures (Financial ratios) to determine the sustainability and viability of investor-owned utilities. The study concluded that nonfinancial performance measures are significant in determining investor-owned utility abandonments and transfers comparatively to financial performance measures; the drivers for utility transfers are different from utility abandonments, and each utility class should be treated with its own merits.

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KEYWORDS: Abandonments, Financial Performance Measures, Nonfinancial Performance Measures, Sustainability, Viability, Investor-Owned, Authorized Territory

INTRODUCTION

Investor-owned utilities (IOUs) are essential in serving rural communities and areas where city and municipal utilities are unavailable; these IOUs serve anywhere from 50 to over 5,000 customers. These utilities must operate continuously to ensure the supply of utility services to ratepayers. The required essential services provided by these utilities and the capital requirement in supplying utility services necessitate the use of authorized territory to avoid competition. Hence, most states, such as Florida, prevent bankruptcy filing by utility companies; consequently, utilities with going-concern issues either abandoned or transferred their operations to another utility. (Acheampong, 2019). The sustainability and viability of these utilities are significant to the various state regulators to avoid abandonments and minimize transfers. These utilities' sustainability should incorporate the utilities' technical, managerial, and financial performance measures (Teumim & Radigan, 2011). Prior research by National Regulatory Research Institute (NRRI, 2009) (NARUC, 2007); Wirick et al. (1997), Acheampong et al. (2018), and other researchers have primarily focused on the financial performance measures (NRRI Viability Ratios) to determine the sustainability of these utilities. Beaver (1966) established six categories of financial performance measures comprising thirty different financial ratios. Wirick et al. (1997) identified three financial performance measures (liquidity, leverage ratios, and earnings trend); these ratios are used to evaluate the financial sustainability of water utility systems.

Teumim and Radigan's (2011) assertion motivates the need to research the inclusion of technical and managerial performance measures in determining the viability and sustainability of the investor-owned utility industry. The study identifies and examines seven financial performance measures. These measures are the capital structure/equity ratios, coverage ratios, leverage ratios, profitability ratios, solvency ratios, efficiency ratios, and activity ratios). The study further identifies four categories of nonfinancial performance measures (output, quality, owner's equity, and regulatory measures) on utility abandonments and transfers (Acheampong, 2019). Most sustainability prediction models for financial distress focus on failures and bankruptcy; this does not directly apply to IOUs abandonments and transfers. This study uses empirical evidence to address the performance measures (financial and nonfinancial) that drive utility abandonments and transfers. The research further assesses the impact of the nonfinancial performance measures on utility abandonments and transfers and addresses the prior research limitations, whether nonfinancial performance makes a difference in evaluating utility abandonments and transfers. The study also assesses the impact of time on utility abandonments and transfers. The rest of the paper is organized by reviewing the literature on the financial and nonfinancial performance of organization sustainability and viability in the literature section. The third section concentrates on the question and hypothesis development for the study, followed by the methodology section. The Methodology section presents the study's empirical approach, the sample size's descriptive statistics, and the development of the logistic regression model for the study. The fifth section presents the empirical findings, and the sixth section offers discussions of the results, with a final part concluding the research.

LITERATURE REVIEW

A sustainable utility system commits to the financial, managerial, and technical capability to meet long-term performance requirements (Miller & Cromwell, 1987). Nonviable or unstable systems are a function of lack of motivation to operate appropriately, lack of ability to function correctly, lack of financial resources to run successfully, and lack of ability to sell services at a reasonable rate due to lack of rate base, size, or geographic location (Beecher et al. 1996). Hence, financial instability is not equivalent to the unsustainability of the entire water system, but it is one variable that contributes to sustainability. The United States Environmental Protection Agency (EPA) (1995) noted that financial distress models are used to assess the financial instability of systems by focusing on the ratios that concentrate on the operating capabilities of the utility in generating revenues. The EPA (1995) defined a sustainable utility as a utility that consistently provides quality services at an affordable cost exhibits financial, technical, and managerial capabilities, and complies with current regulations and proposed rules. The Washington State Department of Health (2013) affirms the EPA definition by describing sustainable water or wastewater system as a utility that can generate enough revenue to improve, construct, operate, maintain, and manage the utility to comply with local, state, and federal regulations continuously.

The universal census is that a sustainable utility should be assessed on financial and nonfinancial performance measures. The reviewed literature establishes a positive correlation between financial and nonfinancial performance measures and the economic returns of an organization separately. However, this study combines the financial and nonfinancial performance measures compared to the prior studies, which separate financial measures from nonfinancial measures and assess their impact on organizational performance improvement (Acheampong, 2019). Financial performance measures such as ratio analysis have been successfully used to predict the viability and sustainability of a firm's ability to continue its operations (Beaver,1966); Neter (1966), (Wilcox, 1971), (Edmister, 1972), (Jordan, Witt, & Wilson, 1996), (Wirick et al., 1997), (Acheampong et al. 2018). However, most of these studies using statistically sophisticated models have focused on medium to large organizations with little or no attention to small firms such as investor-owned water and wastewater utilities. Edmister (1972) asserts that such sophisticated models or comprehensive studies can be done on small businesses, employing financial performance measures. Using the propositions from Beaver's 1966 study, Wilson et al. (1997) extracted ninety-six financial ratios to predict the failures of a small water system. Financial performance measures, especially ratios, have been used consistently to predict organizations' failures, sustainability, and viabilities, including investor-owned water utilities; however, limited literature exists on the combination of financial and nonfinancial performance measures in assessing small-scale organizations such as investor-owned utilities.

Many studies have focused on seasonal financial performance processes as too accumulated, historical, and lacking appropriate, timely solutions to organizational root challenges (Chow & Van Der Stede, 2006). The periodic nature of financial performance measures does not clarify the root cause of identifying problems with an organization; for instance, an unfavorable variance may have different meanings and different causes, but from a financial performance ratio perspective, it may have a different purpose and total implications (Chow & Van Der Stede, 2006). Hence, complementing financial measures with nonfinancial performance measures may be necessary.

Edmund (1969) used data from the Commerce Department, which captured nonfinancial data, to prove an enhancement of decision-making by financial analysts. Edmund identified the overall corporate product, price deflector, inventory gains, and the involvement of domestic operations to enhance the reporting of a firm's earnings. Neely (1999) examined the economic environment, ranging from manufacturing to politics to commerce, assessing the need to include business performance measures in decision-making. The study revealed that government agencies, corporate management, and academic conferences focus on business sustainability and growth performance measurements. The study examined nonfinancial performance measures identified from the various reported financial statements and determined the impact of nonfinancial performance measures on economic indicators discussed by the various Chief Executive Officers (CEOs). Neely (1999) used the MORI report and concluded that 72% of management surveyed concurs that nonfinancial performance instruments such as the needs of employees, customers, and suppliers will improve shareholder value.

Anderson, Fornell, and Lehmann (1994) examined the Swedish market to determine the impact of nonfinancial measures such as customer satisfaction on superior economic returns. They concluded that nonfinancial measures positively correlate to the financial returns of an organization. Milost (2013) explains that external stakeholders have primarily used accounting financial data to make decisions; however, the financial statements published contain other nonfinancial information that complements the financial data; hence, it is proper to use nonfinancial performance measures to supplement the financial information to obtain sufficient information in defining the future economic value of an organization. The literature review on nonfinancial performance measures confirms that the use improves decisions both within the company and the organization's stakeholders; it has been applied to many different industries ranging from internal information and information from published financial statements. However, the investor-owned utility industry is a regulatory industry and requires various nonfinancial measures compared to other non-regulatory industries. Most of the research evaluated highlights customer satisfaction, quality, size, etc., as nonfinancial performance measures. The study identifies four categories of nonfinancial measures consistent with the regulatory industry. The first category is the output measures, compatible with plant outputs and customer-related measures. The second category focuses on quality measures, measuring compliance with the various required regulatory quality issues; the third group measures the structure of the owners' equity in the utility; and the fourth category is the regulatory measures, measuring compliance with statutory financial reporting and other criteria not related to quality. Table 1 presents the identified nonfinancial performance measure. These measures are integrated with the financial performance measures to assess the drivers of utility abandonments and transfers.

The financial instability of water systems relies heavily on performance dimensions, such as the financial management and technical operation of these utilities and the managerial functions leading to system upgrades and new investments. Regulation by the various state bodies also presents institutional challenges to these utilities by establishing a rate base (Acheampong et al., 2018). The study examines financial and nonfinancial measures relating to utility abandonments and transfer drivers. The methodology section discusses the logistic regression model and the sample (Florida investor-owned utilities) used in the study.

Table 1: Nonfinancial Performance Measures

Classification	Variables
Output measures	Plant output / (gallonage per customer)
	Plant output /Total Number of Meter Equivalents
	Number of Customers served
	Gross water output per Customer
Quality Measures	Compliance with FPSC Quality Measures
	Compliance with DEP Quality requirements
	Compliance with CUP Quality requirements
Owner's Equity Structure	Type of Corporation for Tax filing purposes
	Management Compensation
	Owners' Involvement in Direct operations of the Utility
	Utility Classification
	Donated Capital -CIAC
Regulatory Measures	Business Taxes - Indirect Taxes, such as Taxes Other than Income (PSC Funding)
	compliance with the Uniform System Of Accounts (NARUC)
	No deficiency communications from regulatory agencies (financial reporting)
	Utility Compliance-annual report filing
	Utility Classification
	leverage scale

All IOUs' annual required regulatory filings extracted the eighteen nonfinancial performance measures. IOUs are required to complete additional forms reporting the operating activities of the utilities, which is necessary to determine the continuity of the utility. The nonfinancial performance measures were extracted from the water and wastewater sections of the annual filing. The output measures relate to the utility's productivity, and the quality measures inform regulators about compliance with various regulations. The owners' equity structure information was extracted from the executive summary, and the regulatory measures are associated with compliance with state regulations and federal and external regulatory bodies.

DATA AND METHODOLOGY

The study theorizes that financial and nonfinancial performance measures impact utility abandonments and transfers. However, the variables that impact utility abandonments differ from those that affect utility transfers. Prior research has heavily focused on financial performance; hence, the study identified and introduced nonfinancial performance to determine its impact on utility abandonments and transfers; with the assessment of the nonfinancial performance measures, the research assesses the influence of time on abandonments and transfers. The study addresses the following questions:

RQ1: What financial and nonfinancial performance measures drive utility abandonments and transfers? The study hypothesizes that financial and nonfinancial performance measures impact IOU utility abandonments and transfers compared to prior research that has relied heavily on financial performance measures.

RQ2: Are the drivers for utility abandonments and transfers correspond with each other and by utility classification? The study posits that the drivers for utility abandonments and transfers are different, and the utility classification impacts the abandonments and transfer drivers. Hence, Class A, Class B, and Class C utilities should be treated differently. Transfers and abandonments should be treated on their own merits, not together.

RQ3: Does time impact utility abandonments and transfers? The research theorizes that abandonments and transfers of utilities worsen over time, and the older the utility assets (longer in service), the more likely the utility may abandon or transfer the utility facility.

Identifying and separating the drivers for utility abandonments and transfers by a utility class enhances and promotes finding managerial solutions to the current down-trending of IOUs. Including the nonfinancial performance, measures offer both state regulators and utility owners a new approach to resolve the current down-trending situations, especially dilapidated assets from managerial and financial perception, and urge informed decisions during rate case proceedings.

Research Methodology

Quantitative research empirically examines models by assessing the correlations among variables statistically studied to address a question (Creswell, 2009; Creswell & Creswell, 2017). The study follows Creswell's (2009) proposals and uses a quantitative approach to explore the financial and nonfinancial performance measures that impact the performance of the investor-owned utility industry, using evidence from the state of Florida. The study deductively adopts the modified financial ratios by Acheampong et al. (2018) and identifies sixteen nonfinancial measures in four categories of nonfinancial performance measures of investor-owned as the explanatory variables to predict utility abandonments and transfers. The following logit model is used to conduct the analyses of RQ1, RQ2, and RQ3:

$$\mathrm{IOUi,t} = 1/[1 + \exp - 1(\beta 0 + \beta 1\mathrm{LIQit} + \beta 2\mathrm{LEVit} + \beta 3\mathrm{LEV\_DTit} + \beta 4\mathrm{COVit} + \beta 5\mathrm{GROEFFit} + \beta 6\mathrm{EFF\&PROFit} + \beta 7\mathrm{PROFit} + \beta 8\mathrm{Cust\_Servit} + \beta 9\mathrm{PLTOUTPit} + \beta 10\mathrm{EQVMETERit} + \beta 11\mathrm{GROSS\_REVit} + \beta 12\mathrm{COM\_FPSCit} + \beta 13\mathrm{COM\_DEPit} + \beta 14\mathrm{COM\_CUPit} + \beta 15\mathrm{MAN\_COMPit} + \beta 16\mathrm{MAN\_OPit} + \beta 17\mathrm{UTILTY\_CLit} + \beta 18\mathrm{CIACit} + \beta 19\mathrm{TAX\_CLit} + \beta 20\mathrm{TAX\_TOTIit} + \beta 21\mathrm{COM\_USoAit} + \beta 22\mathrm{NoDCit} + \beta 23\mathrm{COM\_UCARit} + \beta kXk)\ ]\beta 23\mathrm{COM\_UCAR}_{it} + \beta kXk)\ ]$$

The model is based on the modified Platt and Platt model by Acheampong et al. (2018); the subscripts "i and t" indicate the utility and the period (year), respectively. IUOi,t symbolizes the odds of failure of the ith utility within a period. That is the probability that a selected or qualified investor-owned utility is subject to abandonment or transfers resulting from financial and nonfinancial performance variables within a specific time. The β0 is the intercept, and the βs are the regression coefficients. The predictor or the independent variable LIQ is the liquidity ratio, measuring the utility's abilities to meet operating expenses as they come due; a higher LIQ over one is a good indicator of financial health for the utility. LEV is the leverage ratio measuring the utility's relative debt level to asset and equity; it evaluates the strength of the utility's assets to protect its creditors, Myers (1984) asserts. State commissioners urge utility owners to increase their leverage to about 90% compared to the standard 20%. A higher LEV indicates higher equity or asset in the operating asset of the utility. LEV_DT is the leverage debt to equity ratio, a predictor measured by the long-term debt of the utility divided by the common stock. It measures the degree to which a utility's long-term assets are financed by debt compared to the owner's (common stock). The independent variable COV is the coverage ratio, measuring the utility's ability to honor its financial obligations; a higher ratio is a good indicator of a utility's ability to meet its financial commitments. GROEFF is the growth and efficiency ratio, EFF&PROF is the efficiency and profitability ratio, and PROF is the profitability ratio measuring the efficient use of the operating assets of a utility to generate profit. The model has a total of seven financial performance ratios. These ratios have been widely used in the utility industry. Wirick et al. (1997) and Beecher et al. (1992) used these ratios to predict performance failures in the utility industry.

Sixteen nonfinancial performance measures were identified based on the available information provided by utility filings. Cust_Serv is the number of customers served by the utility, PLTOUTP indicates the plant output (gallonage per customer), EQVMETER is the number of equivalent meters serviced by the utility, and the GROSS_REV is the gross revenue generated by the utility per customer; these are the output measures, directly impacting the gross utility revenues based on the rates set by the state commissioners. The following three predictors are the quality measures assessing the utility's compliance with state and federal quality standards. The COM_FPSC is the compliance with the state quality measures, the COM_DEP measures the utility's compliance with the Department of Environmental Protection (DEP) quality measures, and the COM_CUP measures the utility's compliance with a consumptive use permit (permit for mining groundwater). The owner's equity structure and participation in the utility operations were also identified as predictors that may drive the utility's abandonments or transfers. The predictor MAN_COMP represents management compensation; most states, such as Florida, do not recognize management salaries as allowable expenses. Hence, the study included it in determining its impact on transfers and abandonments, should the various states allow it to motivate management to improve the efficiency of a utility's operations. MAN_OP is the management's direct involvement in the utility operations; some of the utility is directly operated by the owner (s), and others are not. UTILTY_CL represents the utility's classification; utilities belong to three categories (Class A, B, or C). The CIAC indicates contribution in aid of construction; most states do not allow utilities to recover the use of donated capital in their rate base; hence, it impacts the utility rate-setting (Acheampong & Benford, 2020). The Tax classification of the utility was also included in the owner's equity structure; TAX_CL represents the tax classification of the utility; depending on the tax classification, the net results of the utility will impact the owner's annual taxes directly or indirectly.

The last group is the Regulatory measures, measuring compliance, but different from the quality measures, these predictors require regulatory compliance but do not impact customer service quality. TAX_TOTI is the indirect business taxes (Taxes other than Income Taxes); COM_USoA represents compliance with NARUC (NARUC, 1996) Uniform System of Accounts. NoDC is the No Deficiencies Communication from the regulatory commissioners; the NoDC measures utility compliance with the state utility rules and regulations. COM_UCAR represents the utility's compliance with filing the required annual reports. The study outcome suggests that the drivers for utility abandonments differ from utility transfers; the utility classification impacts the drivers for abandonments and transfers. Hence, Class A utility differs from Class B and Class C. Depending on the utility class, time may also impact the drivers for utility abandonments and transfers.

Sample Selection

The study used all the financial and nonfinancial information measures data of the investor-owned utilities (water and wastewater) from the 2008 to 2018 filing periods (Florida State Utility Data). The data for the sample is publicly available on the Florida Public service Commission website. The study employed the "Rand" command in Excel to randomly select 60% of the utility data. Eighty-seven utilities were chosen randomly; eleven of the utilities selected did not have the required information. They were dropped from the samples, and the final sample size qualified for the study totaled seventy-six utilities, comprising class A, B, and C utilities. To address the relationship between financial and nonfinancial performance measures, the study follows Sormunen and Laitinen (2012) assertion about the instability of financial ratios. Overtime financial ratios undermine the significance of the time interval in distressed utility prediction models; to preserve and maintain the predictive capability of the financial ratios, the study used a robust logistic regression investigation to predict the drivers of utility abandonments and transfers. The Balcaen and Ooghe (2006) study also motivates the adoption of logistic regression. They explained that the statistical importance of financial ratios shifts at various stages; therefore, optimal cross-sectional models change at multiple stages; hence, the logistic regression is used to strengthen the predictive power of the study's model and the Variance Inflation Factor (VIF) to resolve collinearity issues.

The VIF identifies the severity of multicollinearity problems among the explanatory (independent) variables. The VIF is one of the usual; traditional collinearity analytical procedures focused on ordinary or weighted least squares regressions. The VIF recognizes the slope estimate initiated by the nonorthogonality of the independent variables (predictors) on top of the orthogonality variance (Liao & Valliant, 2012). Removing the predictors with collinearity issues reduces the impact of one explanatory variable affecting the other measures. The research explored the VIF to eliminate all predictors with VIFs higher than four. Hair et al. (2010) explained that logistics regression utilizes a maximum likelihood procedure, the

Nagelkerke R2, established as a modification of Cox and Snell R2. The Nagelkerke R2 reinforces the relationship and measures the logistic regression fitness of the data, and it determines the intercept of the logistic regression model. The logistic regression model for the study utilized the Hosmer-Lemeshow Chi-square test and combined it with the R2 to establish the goodness of fit (Sormunen & Laitinen, 2012). The model categorizes, predicts, or measures probabilities into deciles and then calculate the Chi-square to analyze the predictive value of the observed frequencies. The p-value determines the logit linearity test; a higher p-value signifies an excellent fit to the data. The study used abandonments and transfers as the dependent variables. The "Transferred utilities" are investor-owned utilities that could not continue operations and were transferred to another utility or a municipality within the study period. The transferred utility may be reorganized into a new utility with a new name or retain the same name. "Non-transferred" utilities continue operations without interruptions and remain unchanged during the ten-year study period. "Abandoned utilities" are all utilities that handed over the utility operations to the territorial county and all utilities that did not follow the abandonment procedure; however, the owners decided to leave the facility for the county to take over without proper notification. The study classified abandonments and transfers as dependent variables. All the selected financial and nonfinancial performance measures after the VIF elimination process were used as the explanatory variables. The study rejects the null hypothesis If the $p \leq \alpha$, which may indicate evidence supporting that these investor-owned utilities' transfers and abandonments depend on the explanatory variables.

RESULTS

The purpose and motivation of the research are to employ financial and nonfinancial performance measures that drive Investor-Owned utility abandonments and transfers. The study created dummy variables to represent transferred and abandonments, using the improved financial ratios by Acheampong et al. (2018). The study further identified twenty nonfinancial performance measures. Sixteen nonperformance measures out of the twenty had data to support the study. The study used the VIF to vigorously examine multicollinearity issues among the independent variables. A typical rule of VIF of ten or less is desirable (Belsley, 1984). However, other authors prefer four and below VIF; the study followed Mason and Perreault (1991) and used a VIF of four and below. PLTOUTP (gallonage per customer) and EQVMETER (the number of equivalent meters serviced by a utility) were excluded from the initial analysis since their VIF was high (EQVMETER 1474.7 & PLTOUTP 1469.22). Table 2 presents the descriptive statistics for the selected samples. Utility codes are the assigned numbers to the selected utilities for the study. The selected sample is an unbalanced sample size with 763 observations.

Financial and Nonfinancial Performance Results

The study examined the financial performance measures (ratios) separately from the nonfinancial measures based on the qualified explanatory variables. The financial performance model used all the 763 observations in the selected sample (transfers and abandonments). The likelihood ratio chi-square of 39.97 with a p-value of 0.0000 indicates a statistically significant model consistent with Acheampong et al. 2018. model. The financial explanatory variables were not statistically significant except for the "Liquidity" ratio. The liquidity ratio signifies the utilities' capability to pay current liabilities as they come due without considering external financial resources. The liquidity ratio improves the utility's ability to cover short-term responsibilities and cash flow needs. The resulting coefficient for the liquidity ratio is negative .019, confirming an inverse association with transfers/abandonment. For every one-unit increase (i.e., moving from 0 to 1), we expect 0.019 reductions in the log odds of being in the transfers and abandonments category, given that all other predictors are held constant in the model. Table 3 presents the results of financial performance measures. A Linktest was used to confirm the specification of the overall financial model. The linktest identifies specification errors and determines if a model possibly included all the relevant variables. A specified model indicates that no significant additional independent variable should emerge unless by chance. The hatsq is not significant with a p-value = 0.070, a confirmation of a specified model, signifying the possibility of inclusion of all relevant financial explanatory variables to predict the dependent variables. A separate model was run to predict abandonments and transfers using the fourteen nonfinancial performance explanatory variables with a VIF of four or below. The model employed 763 observations in the selected sample based on the VIF results.

Table 2: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
UtilityCode	7,500.3	1,399.6	5,013.0	9,965.0
TransferAb~d	1.494	0.6155	1.000	3.00
LIQ	25.771	221.81	-52.680	5,357.1
LEV	1.3365	22.231	-442.42	281.50
LEV_DT	6,926.9	116,804	-529.07	2,685,696
COV	1.4002	3.373	-33.090	39.990
GROEFF	0.3215	7.397	-198.47	26.320
EFFPROF	0.8275	0.3279	0.0000	3.270
PROF	-1.5813	11.777	-252.82	0.6900
PLTOUTP	403.28	2,759.6	0.0000	35,311.32
EQVMETER	382.95	2,758.3	0.0000	35,311.32
Cust_Serv	457.00	524.66	3.000	2,528.00
GROSS_REV	638.00	897.56	0.0000	12,174.00
COM_FPSC	1.8322	0.3774	0.0000	2.000
COM_DEP	1.9633	0.1881	1.000	2.000
COM_CUP	1.9581	0.2006	1.000	2.000
TAX_CL	2.7837	1.078	1.000	4.000
MAN_COMP	1.4260	0.4948	1.000	2.000
MAN_OP	1.5229	0.4998	1.000	2.000
UTILTY_CL	2.7602	0.5387	1.000	3.000
CIAC	451,347	1,408,583	229,964	12,400,000
TAX_TOTI	20,055	33,619	0.0000	222,844
COM_USoA	1.536	0.4990	1.00	2.00
NoDC	1.831	0.3751	1.00	2.00
COM_UCAR	1.957	0.2036	1.00	2.00

Table two presents the descriptive statistics of all utility classes. Forty-one out of the total observation (763 observations) represent Class A utilities, a hundred and one represent Class B utilities, and six hundred and twenty-one represent Class C utilities. Four hundred thirty-six utilities within the selected period have either transferred into a new utility or merged into a new utility. Forty-nine utilities were abandoned, and 278 utilities did not experience transfer or abandonment.

Table 3: Logistic Regression Output: Financial Performance Predictors

Transfer Abandoned	Coef.	Std. Err.	Z	P>|Z|	[95% Conf. Interval	
LIQ	-0.0185	0.0058	-3.2200	0.0010**	-0.0298	-0.0073
LEV	0.0018	0.0035	0.5100	0.6080	-0.0050	0.0086
LEV_DT	0.0000	0.0000	-0.7000	0.4840	0.0000	0.0000
COV	-0.0206	0.0256	-0.8000	0.4220	-0.0708	0.0296
GROEFF	-0.0089	0.0173	-0.5100	0.6080	-0.0428	0.0251
EFFPROF	0.2014	0.2802	0.7200	0.4720	-0.3477	0.7505
PROF	-0.0284	0.0287	-0.9900	0.3220	-0.0847	0.0279
_cons	-0.3274	0.2653	-1.2300	0.2170	-0.8474	0.1926

Table 3 shows the results of the financial performance measures output.; $TransferAbandoned = \beta 0 + \beta 1\ (LIQ) + \beta 2(LEV) + \beta 3(LEV\_DT) + \beta 4(COV) + 5\beta(GROEFF) + \beta 6(EFFPROF) + 7\beta(PROF) + Ei$ *the model number of observations for the selected sample is 763, with a likelihood ratio chi-square of 39.97. Prob > chi2 (the probability of obtaining the chi-square statistic assuming a true null hypothesis) = 0.000. the Pseudo R2 (the model fit) = 0.0384. The liquidity ratio was significant with p-value = 0.0010, at a 0.05 significant level. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

The results show a likelihood ratio chi-square of 259.51 and a p-value of 0.0000, an overall statistically significant model for the nonfinancial performance predictors. Nine out of the fourteen nonfinancial performance measures were statistically significant (compliance with the state quality measures, COM_DEP, tax classification of the utility, management compensation, management's direct involvement in the operations of the utility, utility's classification, indirect business taxes, No Deficiencies Communication from the regulatory commissioners, & utility compliance with Annual filing). Only one measure (liquidity ratio) was statistically significant compared to the financial performance measures. The coefficients for compliance with the state quality measures, Tax filing classification, Utility classification, No deficiencies communication from the regulatory commissioners, and utility compliance with annual filing were negative, indicating an inverse relationship with the dependent variable (Kremelberg, 2011). All the other regressors had a positive connection with abandonments and transfers. To ensure an unintentional drop of any of the explanatory variables, a linktest was run for the model to determine a specified model. The hatsq is not significant with a p-value = 0.9620, a confirmation of a specified model, suggesting the possibility of inclusion of all relevant explanatory variables to predict the dependent variables. Table 4 shows the results of the nonfinancial performance measures model.

Table 4: Logistic Regression Output Nonfinancial Performance Predictors

TransferAbandoned	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval	
Cust_Serv	0.0000	0.0003	-0.0100	0.9910	-0.0006	0.0006
GROSS_REV	0.0001	0.0001	0.6100	0.5390	-0.0002	0.0004
COM_FPSC	3.5964	0.6182	5.8200	0.0000**	2.385	4.808
COM_DEP	-1.3745	0.4223	-3.2500	0.0010**	-2.202	-0.5468
COM_CUP	-0.4663	0.4210	-1.1100	0.2680	-1.296	0.3588
TAX_CL	-0.4991	0.0978	-5.1100	0.0000**	-0.6908	-0.3075
MAN_COMP	0.7103	0.2020	3.5200	0.0000**	0.3144	1.106
MAN_OP	1.1378	0.2084	5.4600	0.0000**	0.7293	1.546
UTILTY_CL	-0.5852	0.2759	-2.1200	0.0340**	-1.126	-0.0444
CIAC	0.0000	0.0000	-1.7700	0.0770	0.0000	0.0000
TAX_TOTI	0.0000	0.0000	2.5700	0.0100**	0.0000	0.0000
COM_USoA	-0.3743	0.2102	-1.7800	0.0750	-0.786	0.0378
NoDC	-2.1627	0.3169	-6.8200	0.0000**	-2.784	-1.547
COM_UCAR	-1.7197	0.7790	-2.2100	0.0270**	-3.247	-0.1928
_cons	4.4549	1.8456	2.4100	0.0160	0.8376	8.072

Table 4 presents the results of the nonfinancial performance measures output: $TransferAbandoned = \beta 0 + \beta 1(Cust\_Serv) + \beta 2(GROSS\_REV) + \beta 3(COM\_FPSC) + \beta 4(COM\_DEP) + \beta 5(COM\_CUP) + \beta 6(TAX\_CL) + \beta 7(MAN\_COMP) + \beta 8(MAN\_OP) + \beta 9(UTILTY\_CL) + \beta 10(CIAC) + \beta 11(TAX\_TOTI) + \beta 12(COM\_USoA) + \beta 13(NoDC) + \beta 14(COM\_UCAR) + Ei$ *the model number of observations for the selected sample is 763, with a likelihood ratio chi-square of 259.51. Prob > chi2 (the probability of obtaining the chi-square statistic assuming a true null hypothesis) = 0.000. the Pseudo R2 (the model fit) = 0.2490. At a 0.05 significant level, the Compliance with FPSC Quality Measures, Compliance with DEP Quality requirements, tax classification of the utility, management compensation, management's direct involvement in the utility operations, utility's classification, Taxes other than Income Taxes, No Deficiencies Communication from regulatory commissioners, and utility's compliance with annual filing requirements, were statistically significant. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

Combined Financial and Nonfinancial Performance Results

An overall model combining financial and nonfinancial performance measures was analyzed to test further the significance of nonfinancial performance measures in determining transfers and abandonments. The overall model used twenty-one explanatory variables from the VIF results. The overall model used all the 763 observations in the selected sample. The overall model revealed a likelihood ratio chi-square of 281.85 and a p-value of 0.0000, an overall statistically significant model. The liquidity ratio is the only financial performance measure that is statistically significant. However, ten out of the fourteen nonfinancial performance measures were statistically significant. A linktest test was run to determine the specification for the overall model. The hatsq is not significant with a p-value = 0.0940, a confirmation of a specified model, signifying the possibility of inclusion of all relevant explanatory variables to predict utility abandonments/transfers. Table 5 presents the results of the overall model, employing both financial and nonfinancial performance measures for the selected utilities.

Table 5: Overall Model Output: Financial and Nonfinancial Performance Predictors

TransferAbandoned	Coef.	Std. Err.	z	P>|z|	[95% Conf.Interval	
LIQ	-0.0221	0.0071	-3.100	0.0020**	-0.0360	-0.0081
LEV	0.0001	0.0035	0.0300	0.9770	-0.0068	0.0070
LEV_DT	0.0000	0.0000	-0.5000	0.6170	0.0000	0.0000
COV	-0.0047	0.0334	-0.1400	0.8890	-0.0701	0.0608
GROEFF	-0.0068	0.0194	-0.3500	0.7240	-0.0448	0.0311
EFFPROF	-0.1141	0.3276	-0.3500	0.7280	-0.7562	0.5279
PROF	-0.0196	0.0151	-1.300	0.1950	-0.0493	0.0101
Cust_Serv	0.0001	0.0003	0.2500	0.8030	-0.0005	0.0006
GROSS_REV	0.0001	0.0001	0.8200	0.4110	-0.0002	0.0004
COM_FPSC	3.554	0.6282	5.660	0.0000**	2.323	4.785
COM_DEP	-1.324	0.4225	-3.130	0.0020**	-2.152	-0.4961
COM_CUP	-1.169	0.5359	-2.180	0.0290**	-2.219	-0.1186
TAX_CL	-0.5210	0.1002	-5.200	0.0000**	-0.717	-0.3247
MAN_COMP	0.7010	0.2056	3.410	0.0010**	0.298	1.104
MAN_OP	1.140	0.2133	5.340	0.0000**	0.722	1.558
UTILTY_CL	-0.5465	0.2844	-1.920	0.0540**	-1.104	0.0110
CIAC	0.0000	0.0000	-1.920	0.0540**	0.0000	0.0000
TAX_TOTI	0.0000	0.0000	2.630	0.0080**	0.0000	0.0000
COM_USoA	-0.3724	0.2134	-1.750	0.0810	-0.7907	0.0458
NoDC	-2.259	0.3243	-6.960	0.0000**	-2.894	-1.623
COM_UCAR	-1.330	0.7985	-1.670	0.0960	-2.895	0.2347
_cons	5.309	1.938	2.740	0.0060	1.511	9.107

Table 5 presents the results of the combination of the financial and nonfinancial performance measures output: $TransferAbandoned = \beta 0 + \beta 1\ (LIQ) + \beta 2(LEV) + \beta 3(LEV\_DT) + \beta 4(COV) + 5\beta(GROEFF) + \beta 6(EFFPROF) + 7\beta(PROF) + \beta 7(Cust\_Serv) + \beta 8(GROSS\_REV) + \beta 9(COM\_FPSC) + \beta 10(COM\_DEP) + \beta 11(COM\_CUP) + \beta 12(TAX\_CL) + \beta 13(MAN\_COMP) + \beta 14(MAN\_OP) + \beta 15(UTILTY\_CL) + \beta 16(CIAC) + \beta 17(TAX\_TOTI) + \beta 18(COM\_USoA) + \beta 19(NoDC) + \beta 20(COM\_UCAR) + Ei$ *the model number of observations for the selected sample is 763, with a likelihood ratio chi-square of 281.85. Prob > chi2 (the probability of obtaining the chi-square statistic assuming a true null hypothesis) = 0.000. the Pseudo R2 (the model fit) = 0.2705. At a 0.05 significant level, only the liquidity ratio was the financial, statistically significant variable, while the nonfinancial variables had ten significant variables. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

The study theorizes that the drivers for utility abandonments and transfers are different, and the utility classification influences the drivers for either abandonments or transfers. Analyzing utilities' drivers to determine if utility abandonments correspond with utility transfers, the study used the twenty-one VIF-qualified explanatory variables and created two dummy variables (Abandonments & Transfers). Besides, the utility classification is posited to impact abandonments and transfers differently; hence, the study generated dummy variables for Class A, Class B, and Class C utilities to analyze them separately. The twenty-one VIF variables did not yield a specified model for the abandonment; a further robust check with the Hosmer–Lemeshow test revealed a poor model. The study then used all the twenty-three explanatory variables; for the abandonment model, the model dropped two variables (compliance with DEP and CUP) for perfect prediction. The abandonment model was statistically significant, with Pseudo R^2 of 0.5842 and p-value = 0.0000. The model used 703 observations, dropping 60 of the observations. The model outcome indicates that two financial performance measures (liquidity and the growth & efficiency ratios) were statistically significant. Five nonfinancial performance measures (gross water revenues per customer, utility tax classification, utility classification, compliance with NARUC, and no deficiencies) were statistically significant. Utility Class was significant in the utility abandonment model, having a positive coefficient and a direct relationship between utility classification and abandonment. A linktest to determine if the abandonment model is specified was tested. The model is not specified with _hatsq significant with p-value = 0.0000. the linktest determines the possibility of not including all the explanatory variables in the model. However, all the variables were used in the model. Hence, a further robust test using the Hosmer-Lemeshow goodness of test was run to determine the model's fitness to the data. Hosmer and Lemeshow (1989) established that the suitability of utilizing the chi-square statistics on dichotomous dependent variables (whether the utility is abandoned or not abandoned) with a grouping variable (independent variables) does not count on the significant levels of the chi-square to expose the significance level of the variables.

Nevertheless, the chi-square analysis establishes the significant distance of the explanatory variable from zero. The Hosmer and Lemeshow analysis shows how the logistic regression predictors distance away from zero. The Hosmer and Lemeshow test shows a 0.3631 significance level, indicating that the logistic analysis does not reject the null hypothesis. Hence, the chi-square value of 693.33 at the 0.05 probability level specifies a significant logistic regression model (Hosmer, Lemeshow, & Sturdivant, 2013). Table 6 presents the outcome of the abandonment model.

Table 6: Abandonment Output: Financial and Nonfinancial Performance Predictors

Abandonment	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval
LIQ	0.0494	0.0174	2.8400	0.0040**	0.0154	0.0834
LEV	0.0221	0.0199	1.1100	0.2660	-0.0168	0.0610
LEV_DT	0.0000	0.0000	1.3900	0.1630	0.0000	0.0000
COV	-0.0372	0.1446	-0.2600	0.7970	-0.3205	0.2461
GROEFF	0.1785	0.0871	2.0500	0.0400**	0.0078	0.3492
EFFPROF	-2.0455	1.3540	-1.5100	0.1310	-4.6993	0.6082
PROF	0.6323	0.4535	1.3900	0.1630	-0.2566	1.5212
Cust_Serv	0.0010	0.0013	0.7500	0.4520	-0.0015	0.0034
GROSS_REV	0.0013	0.0006	2.3700	0.0180**	0.0002	0.0024
COM_FPSC	68.0020	1537.4940	0.0400	0.9650	-2945.4310	3081.4350
TAX_CL	0.5375	0.2418	2.2200	0.0260**	0.0636	1.0113
MAN_COMP	0.3273	0.5510	0.5900	0.5530	-0.7527	1.4073
MAN_OP	0.4399	0.6004	0.7300	0.4640	-0.7369	1.6166
UTILTY_CL	2.7367	1.2391	2.2100	0.0270**	0.3080	5.1653
CIAC	0.0000	0.0000	0.9000	0.3660	0.0000	0.0000
TAX_TOTI	0.0000	0.0000	-0.6000	0.5510	-0.0001	0.0000
COM_USoA	21.9761	9.0922	2.4200	0.0160**	4.1557	39.7965
NoDC	-25.2432	9.1796	-2.7500	0.0060**	-43.2348	-7.2516
COM_UCAR	-68.4673	1537.4900	-0.0400	0.9640	-3081.8920	2944.9570
PLTOUTP	0.0090	0.0057	1.5900	0.1110	-0.0021	0.0201
EQVMETER	-0.0308	0.0141	-2.1800	0.0290**	-0.0585	-0.0031
_cons	-5.4262	4.7071	-1.1500	0.2490	-14.6519	3.7995

Table 6 presents the results of the combination of the financial and nonfinancial performance measures output on utility abandonment: $Abandonment = \beta 0 + \beta 1\ (LIQ) + \beta 2(LEV) + \beta 3(LEV\_DT) + \beta 4(COV) + 5\beta(GROEFF) + \beta 6(EFFPROF) + 7\beta(PROF) + \beta 7(Cust\_Serv) + \beta 8(GROSS\_REV) + \beta 9(COM\_FPSC) + \beta 10(PLTOUTP) + \beta 11(EQVMETER) + \beta 12(TAX\_CL) + \beta 13(MAN\_COMP) + \beta 14(MAN\_OP) + \beta 15(UTILTY\_CL) + \beta 16(CIAC) + \beta 17(TAX\_TOTI) + \beta 18(COM\_USoA) + \beta 19(NoDC) + \beta 20(COM\_UCAR) + Ei$ *the model number of observations for the selected sample is 703, with Pseudo R2 of 0.5842 and p-value = 0.0000. The results show that two financial performance measures (liquidity and the growth & efficiency ratios) and five nonfinancial performance measures (gross water revenues per customer, utility tax classification, utility classification, compliance with NARUC, and no deficiencies) were statistically significant. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

The transfer model was statistically significant, with Pseudo R^2 of 0.2705 and p-value = 0.0000. All 763 observations indicate that one financial performance predictor (the liquidity ratio) and eight nonfinancial performance predictors were statistically significant. A linktest to determine the specification of the transfer model resulted in a specified model. The model is specified with _hatsq p-value = 0.0640. the linktest determines the possibility of not including all the explanatory variables in the model. A specified model suggests the possibility of including adequate predictors for the model. Table 7 presents the results of the transfer model.

Table 7: Transfer Output: Financial & Nonfinancial Performance Predictors

Transfer	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval	
LIQ	0.0221	0.0071	3.100	0.0020**	0.0081	0.0360
LEV	-0.0001	0.0035	-0.0300	0.9770	-0.0070	0.0068
LEV_DT	0.0000	0.0000	0.5000	0.6170	0.0000	0.0000
COV	0.0047	0.0334	0.1400	0.8890	-0.0608	0.0701
GROEFF	0.0068	0.0194	0.3500	0.7240	-0.0311	0.0448
EFFPROF	0.1141	0.3276	0.3500	0.7280	-0.5279	0.7562
PROF	0.0196	0.0151	1.300	0.1950	-0.0101	0.0493
Cust_Serv	-0.0001	0.0003	-0.2500	0.8030	-0.0006	0.0005
GROSS_REV	-0.0001	0.0001	-0.8200	0.4110	-0.0004	0.0002
COM_FPSC	-3.554	0.6282	-5.660	0.0000**	-4.785	-2.323
COM_DEP	1.324	0.4225	3.130	0.002**	0.4961	2.152
COM_CUP	1.169	0.5359	2.180	0.029**	0.1186	2.219
TAX_CL	0.5210	0.1002	5.200	0.0000**	0.3247	0.7173
MAN_COMP	-0.7010	0.2056	-3.410	0.0010**	-1.104	-0.2981
MAN_OP	-1.140	0.2133	-5.340	0.0000**	-1.558	-0.7218
UTILTY_CL	0.5465	0.2844	1.920	0.0550	-0.0110	1.104
CIAC	0.0000	0.0000	1.920	0.0540	0.0000	0.0000
TAX_TOTI	0.0000	0.0000	-2.630	0.0080**	0.0000	0.0000
COM_USoA	0.3724	0.2134	1.750	0.0810	-0.0458	0.7907
NoDC	2.259	0.3243	6.960	0.0000**	1.623	2.894
COM_UCAR	1.330	0.7985	1.670	0.0960	-0.2347	2.895
_cons	-5.309	1.938	-2.740	0.0060	-9.107	-1.511

Table 7 presents the results of the transfer model using both the financial and nonfinancial performance measures output: $Transfer = \beta 0 + \beta 1\,(LIQ) + \beta 2(LEV) + \beta 3(LEV\_DT) + \beta 4(COV) + 5\beta(GROEFF) + \beta 6(EFFPROF) + 7\beta(PROF) + \beta 7(Cust\_Serv) + \beta 8(GROSS\_REV) + \beta 9(COM\_FPSC) + \beta 10(COM\_DEP) + \beta 11(COM\_CUP) + \beta 12(TAX\_CL) + \beta 13(MAN\_COMP) + \beta 14(MAN\_OP) + \beta 15(UTILTY\_CL) + \beta 16(CIAC) + \beta 17(TAX\_TOTI) + \beta 18(COM\_USoA) + \beta 19(NoDC) + \beta 20(COM\_UCAR) + Ei$ *the model number of observations for the selected sample is 763, with a likelihood ratio chi-square of 281.85. Prob > chi2 (the probability of obtaining the chi-square statistic assuming a true null hypothesis) = 0.000. the Pseudo R2 (the model fit) = 0.2705. At a 0.05 significant level, one financial performance predictor (the liquidity ratio) and eight nonfinancial performance predictors were statistically significant. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

Simultaneous Comparison of the Utility Abandonment and Transfer Models

The study examined the differences in the coefficients between the abandonments and transfers to determine the significant differences between the coefficients. The study used the seemingly unrelated estimation to examine all the abandonment and transfer models simultaneously to determine that the coefficients differ. The simultaneous comparison of the utility abandonments and transfers resulted in different coefficients and variables for the two models. Both models used twenty-one predictors; however, the abandonment model included the plant output per customer and the equivalent output per meter, while these two were not included in the transfer model. The abandonment model rejected compliance with DEP quality measures and compliance with CUP; however, the transfer model included these predictors. All the predictors had different coefficients. The utility class was statistically significant, with a positive coefficient indicating a direct prediction of utility abandonment. George and Mallery (2010) explain that a significant explanatory variable level indicates whether an independent variable significantly affects the dependent variable without interference from the other explanatory variables. The study hypothesis is that utility classification impacts the drivers for utility abandonments and transfers. Table 8 shows the results of the simultaneous comparison of the abandonment and transfer models.

Table 8: Simultaneous Comparison of the Utility Abandonment and Transfer Models

Abandonment	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf. Interval	
LIQ	-0.0419	0.0144	2.920	0.0040**	0.0138	0.0701
LEV	0.0162	0.0104	1.560	0.1180	-0.0041	0.0366
LEV_DT	0.0000	0.0000	1.290	0.1980	0.0000	0.0000
COV	-0.0360	0.1215	-0.300	0.7670	-0.2742	0.2021
GROEFF	0.1595	0.0842	1.890	0.0580	-0.0056	0.3246
EFFPROF	-1.472	1.106	-1.330	0.1830	-3.6395	0.6953
PROF	0.586	0.2708	2.160	0.0300**	0.0552	1.1167
Cust_Serv	0.0005	0.0016	0.3200	0.7510	-0.0026	0.0036
GROSS_REV	0.0007	0.0002	2.880	0.0040**	0.0002	0.0012
COM_FPSC	72.304	21.395	3.380	0.0010**	30.3708	114.2367
TAX_CL	0.3826	0.1683	2.270	0.0230**	0.0528	0.7124
MAN_COMP	0.2334	0.4813	0.4900	0.6280	-0.7098	1.1767
MAN_OP	0.2268	0.5441	0.4200	0.6770	-0.8396	1.2932
UTILTY_CL	7.293	4.041	1.800	0.0710	-0.6275	15.2127
CIAC	0.0000	0.0000	0.9100	0.3620	0.0000	0.0000
TAX_TOTI	0.0000	0.0000	-0.1400	0.8880	0.0000	0.0000
COM_USoA	4.896	2.496	1.960	0.0500**	0.0042	9.7867
NoDC	-7.997	2.693	-2.970	0.0030**	-13.2750	-2.7179
COM_UCAR	-72.580	21.218	-3.420	0.0010**	-114.1657	-30.9947
_cons	-19.762	12.919	-1.530	0.1260	-45.0829	5.5584
Transfer						
LIQ	0.0221	0.0079	2.790	0.0050**	0.0066	0.0376
LEV	-0.0001	0.0041	-0.0200	0.9800	-0.0082	0.0080
LEV_DT	0.0000	0.0000	3.090	0.0020**	0.0000	0.0000
COV	0.0047	0.0286	0.1600	0.8710	-0.0515	0.0608
GROEFF	0.0068	0.0087	0.790	0.4310	-0.0102	0.0239
EFFPROF	0.1141	0.3319	0.3400	0.7310	-0.5364	0.7646
PROF	0.0196	0.0074	2.670	0.0080**	0.0052	0.0340
Cust_Serv	-0.0001	0.0003	-0.2400	0.8120	-0.0007	0.0005
GROSS_REV	-0.0001	0.0001	-1.360	0.1750	-0.0003	0.0001
COM_FPSC	-3.554	0.6064	-5.860	0.0000**	-4.7426	-2.3656
COM_DEP	1.324	0.4081	3.240	0.0010**	0.5243	2.1242
COM_CUP	1.169	0.5706	2.050	0.0410**	0.0506	2.2873
TAX_CL	0.5210	0.0913	5.710	0.0000**	0.3421	0.6998
MAN_COMP	-0.7010	0.2132	-3.290	0.0010**	-1.1189	-0.2831
MAN_OP	-1.140	0.2251	-5.060	0.0000**	-1.5810	-0.6986
UTILTY_CL	0.547	0.2634	2.070	0.0380**	0.0303	1.0627
CIAC	0.0000	0.0000	1.270	0.2040**	0.0000	0.0000
TAX_TOTI	0.0000	0.0000	-2.260	0.0240**	0.0000	0.0000
COM_USoA	0.3724	0.2247	1.660	0.0970	-0.0679	0.8128
NoDC	2.257	0.3946	5.720	0.0000**	1.4853	3.0319
COM_UCAR	1.330	0.8000	1.660	0.0960	-0.2378	2.8982
_cons	-5.309	1.844	-2.880	0.0040**	-8.9223	-1.6949

*Table 8 presents the results of the simultaneous comparison of the utility abandonment and transfer models to determine the significant differences between the coefficients. The Simultaneous Comparison resulted in different coefficients and variables for the two models. Both models used twenty-one predictors; however, the abandonment model included the plant output per customer and the equivalent output per meter, while these two were not included in the transfer model. The abandonment model rejected compliance with DEP quality measures and compliance with CUP. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

The Utility class has a direct relationship with abandonments with a positive coefficient of 2.74; there are three utility classifications (Class A, B, & C); hence, further analysis of the overall model considering the utility class was analyzed to determine the impact a utility class has on abandonments and transfers, holding the other utility classes constant. The Class A model was statistically significant, with Pseudo R^2 of 0.8999 and p-value = 0.0000. The model used 680 observations with three nonfinancial performances statistically significant, and none of the financial performance measures was statistically significant. A linktest _hatsq = 1 and Hosmer-Lemeshow goodness of test Prob > chi2 = 0.9999, indicating a specified model. Table 9 shows the outcomes of the logistic regression for Class A utilities.

Table 9: Logistic Regression Output for Class A Utilities

Class_A	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval	
LIQ	0.0372	0.0390	0.9600	0.3390	-0.0391	0.1136
LEV	-0.2646	0.2039	-1.300	0.1940	-0.6642	0.1350
LEV_DT	-0.0327	0.0270	-1.210	0.2260	-0.0857	0.0203
COV	2.562	1.567	1.640	0.1020	-0.5091	5.6338
GROEFF	2.156	4.248	0.5100	0.6120	-6.169	10.486
EFFPROF	1.142	3.492	0.330	0.7440	-5.702	7.985
PROF	11.138	7.106	1.570	0.1170	-2.789	25.065
Cust_Serv	0.0155	0.0049	3.150	0.0020**	0.0059	0.0252
GROSS_REV	0.0175	0.0065	2.680	0.0070**	0.0047	0.0303
COM_FPSC	-3.587	26.907	-0.1300	0.8940	-56.324	49.150
TAX_CL	9.858	6.521	1.510	0.1310	-2.924	22.639
MAN_COMP	-12.023	5.527	-2.180	0.030**	-22.856	-1.192
MAN_OP	-4.273	4.214	-1.010	0.3110	-12.533	3.986
CIAC	0.0000	0.0000	0.8700	0.3840	0.0000	0.0000
TAX_TOTI	-0.0001	0.0000	-1.700	0.0880	-0.0001	0.0000
COM_USoA	9.482	3.981	2.380	0.0170**	1.679	17.285
NoDC	-1.943	2.598	-0.7500	0.4550	-7.034	3.149
PLTOUTP	-37.884	44.144	-0.8600	0.3910	-124.41	48.638
EQVMETER	37.822	44.138	0.860	0.3910	-48.687	124.33
_cons	-56.516	61.576	-0.920	0.3590	-177.20	64.170

Table 9 shows the outcomes of the class A utility impact on the abandonments and transfers, employing both financial and nonfinancial performance measures: $Class\ A = \beta 0 + \beta 1\ (LIQ) + \beta 2(LEV) + \beta 3(LEV\_DT) + \beta 4(COV) + 5\beta(GROEFF) + \beta 6(EFFPROF) + 7\beta(PROF) + \beta 7(Cust\_Serv) + \beta 8(GROSS\_REV) + \beta 9(COM\_FPSC) + \beta 10(EQVMETER) + \beta 11(PLTOUTP) + \beta 12(TAX\_CL) + \beta 13(MAN\_COMP) + \beta 14(MAN\_OP) + \beta 15(CIAC) + \beta 16(TAX\_TOTI) + \beta 17(COM\_USoA) + \beta 18(NoDC) + \beta 19(COM\_UCAR) + Ei$ *The Class A model was statistically significant, with Pseudo R2 of 0.8999 and p-value = 0.0000. The model used 680 observations with three nonfinancial performances statistically significant, and none of the financial performance measures was statistically significant. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

Class B and Class C utilities were also analyzed separately. The Class B model was statistically significant, with Pseudo R^2 of 0.4875 and p-value = 0.0000. The model used 586 observations with six nonfinancial performances statistically significant, and similar to the Class A model, none of the financial performance measures was statistically significant. A linktest _hatsq = 0.000, indicating the possibility of an omitted variable, was confirmed with the Hosmer-Lemeshow goodness of test Prob > chi2 = 0.9999, indicating the model fits the data. On the other hand, the Class C model had one financial performance measure (efficiency and profitability ratio) statistically significant with a negative coefficient of 2.03. The efficiency and profitability ratio analyzes the ability of a utility to generate profits relative to the utility industry standards. There were nine nonfinancial performance measures statistically significant for the Class C utility model Table ten presents the outcome of the Class B logistic regression model, and table 11 presents the results of the Class C utility logistic regression model.

There are no available utility standards to compare these ratios; however, among the three Classes of utilities, Class A and B were not independently significantly impacted by the financial ratios compared to the Class C utility. Ten nonfinancial performance measures were statistically significant. Among the ten is the management participation in the utility operation; this was unique among the three utility classes. Class C was the only utility with a statistically significant outcome for management participation in operations. The coefficient for this explanatory variable is a positive 1.86. An increase in management participation in operating a Class C utility is likely to increase an abandonment by 1.86 times. Plant output per customer was also unique among the three classes of utilities. The Class C model used 680 observations, with a Pseudo R^2 of 0.8293 and p-value = 0.0000. A linktest _hatsq = 0.000, indicating the possibility of an omitted variable, was confirmed with the Hosmer-Lemeshow goodness of test Prob > chi2 =1, indicating the model fits the data.

Table 10:Logistic Regression Output for Class B Utilities

Class_B	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval	
LIQ	-0.0022	0.0090	-0.2500	0.8050	-0.0199	0.0154
LEV	-0.0057	0.0062	-0.9100	0.3640	-0.0179	0.0066
LEV_DT	-0.0010	0.0026	-0.4000	0.6910	-0.0062	0.0041
COV	0.0318	0.1176	0.2700	0.7870	-0.1987	0.2622
GROEFF	-0.0095	0.0368	-0.2600	0.7970	-0.0816	0.0627
EFFPROF	-0.3619	0.7612	-0.4800	0.6350	-1.854	1.130
PROF	0.4574	0.5258	0.8700	0.3840	-0.5732	1.488
Cust_Serv	0.0018	0.0003	5.120	0.0000**	0.0011	0.0025
GROSS_REV	0.0033	0.0005	6.540	0.0000**	0.0023	0.0043
TAX_CL	0.0714	0.1780	0.4000	0.6880	-0.2774	0.4203
MAN_COMP	0.2220	0.3939	0.5600	0.5730	-0.5501	0.9940
MAN_OP	-0.5904	0.3787	-1.560	0.1190	-1.333	0.1519
CIAC	0.0000	0.0000	-5.510	0.0000**	0.0000	0.0000
TAX_TOTI	0.0000	0.0000	3.770	0.0000**	0.0000	0.0001
COM_USoA	0.0384	0.3577	0.1100	0.9150	-0.6627	0.7395
NoDC	-0.5595	0.4272	-1.310	0.1900	-1.397	0.2777
PLTOUTP	-2.217	0.8999	-2.460	0.0140**	-3.981	-0.4530
EQVMETER	2.217	0.8999	2.460	0.0140**	0.4530	3.981
_cons	-2.710	1.404	-1.930	0.0540	-5.463	0.0419

Table 10 shows the outcomes of the class B utility impact on the abandonments and transfers, employing both financial and nonfinancial performance measures: $Class\ B = \beta 0 + \beta 1\ (LIQ) + \beta 2(LEV) + \beta 3(LEV\_DT) + \beta 4(COV) + 5\beta(GROEFF) + \beta 6(EFFPROF) + 7\beta(PROF) + \beta 7(Cust\_Serv) + \beta 8(GROSS\_REV) + \beta 9(TAX\_CL) + \beta 10(MAN\_COMP) + \beta 11(MAN\_OP) + \beta 12(CIAC) + \beta 13(TAX\_TOTI) + \beta 14(COM\_USoA) + \beta 15(NoDC) + \beta 16(PLTOUTP) + \beta 17(EQVMETERI) + Ei$ *The Class B model was statistically significant, with Pseudo R2 of 0.4875 and p-value = 0.0000. The model used 586 observations with six nonfinancial performances statistically significant, and none of the financial performance measures was statistically significant. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

Table 11: Logistic Regression Output for Class C Utilities

Class_C	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval	
LIQ	0.0029	0.0112	0.2600	0.7940	-0.0191	0.0249
LEV	0.0166	0.0091	1.840	0.0660	-0.0011	0.0344
LEV_DT	0.0010	0.0041	0.2500	0.8040	-0.0070	0.0090
COV	-0.1646	0.1681	-0.9800	0.3270	-0.4942	0.1649
GROEFF	0.0470	0.0685	0.6900	0.4920	-0.0873	0.1813
EFFPROF	-2.026	0.9429	-2.150	0.0320**	-3.874	-0.1782
PROF	0.0239	0.0410	0.5800	0.5610	-0.0566	0.1043
Cust_Serv	-0.0100	0.0017	-5.700	0.0000**	-0.0134	-0.0065
GROSS_REV	-0.0060	0.0009	-6.600	0.0000**	-0.0077	-0.0042
COM_FPSC	-4.554	11.565	-0.3900	0.6940	-27.222	18.114
TAX_CL	-1.562	0.4381	-3.560	0.0000**	-2.421	-0.7030
MAN_COMP	-0.3268	0.6723	-0.4900	0.6270	-1.645	0.9909
MAN_OP	1.863	0.7083	2.630	0.0090**	0.4742	3.251
CIAC	0.0000	0.0000	2.910	0.0040**	0.0000	0.0000
TAX_TOTI	-0.0001	0.0000	-2.730	0.0060**	-0.0001	0.0000
COM_USoA	-2.241	0.6660	-3.360	0.0010**	-3.546	-0.9356
NoDC	2.075	0.7573	2.740	0.0060**	0.5910	3.559
PLTOUTP	3.866	1.476	2.620	0.0090**	0.9735	6.757
EQVMETER	-3.865	1.476	-2.620	0.0090**	-6.757	-0.9734
_cons	23.199	23.473	0.9900	0.3230	-22.808	69.206

Table 11 shows the outcomes of the class B utility impact on the abandonments and transfers, employing both financial and nonfinancial performance measures: $Class\ C = \beta 0 + \beta 1\ (LIQ) + \beta 2(LEV) + \beta 3(LEV\_DT) + \beta 4(COV) + 5\beta(GROEFF) + \beta 6(EFFPROF) + 7\beta(PROF) + \beta 7(Cust\_Serv) + \beta 8(GROSS\_REV) + \beta 9(TAX\_CL) + \beta 10(MAN\_COMP) + \beta 11(MAN\_OP) + \beta 12(CIAC) + \beta 13(TAX\_TOTI) + \beta 14(COM\_USoA) + \beta 15(NoDC) + \beta 16(PLTOUTP) + \beta 17(EQVMETERI) + Ei$ *The Class C model was statistically significant, with Pseudo R2 of 0.8293 and p-value = 0.0000. The model used 680 observations with ten nonfinancial performances statistically significant, and the efficiency ratio was the only financial variable that was statistically significant. * p-value < 0.1 level of significance; ** p-value < 0.05 level of significance; *** p-value < 0.001 level of significance*

The study examined the differences in the coefficients across the utility class to determine if they significantly differ across each utility class. The study employed the seemingly unrelated estimation to examine all three classes simultaneously to determine that the coefficients differ and a Wald chi-square test for the three groups to determine that the predictor variables are statistically significant to improve the model (William, 2015). The simultaneous comparison of the three classes (Class A, B, & C) for abandonments resulted in different coefficients and variables for each class. Class A and C used nineteen predictors compared to Class B, which used eighteen predictors. Class A had one financial predictor (the liquidity ratio) and two nonfinancial predictors (management compensation & compliance with state quality measures) that were statistically significant. Class B had six nonfinancial predictors that were statistically significant; Class C had two financial predictors (the leverage ratio & profitability ratio) and eleven statistically significant nonfinancial predictors. The overall outcome yielded Wald chi-square results of chi2(3) = 64.93 with Prob > chi2 =0.0000. The coefficients of the utility categories are different, and the number of predictors for each class differs from each other. Table 12 presents the outcome of the simultaneous comparison of the three classes of utility (Class A, B, & C) models.

Table 12:Simultaneous Comparison of the Utility Class Models

Class_A	**Coef.**	**Robust Std. Err.**	**z**	**P>|z|**	**[95% Conf. Interval**	
LIQ	0.0372	0.0194	1.920	0.0540**	-0.0007	0.0752
LEV	-0.2646	0.1561	-1.700	0.0900	-0.5705	0.0413
LEV_DT	-0.0327	0.0185	-1.770	0.0760	-0.0689	0.0034
COV	2.562	1.695	1.510	0.1310	-0.7599	5.885
GROEFF	2.156	2.109	1.020	0.3070	-1.977	6.290
EFFPROF	1.142	3.276	0.3500	0.7270	-5.278	7.562
PROF	11.138	4.983	2.240	0.0250	1.372	20.904
Cust_Serv	0.0155	0.0068	2.270	0.0230	0.0021	0.0289
GROSS_REV	0.0175	0.0110	1.590	0.1120	-0.0041	0.0391
COM_FPSC	-3.587	0.6755	-5.310	0.0000**	-4.911	-2.263
TAX_CL	9.856	6.585	1.500	0.1340	-3.049	22.764
MAN_COMP	-12.024	6.192	-1.940	0.0520**	-24.161	0.1132
MAN_OP	-4.273	4.899	-0.870	0.3830	-13.875	5.328
CIAC	0.0000	0.0000	0.8500	0.3930	0.0000	0.0000
TAX_TOTI	-0.0001	0.0000	-1.170	0.2410	-0.0001	0.0000
COM_USoA	9.482	7.654	1.240	0.2150	-5.520	24.484
NoDC	-1.943	2.934	-0.6600	0.5080	-7.693	3.8073
PLTOUTP	-37.884	22.058	-1.720	0.0860	-81.117	5.3485
EQVMETER	37.823	22.038	1.720	0.0860	-5.371	81.016
_cons	-56.516	38.002	-1.490	0.1370	-131.00	17.967
Class_B						
LIQ	-0.0022	0.0054	-0.4100	0.6830	-0.0129	0.0084
LEV	-0.0057	0.0037	-1.540	0.1230	-0.0129	0.0015
LEV_DT	-0.0010	0.0008	-1.330	0.1840	-0.0026	0.0005
COV	0.0318	0.0796	0.4000	0.6900	-0.1242	0.1878
GROEFF	-0.0095	0.0154	-0.6200	0.5370	-0.0396	0.0207
EFFPROF	-0.3619	1.157	-0.3100	0.7540	-2.629	1.905
PROF	0.4574	1.211	0.3800	0.7060	-1.916	2.831
Cust_Serv	0.0018	0.0003	5.160	0.0000**	0.0011	0.0025
GROSS_REV	0.0033	0.0004	8.610	0.0000**	0.0026	0.0041
TAX_CL	0.0714	0.1873	0.3800	0.7030	-0.2957	0.4386
MAN_COMP	0.2220	0.3995	0.5600	0.5780	-0.5610	1.005
MAN_OP	-0.5904	0.3836	-1.540	0.1240	-1.342	0.1615
CIAC	0.0000	0.0000	-5.470	0.0000**	0.0000	0.0000
TAX_TOTI	0.0000	0.0000	3.470	0.0010**	0.0000	0.0001
COM_USoA	0.0384	0.3346	0.1100	0.9090	-0.6175	0.6943
NoDC	-0.5595	0.4038	-1.390	0.1660	-1.351	0.2319
PLTOUTP	-2.217	0.6208	-3.570	0.0000**	-3.434	-1.000
EQVMETER	2.217	0.6208	3.570	0.0000**	1.000	3.434
_cons	-2.710	2.106	-1.290	0.1980	-6.838	1.417

Table 12 shows the results of the simultaneous comparison of the Utility classes (class A, B, & C) models to determine the significant differences between the coefficients among the utility classes. The simultaneous comparison of the three classes (Class A, B, & C) for abandonments resulted in different coefficients and variables for each class. The overall outcome yielded Wald chi-square results of chi2(3) = 64.93 with Prob > chi2 =0.0000. The coefficients of the utility categories are different, and the number of predictors for each class differs for each utility class.

Table 3: Simultaneous Comparison of the Utility Class Models (Continued)

Class_C						
LIQ	0.0029	0.0062	0.4700	0.6370	-0.0092	0.0151
LEV	0.0166	0.0045	3.680	0.0000**	0.0078	0.0255
LEV_DT	0.0010	0.0006	1.680	0.0930	-0.0002	0.0022
COV	-0.1646	0.1281	-1.290	0.1990	-0.4157	0.0864
GROEFF	0.0470	0.0281	1.670	0.0950	-0.0081	0.1022
EFFPROF	-2.026	1.034	-1.960	0.0500	-4.053	0.0003
PROF	0.0239	0.0068	3.530	0.0000**	0.0106	0.0371
Cust_Serv	-0.0100	0.0014	-7.040	0.0000**	-0.0127	-0.0072
GROSS_REV	-0.0060	0.0011	-5.350	0.0000**	-0.0081	-0.0038
COM_FPSC	-4.554	0.7999	-5.690	0.0000**	-6.122	-2.986
TAX_CL	-1.562	0.3527	-4.430	0.0000**	-2.253	-0.8705
MAN_COMP	-0.3268	0.6697	-0.4900	0.6260	-1.639	0.9858
MAN_OP	1.863	0.7913	2.300	0.0190**	0.3115	3.414
CIAC	0.0000	0.0000	3.120	0.0020**	0.0000	0.0000
TAX_TOTI	-0.0001	0.0000	-2.710	0.0070**	-0.0001	0.0000
COM_USoA	-2.241	0.5196	-4.310	0.0000**	-3.259	-1.223
NoDC	2.075	0.7187	2.890	0.0040**	0.6665	3.484
PLTOUTP	3.866	1.605	2.410	0.0160**	0.7195	7.0114
EQVMETER	-3.865	1.605	-2.410	0.0160**	-7.011	-0.7194
_cons	23.199	3.729	6.220	0.0000	15.891	30.507

Table 12 shows the results of the simultaneous comparison of the Utility classes (class A, B, & C) models to determine the significant differences between the coefficients among the utility classes. The simultaneous comparison of the three classes (Class A, B, & C) for abandonments resulted in different coefficients and variables for each class. The overall outcome yielded Wald chi-square results of chi2(3) = 64.93 with Prob > chi2 =0.0000. The coefficients of the utility categories are different, and the number of predictors for each class differs for each utility class.

Fixed Effects and Random Effects-Outcome

The study theorizes that abandonments and transfers of utilities are impacted by time. For instance, the length of time the utility has been in existence may impact the utility's ability to abandon its facility or transfer to another utility. The study investigated the panel logistic regression (xtlogit) to determine the impact of time on utility abandonment and transfers. Williams (2015) explains that both fixed and random effects impact the explanatory variables in determining the time impacts on the dependent variable (Abandonments and Transfers). The study explored both fixed effects and random effects on abandonments and transfers. Fixed effects explore the connection between explanatory and dependent variables (Torres-Reyna, 2007). Each utility has features that may or may not impact the explanatory variables; fixed effect assumes that a utility's characteristics may impact its abandonments or transfers (correlation between entity's error term and predictor variables) (Torres-Reyna, 2007). If there is a correlation between the utility's error term and the explanatory variables, a fixed effect removes the time-invariant features to enhance the assessment of the net impact of the explanatory variables on abandonments and transfers.

The study used the Hausman test to determine if the error terms are correlated with the explanatory variables. The study hypothesis is that the random effect model is preferred to the fixed effect model; hence the error terms of a utility are correlated with the explanatory variables. The overall model (both Abandonments and Transfers), Hausman test Prob>chi2 = 1. Torres-Reyna (2007) explains that the fixed effect is recommended if the Prob>chi2 is statistically significant. However, the overall model is not statistically significant; hence, the study used the random effect model to analyze the time impact on utility abandonments and transfers. The Random effect model assumes that the variation across utilities is random and uncorrelated with the explanatory variables. Furthermore, the predictors for utility classes differ based on the prior results; hence, the study assumes that differences across utility classifications impact the abandonments and transfers. Table 13 presents the outcomes of the Abandonment random effect.

Table 13: Abandonment Random Effects-Outcome

Abandoned	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval	
LIQ	0.0026	0.0136	0.1900	0.8460	-0.0241	0.0294
LEV	0.1005	0.1251	0.8000	0.4220	-0.1448	0.3457
LEV_DT	0.0000	0.0000	0.2400	0.8090	0.0000	0.0000
COV	-0.6290	1.143	-0.5500	0.5820	-2.869	1.611
GROEFF	0.8029	2.196	0.3700	0.7150	-3.501	5.107
EFFPROF	-0.6377	5.504	-0.1200	0.9080	-11.425	10.150
PROF	0.8357	1.339	0.6200	0.5330	-1.789	3.460
Cust_Serv	0.0041	0.0068	0.6000	0.5450	-0.0092	0.0174
GROSS_REV	0.0027	0.0023	1.160	0.2460	-0.0019	0.0073
TAX_CL	0.6758	1.432	0.4700	0.6370	-2.130	3.482
MAN_COMP	-8.511	3.481	-2.450	0.0140**	-15.332	-1.688
MAN_OP	-3.061	3.033	-1.010	0.3130	-9.005	2.883
UTILTY_CL	11.830	6.404	1.850	0.0650	-0.7240	24.378
CIAC	0.0000	0.0000	-0.0500	0.9610	0.0000	0.0000
TAX_TOTI	-0.0001	0.0002	-0.4600	0.6460	-0.0004	0.0002
COM_USoA	18.845	5.532	3.410	0.0010**	8.002	29.689
NoDC	-30.991	6.552	-4.730	0.0000**	-43.833	-18.149
COM_UCAR	-5.622	4.578	-1.230	0.2190	-14.594	3.350
Year						
2008	-1.055	3.332	-0.3200	0.7520	-7.586	5.476
2009	0.4402	3.122	0.1400	0.8880	-5.679	6.560
2010	-1.382	4.249	-0.3300	0.7450	-9.710	6.947
2011	-2.315	3.945	-0.5900	0.5570	-10.046	5.416
2012	-2.145	4.462	-0.4800	0.6310	-10.890	6.601
2013	-9.128	7.578	-1.200	0.2280	-23.980	5.724
2014	-8.193	5.363	-1.530	0.1270	-18.704	2.318
2015	-17.922	11.941	-1.500	0.1330	-41.325	5.482
2016	-20.280	9.549	-2.120	0.0340	-38.996	-1.564
2017	0.0000	(empty)				
2018	-19.032	19.914	-0.9600	0.3390	-58.062	19.999
_cons	-3.278	25.402	-0.1300	0.8970	-53.065	46.509
/lnsig2u	5.022	0.4936			4.055	5.990
sigma_u	12.320	3.041			7.595	19.984
rho	0.9788	0.0103			0.9460	0.9918
LR test of rho=0:	chibar2(01) = 98.860			Prob >= chibar2 = 0.000		

Table 13 presents the Abandonment random effect model. The model estimates the odds ratio for a utility to abandon their facility in any given two years at 3,346.56, with a Pearson's correlation coefficient of 0.78 (square = 0.60), indicating a lower manifest than a latent association. The random effect model yielded three statistically significant predictors: management compensation, compliance with NARUC reporting standards, and the No deficiencies communications from the state regulatory body.

The Abandonment random effect had three statistically significant predictors: management compensation, compliance with NARUC reporting standards, and the No deficiencies communications from the state regulatory body. Management charging salary to the utility had a negative coefficient of 8.51, revealing an inverse relationship of utility abandonment. One increase in utilities with management charging salary to the utility has log odds of 8.51 of not abandoning the utility over time. The No deficiencies communications from regulatory agencies had a negative 30.99 coefficient. An indication of one increase in issuing a deficiency notice has a log odds of 30.99 for utility abandoning their facility over time. Compliance with the Uniform System of accounts for abandoned utilities had a positive 18.85 coefficient, indicating that abandoning utilities complied with the annual report of a log odds of 18.85. A utility whose observed propensity equals the sample median reveals a marginal probability for the utility to abandon their facility to be 0.005 (0.5%) within a year, and a joint probability of abandoning the utility facility within any two years is 0.004 (0.4%). The model estimates the odds ratio for a utility to abandon their facility in any given two years at 3,346.56; that is, the odds for a utility to abandon their facility in any given year (e.g., 2008) are nearly 3,346.56 times the corresponding odds for a utility with similar observed attributes in any other year (e.g., 2017). Pearson's correlation coefficient is 0.78 (square = 0.60), which indicates a lower manifest than a latent association. An abandonment in any given year is explained by 60% of the utility behaviors in another year instead of the continual unobserved traits explaining 98% latent propensity for a utility to abandon their facility in any given year. The Yule's Q is 0.999, with the linear predictor at a median. The probability of any two randomly selected utilities with median observed characteristics within any given two years would be; that an abandoned utility(concordant) exceeds the probability that a utility will abandon its facility (discordant) by 99.9 percentage points. Table 14 presents the results of the Intra-class Correlation and manifest association in random effects for the abandonment model.

Table 4: Abandonment Intra-Class Correlation and Manifest Association in Random Effects

Measure	**Estimate**	**[95% Conf.Interval]**			
Marginal probability.	0.0050	0.0000	0.0370		
Joint probability.	0.0040	0.0000	0.0330		
Odds ratio	3,346.6	3,5156.9	1,727.9		
Pearson's r	0.7750	0.5540	0.8800		
Yule's Q	0.9990	1.000	0.9990		
Manifest Association					
Measure	p1	p25	p50	p75	p99
Marginal probability.	0.0000	0.0000	0.0050	0.0650	0.7380
Joint probability.	0.0000	0.0000	0.0040	0.0550	0.7130
Odds ratio	7,1000,000	32,993	3346.6	539.88	269.57
Pearson's r	0.576	0.7140	0.775	0.8390	0.8700
Yule's Q	1.000	1.000	0.999	0.9960	0.9930

Table 14 presents the results of the abandonment Intra-class Correlation and manifest association in the Random Effects Model. The Yule's Q is 0.999, with the linear predictor at a median and a Person's r = 0.775. The marginal probability of abandoning a utility ranges from 0.000 to 0.738 in any given year, from one percentile to the 99th percentile.

The Abandonment Intra-class Correlation output reveals a confidence interval for each measure. The study explored how the measures vary across the selected sample, using the Intra-class manifest association in random effects. The marginal probability of abandoning a utility ranges from 0.000 to 0.738 in any given year, from one percentile to the 99th percentile. The variation in the marginal probability impacts both Pearson's r, and Yule's Q. Pearson's r is higher among the utility more likely to abandon their facility than Yule's Q. Its odds ratio is higher among utilities least likely to abandon their facility. With an average of 74% abandoning their facility within any given year, utilities are associated with a two-hundred-fold increase in the odds of abandoning their facility in another year. However, a utility with 0.00% of abandoning its facility in one year is associated with a seventy-one million-fold increase in the odds of abandoning its facility in another year.

The transfer random effect model indicates that two statistically significant explanatory variables are management compensation, compliance with state regulators' quality measures, and management compensation. Consistent with the abandonment model, the management compensation had a negative coefficient of 4.54, indicating an inverse relationship to utility transfers. One increase in utilities with management charging salary to the utility has log odds of 4.54 of not transferring the utility over time. Utilities complying with state regulatory quality measures are not likely to transfer the utility over time, with an odd log of 10.29. A utility whose observed propensity equals the sample median reveals a marginal probability for the utility to transfer utility to be 0.574 (57%) within a year, and a joint probability of transferring the utility facility within any two years is 0.539 (54%). The model estimates the odds ratio to transfer to a new utility in any given two years at 169.88. The odds for a utility to transfer to a new utility in any given year (e.g., 2010) is nearly 169.88 times the corresponding odds for a utility with similar observed attributes in any other year (e.g., 2018). Pearson's correlation coefficient is 0.86 (square = 0.74), which indicates a lower manifest than a latent association. A transfer in any given year is explained by 74% of the utility behaviors in another year instead of the continual unobserved traits explaining 97% latent propensity for a utility to transfer in any given year. Table 15 presents the results of the Intra-class Correlation in Random Effects for the transfer model.

Table 15: Transfer Intra-Class Correlation and Manifest Association in Random Effects

Measure	**Estimate**	**[95% Conf.Interval]**			
Marginal probability.	0.5740	0.6110	0.5480		
Joint probability.	0.5390	0.559	0.525		
Odds ratio	169.88	68.952	417.98		
Pearson's r	0.8560	0.780	0.9060		
Yule's Q	0.9880	0.9710	0.9950		
Manifest association					
Measure	p1	p25	p50	p75	p99
Marginal probability.	0.2110	0.4340	0.5740	0.7020	0.9860
Joint probability.	0.1850	0.3990	0.5390	0.6710	0.9830
Odds ratio	210.00	169.47	169.88	184.89	1,033.3
Pearson's r	0.8440	0.8560	0.8560	0.8510	0.7680
Yule's Q	0.9910	0.9880	0.9880	0.9890	0.9980

Table 15 presents the results of the Transfer Intra-Class Correlation and manifest association in the Random Effects Model. Yule's Q is 0.988 with the linear predictor at a median, and Pearson's correlation coefficient is 0.86 (square = 0.74). A transfer in any given year is explained by 74% of the utility behaviors in another year instead of the continual unobserved traits explaining 97% latent propensity for a utility to transfer in any given year

The Yule's Q is 0.988, with the linear predictor at a median. The probability of any two randomly selected utilities with a median observed characteristic within any given two years would be; that a transfer utility (concordant) exceeds the probability that a utility will transfer their facility (discordant) by 98.8 percentage points. The transfer Intra-class Correlation output reveals a confidence interval for each measure. The marginal probability of transferring a utility ranges from 0.211 to 0.986 in any given year, from one percentile to the 99th percentile. The variation in the marginal probability impacts both Pearson's r and Yule's Q. Pearson's r is higher among the utility more likely to transfer than Yule's Q, and its odds ratio is higher among utilities least likely to transfer to a new utility. Utilities, with an average of 99% of transferring within any given year, are associated with a thousand thirty-three increase in the odds of transferring in another year. However, a utility with 21% of transferring in one year is associated with a two hundred and ten-fold increase in the odds of transferring in another year. Table 16 presents the outcome of the random effect of the transfer model. The abandonment and transfer analysis results inform the public, practitioners, and academicians of the necessary steps needed to assist in evaluating transfers and abandonments in the nonviable water and wastewater industry. The discussion session analyzes the results, the practical and theoretical implications, as well as recommendations and suggestions for future research.

Table 5:Transfer Random Effects-Outcome

Transfer	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval	
Liq	0.0172	0.0448	0.3800	0.7010	-0.0707	0.1051
Lev	0.0080	0.0201	0.4000	0.6900	-0.0313	0.0473
Lev_dt	0.0000	0.0001	0.0400	0.9690	-0.0002	0.0002
Cov	0.0196	0.2694	0.0700	0.9420	-0.5085	0.5476
Groeff	-0.0256	0.1120	-0.2300	0.8190	-0.2451	0.1939
Effprof	-1.545	2.762	-0.5600	0.5760	-6.959	3.8688
Prof	-0.0477	0.0476	-1.000	0.3160	-0.1410	0.0456
Cust_serv	0.0027	0.0019	1.460	0.1430	-0.0009	0.0064
Gross_rev	0.0004	0.0013	0.3000	0.7640	-0.0022	0.0030
Com_fpsc	-10.286	4.122	-2.500	0.0130**	-18.365	-2.207
Com_dep	4.225	11.826	0.3600	0.7210	-18.952	27.403
Com_cup	-2.293	3.123	-0.7300	0.4630	-8.415	3.828
Tax_cl	1.445	0.8326	1.730	0.0830	-0.1875	3.076
Man_comp	-4.543	1.588	-2.860	0.0040**	-7.656	-1.430
Man_op	-2.161	1.722	-1.2600	0.2090	-5.536	1.214
Utilty_cl	3.128	3.208	0.9700	0.3300	-3.160	9.415
Ciac	0.0000	0.0000	0.6700	0.5020	0.0000	0.0000
Tax_toti	0.0000	0.0000	-0.4400	0.6620	-0.0001	0.0001
COM_usoa	2.631	1.675	1.570	0.1160	-0.6525	5.914
Nodc	4.828	2.520	1.920	0.0550	-0.1111	9.766
Com_ucar	8.224	5.223	1.570	0.1150	-2.013	18.461
Year						
2008	-0.3323	2.699	-0.1200	0.9020	-5.622	4.957
2009	-0.8613	3.094	-0.2800	0.7810	-6.926	5.204
2010	-0.2518	2.704	-0.0900	0.9260	-5.552	5.048
2011	-0.3020	2.780	-0.1100	0.9130	-5.751	5.147
2012	-0.2153	2.554	-0.0800	0.9330	-5.220	4.790
2013	0.1215	2.530	0.0500	0.9620	-4.838	5.081
2014	-0.6438	2.578	-0.2500	0.8030	-5.696	4.408
2015	-3.799	2.330	-1.630	0.1030	-8.365	0.7677
2016	-3.779	2.292	-1.650	0.0990	-8.272	0.7138
2017	0.0000	(empty)				
2018	-4.207	2.455	-1.710	0.0870	-9.019	0.6059
_Cons	-13.600	27.603	-0.4900	0.6220	-67.701	40.501
/Lnsig2u	4.794	0.444			3.924	5.663
Sigma_u	10.989	2.437			7.115	16.972
Rho	0.9735	0.012			0.9390	0.9887
LR test of rho=0:	chibar2(01) = 641.98			Prob >= chibar2 = 0.000		

Table 16 presents the Transfer random effect model. The model estimates the marginal probability of transferring a utility ranges from 0.211 to 0.986 in any given year, from one percentile to the 99th percentile. The model estimates the odds ratio to transfer to a new utility in any given two years at 169.88. the transfer random effect model indicates that two statistically significant explanatory variables are management compensation, compliance with state regulators' quality measures, and management compensation

CONCLUDING COMMENTS

The investor-owned utility industry is a growing-cost industry; state regulators, during rate case proceedings, focus on the short-term rate settings instead of the long-term sustainability of these investor-owned utilities by providing appropriate resources for the essential services and a return on investments to shield the interest of investors and continuousness provision of services to the citizens (Beecher et al., 1993). The study's primary objective is to empirically determine the drivers of utility abandonments and transfers and analyze financial and nonfinancial performance measures to determine if nonfinancial measures, as applied to other industries, are helpful to the utility industry. The study evaluated the relationship of both financial and nonfinancial performance measures with utility abandonments and transfers, together and separately, to answer the question; What are the financial and nonfinancial performance drivers of utility abandonments and transfers, and do the nonfinancial performance measures make a difference? Besides, the study analyzed the time effect on utility abandonments and transfers. The study results indicate that utility abandonments and transfers had different drivers impacting the utility's ability to transfer or abandon its facility. Analyzing the financial performance measures separately, the overall model was statistically significant, with only the liquidity ratio being significant among the seven financial variables. The investor-owned utilities are most likely to abandon or transfer their facility if they have cash flow issues and cannot meet the current payments as it comes due. All the other ratios were not independently significant. The study identified eighteen nonfinancial performance measures, and fourteen qualified for the study. The variables are the plant output equivalent units, obtained by dividing the plant output by the total number of meter equivalents as a measure of efficiency. The no deficiency communication from regulators shows that the utility complies with the regulatory requirement. Compliance with the department of environmental protection, the tax filing classification of the utility, the operating style of management measuring utility run by owners or others, and owners charging salaries to the utility were nonfinancial performance measures that were independently significant. The only nonfinancial performance measure that was not independently significant is utility compliance with a consumptive use permit, which allows a utility to mine or withdraw a stipulated amount of water from the ground. The efficiency ratio was consistently significant throughout the analysis combining abandonment and transfers and treating them separately. Utilities that cannot turn over their plant assets to generate enough revenues are likely to transfer or abandon their facility. The study also reveals that a Class C utility's probability of abandoning its facility was higher than Class A and B utilities. Utilities operated by owners and utilities that owners charge salary as part of the management team, over time, are likely to maintain the utility and not abandon the facility. The abandonment analysis identified and accepted ten explanatory variables, two financial and eight nonfinancial variables; however, the transfer model identified and used thirteen performance measures, three financial and ten nonfinancial performance measures. Class A and B utilities were likely to transfer into a new entity or merge into one organization compared to Class C utilities. The study indicates that regulators, investors, owners, and ratepayers should consider the identified nonfinancial performance measures in assessing utility viability and sustainability.

The study compared the established framework of other industries and used it to establish a framework for the utility industry; nonfinancial performance measures make a difference in analyzing utility viability and sustainability, similar to other industries. The study results also determine that the viability of transfers and abandonments should be treated differently. The number of explanatory variables used to predict utility abandonments differs from utility transfers. Some variables, such as the consumptive use permit, were not accepted as a predictor for abandonment but were included in the transfer predictors. The study has significantly contributed to the utility viability and sustainability assessment and has established a framework for the utility industry employing financial and nonfinancial performance measures. The study has shown that nonfinancial performance measures make a difference in assessing utility transfers and abandonments. A further study is recommended using dominance analysis to determine if the nonperformance measures dominate the performance measures. The dominance analysis will further reinforce the established framework for utility viability and sustainability; it will assist regulators, practitioners, and academicians in apportioning resources during rate case analysis. The study outcomes are limited to states that follow similar utility regulations as Florida; other states may have to expand on the study for its applicability to IOUs. Data on capital funding was not readily available; another limitation that could have expanded the financial performance measures beyond the NRRI-modified ratios by Acheampong et al.

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