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Time matters less: Variance partitioning of return on equity for banks in Uganda

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ABSTRACT

This study investigates variations in the return on equity (ROE) and its determinants within Ugandan banks from 2010 to 2020. Using a two-level hierarchical linear model (HLM), we analyze ROE variability at both time and bank levels, considering temporal effects and the impact of specific bank-level variables on ROE. Variance decomposition reveals that the variability in ROE is more attributable to bank-specific factors than to temporal ones, signifying that individual banks' practices have a more pronounced impact on performance than time-bound fluctuations. Our HLM results, marked by high intraclass correlation coefficients (ICC) that range between 64.4% and 85.8%, underscore the dominance of bank-level variables in accounting for ROE variations. Key determinants of ROE identified by the HLM analysis include inflation, policy uncertainty, assets, equity, profits, profit margin, asset turnover, equity multipliers, and non-performing loans. A primary takeaway from our findings is the potential for operational efficiency enhancements and judicious investment decisions to produce favorable shifts in ROE. For banking managers, this highlights the necessity for ongoing process refinement and meticulous investment scrutiny. We recommend that policymakers mull over incentives for these practices, possibly through regulatory concessions or guidelines endorsing efficient operational benchmarks.

1. Introduction

"Bread today is not the same product as bread tomorrow." This assertion, first introduced by Arrow and Debreu [1] and widely adopted by economists to model diverse economic phenomena, delivers a compelling message about the role of time-based variables and their effects on values. In the banking sector, many studies show that myriad channels and mechanisms allow time effects to infiltrate the balance sheet, dramatically altering financial outcomes [2–4]. For instance, banks charge interest on loans based on the duration to maturity, meaning longer-term loans garner more interest than their short-term counterparts. Banks also lean heavily on time when predicting the likelihood of loan defaults and the resultant effects on profitability. Models for loan defaults incorporating time include the conditional expected time to default [5]. Furthermore, time is crucial in estimating a bank's loss given default [6–8]. The prevailing International Financial Reporting Standard 9 (IFRS 9) carries time-related consequences for bank performance [9]. For example, with low credit risk exposure, banks report only the expected credit loss over 12 months resulting from default events on a financial asset within 12 months post-reporting date. However, if there is a significant surge in credit risk, IFRS 9 dictates the

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recognition of a lifetime expected credit loss [10]. Other routine banking practices, such as loan amortization, discounting, interest compounding, and non-current asset depreciation, all hinge on time. Recognizing time's pivotal roles in standard banking operations and as a critical parameter in financial modeling, this study seeks to analyze the importance of time and bank variables by segregating the time-driven and bank-driven components of return on equity (ROE) fluctuations for Ugandan banks.

Regionally, recent financial turmoil in some East African banks serves as a stark early warning, jeopardizing investors' fund safety and the overall stability of the banking sector. Events like the collapse and subsequent liquidation of major banks between 2015 and 2022 are financially disastrous, potentially leading to significant shareholder fund losses and eroding ROE. For instance, in Kenya, Gathaiya [11] documented the downfall of three major banks between 2015 and 2016. Similarly, in Uganda, Crane Bank faced takeover by the Bank of Uganda in 2016 due to risk mismanagement and insufficient capital [12–14]. Moreover, Afriland First Bank Uganda's voluntary liquidation application was approved by the Bank of Uganda on May 25th, 2022, marking another Ugandan bank's exit [15]. These recent episodes underscore concerns about investor fund safety and regional banking sector stability, suggesting potential significant shareholder fund losses and diminished ROE.

For the banking sector, ROE's examination is crucial due to banks' asset and income nature. The operational efficiency of the bank in generating profits, the efficient utilization of the bank's assets, and the level of equity are critical determinants of ROE [16–19]. According to ROE's theoretical definition, multiple studies have confirmed net profit's positive influence on ROE [20–22]. Yet, the inverse relationship observed for some Ugandan banks indicates other ROE influencing factors, necessitating further exploration. This disparity, where excellent profit growth is paired with waning ROE, complicates investment decisions. Some research indicates that ROE positively impacts a company's stock trading volume, serving as a profit measure for the company's capital [23,24]. Consequently, investors are more attracted to how much of the profit they can receive as a reward for their investment rather than just impressive profit growth.

This study aims to answer several research questions, primarily focusing on ROE variabilities of Ugandan banks. Are there significant variabilities in banks' ROE in Uganda? How much of the variabilities in banks' ROE occur at the time and bank levels? Do time variables play a significant role as determinants of banks' ROE in Uganda? Our research contributes to existing literature in two main ways. Firstly, while there is extensive research employing ROE as a metric for evaluating financial performance and exploring its determinants at the firm level [16–19], the application of variables from the DuPont model to analyze ROE variabilities in Ugandan banks remains underexplored in the literature. In addition to the commonly utilized DuPont variables as ROE determinants, we integrate time-level variables as covariates into the hierarchical linear model (HLM). This allows us to differentiate ROE variabilities at both time and bank levels.

Secondly, this study explores the implications of Ugandan policy uncertainty on ROE within the banking sector. Various studies suggest that heightened policy uncertainty could lead banks to adjust their loan pricing strategies, limit credit availability, and potentially influence the stability of the banking sector [25–27]. Much research utilizes the Economic Policy Uncertainty (EPU) index as an uncertainty metric [18,28,29]. However, the EPU index solely addresses uncertainty linked to economic policies without considering uncertainty related to political events. This limitation prompts us to use the World Uncertainty Index (WUI) proposed by Ahir et al. [30] that considers both economic and political events within countries.

The subsequent sections of this paper are organized as follows: Section 2 provides a literature overview, Section 3 describes the dataset, Section 4 introduces the analytical framework, Section 5 presents empirical findings, Section 6 discusses main results and offers policy implications, and the final section concludes.

2. Theoretical framework and literature review

2.1. The determinants of ROE

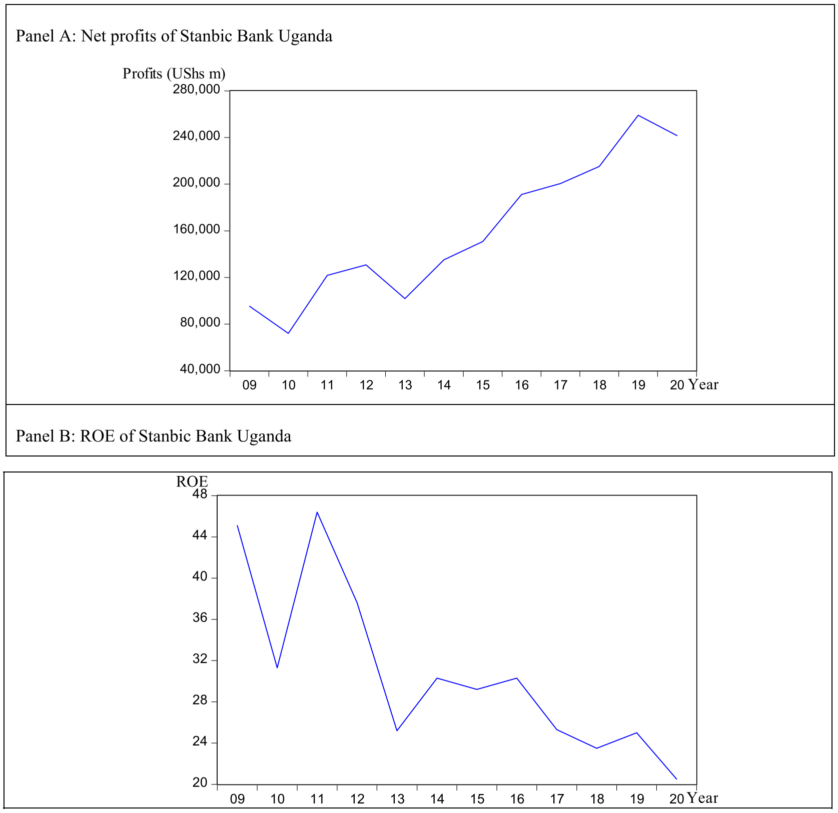
The DuPont model is one of the most widely used models for assessing the factors that determine the ROE [17]. Variance decomposition of ROE in this study relies on how we disaggregate different components of ROE and assess how each component of the DuPont model accounts for the variability in ROE. From the definition, ROE is given by:

$$ROE = \frac{Net\ Profit}{Equity} \tag{1}$$

From equation (1), since net profit is the numerator, net profit and ROE should move in the same direction. However, this is not the case with some banks in East Africa, as depicted in Panels A and B of Fig. 1. The DuPont corporation decomposed the right-hand side of equation (1) into three components, which show how some aspects of the firm's operation affect the ROE. This decomposition gives rise to the DuPont model given by:

$$ROE = \frac{Net\ Profit}{Sales} x \frac{Sales}{Total\ Assets} x \frac{Total\ Assets}{Equity} \tag{2}$$

Equation (2) demonstrates that ROE is a product of three components (activities) which may belong to different responsibility centers of a firm [31]. The first component on the right of equation (2) is the profit margin, the second component is the total asset turnover, and the third component is the equity multiplier or the leverage factor. Accordingly, net profit may increase even if sales have remained constant [32]. For instance, a decrease in the cost of sales and other expenses can lead to an increase in the profit margin and subsequently an increase in ROE. On the other hand, if sales increase but net profits remain unchanged, it suggests that the increase in sales has been accompanied by increased costs, leading to a reduction in the profit margin and ROE. We can think of the profit



Notes: This figure plots net profits (Panel A) and ROE (Panel B) of Stanbic Bank Uganda over the period of 2009 to 2020.

Fig. 1. Net profits and ROE of Stanbic Bank Uganda. Notes: This figure plots net profits (Panel A) and ROE (Panel B) of Stanbic Bank Uganda over the period of 2009–2020.

margin as belonging to the operating activities of the firm. The second component of equation (2) indicates the proportion of sales that is generated by the assets of the firm. It measures the efficiency in asset utilization. As noted earlier, in the banking context, a high proportion of the bank's revenue (interest received) comes from bank loans (bank assets) that the bank gives out.[1] This could lead to an increase in asset turnover and ROE. The third component in equation (2) measures the debt level of an enterprise. The larger the equity multiplier, the higher the debt level of the enterprise. The equity multiplier may fall under the responsibility of the investment function of the firm. If the firm issues more shares while the level of total assets remains unchanged, the equity multiplier decreases and ROE decreases. The complex effects of DuPont variables on ROE have been well explained by Mareta et al. [32].

Some studies have provided a version of the DuPont model that comprises two additional components to capture tax burdens and interest burdens [33,33]. The model is given by:

$$ROE = Tax\ Burden \text{ x } Interest\ Burden \text{ x } Profit\ Margin \text{ x } Asset\ Turnover \text{ x } Equity\ Multiplier \tag{3}$$

According to equations (2) and (3), as the DuPont model is a chain multiplicative model, assessing the impact of a change in a given variable of the DuPont model on ROE becomes difficult. For instance, holding all other factors constant, if sales increase, profit margin will reduce, but total asset turnover will increase. This makes it challenging to determine the net effect on ROE. Similarly, if the firm purchases more assets when the equity level remains unchanged (i.e., using debts to finance assets), total asset turnover will decrease, but equity multiplier will increase. Consequently, determining the net effect of this change in total assets level on ROE may not be straightforward. It is noted that some variables which are important components of equation (3) are computed based on time information. For instance, in a very simple case, if the bank depreciates its assets using the reducing balance method, Francis [34] showed that the depreciated value at the end of the time period t is a function of time, given by:

$$D = B(1 - i)^t \tag{4}$$

[1] Although non-interest income comprises a significant portion of total income for banks in many countries, it is not the case for Ugandan banks. For example, in the financial year 2018, Centenary bank reported total operating income of UGX 512,976,572,000, of which interest income accounted for UGX 426,844,187,000. This represents approximately 83% of the bank's total operating income.

in equation (4), where D denotes the depreciated amount at the end of the time period (the net book value), B denotes the original book value of the asset, i denotes the interest rate, and t denotes the time period, the depreciated amount D is a function of time t. This captures asset utilization, which determines asset turnover and ultimately affects ROE. Additionally, the depreciation expense, obtained from equation (4), is charged against profit and loss accounts in the income statement, thereby impacting the profit margin and ROE. Furthermore, other key banking practices, such as loan amortization, compounding of interest, and valuation of investments, are theoretically and practically computed based on the length of time. Thus, based on this theoretical underpinning, it can be concluded that time effects influence ROE through different channels.

2.2. Hierarchical linear modelling of ROE

The dynamics of ROE are not constant over time but rather uncertain and time-dependent [35]. There are several reasons why ROE tends to be time dependent. ROE is influenced by a wide range of microeconomic factors that can change over time, including changes in company strategies, management decisions, competitive pressures, technological advancements, and shifts in customer preferences [36]. In addition, ROE can vary cyclically due to economic fluctuations. Economic cycles, such as recessions and expansions, can cause ROE to exhibit patterns of growth, decline, or stagnation over time [37]. These factors introduce unpredictability into the ROE's trajectory. Therefore, ROE has both predictable and unpredictable components. The predictable component (drift) represents the expected growth or trend in ROE over time, while the unpredictable component (volatility) represents random fluctuations around this trend.

To capture the random and uncertain nature inherent in ROE, the hierarchical linear model (HLM) integrates fixed and random effects, yielding a nuanced representation that parallels the well-established concepts of drift and volatility in stochastic processes [35]. By utilizing the fixed effect, HLM encapsulates the drift component of the ROE. Just as drift embodies the anticipated growth rate in traditional stochastic models, the fixed effect in the HLM framework encompasses the systematic, predictable trends within the financial data [38]. This fixed effect can be understood as the baseline trajectory of ROE over time, reflecting the underlying trends driven by various external and internal factors that contribute to a company's financial performance. Concurrently, the integration of random effects in the HLM model mirrors the unpredictable and random component evident in equations describing financial variables. The random effect introduced by the HLM framework captures the inherent randomness and uncertainty associated with financial variables such as ROE. This element acknowledges the myriad of complex factors that can influence a company's financial performance in unpredictable ways, echoing the intrinsic volatility witnessed in financial markets. Furthermore, HLM can partition the variance of ROE because it incorporates both fixed effects, which capture systematic trends and expected growth, and random effects, which account for unanticipated variations.

An important distinction arises when comparing HLM to other modeling approaches, such as the Markovian switching models. While Markovian models often rely on a limited set of unobservable state variables to explain changes in financial variables, the HLM approach expands the analytical scope by accommodating a broader range of variables beyond just time [39]. This adaptability is a significant advantage, as it acknowledges the multifaceted nature of financial data. In practical terms, HLM can account for the influence of various exogenous and endogenous factors, including economic indicators, management decisions, industry trends, and more. This capacity to incorporate multiple variables in the estimation of variance components enhances the model's ability to comprehensively capture the intricate dynamics of ROE over time.

2.3. Empirical evidence of ROE determinants

Empirical results from various studies have unveiled that not all components of the DuPont model hold equal significance when assessing a firm's ROE. For instance, Kijewska [40] conducted a study on the determinants of ROE for companies in the metallurgy and mining sector in Poland, discovering that the primary factor contributing to the decline in ROE was the profit margin. Similarly, Sayani et al. [41] investigated the determinants of ROE for commercial banks in the United Arab Emirates and identified efficient asset utilization and the quality of assets on the banks' balance sheets as pivotal factors affecting ROE. Anarfi et al. [42] explored the determinants of ROE for manufacturing companies in the Czech Republic, finding that the profit margin and asset turnover had positive and significant effects on ROE, while the equity multiplier had a negative and significant impact. In a cross-sectional analysis of data from manufacturing firms in the USA, Germany, and Japan, Weidman et al. [19] demonstrated that the net profit margin played the most critical role in determining ROE, whereas total asset turnover had the least influence. Furthermore, certain studies have examined the relationship between ROE and other financial ratios. For example, Şamiloğlu et al. [43] observed a significant and negative correlation between ROE and earnings per share. In the context of commercial banks, Farooq et al. [21] emphasized the significance of additional ratios, such as the deposit ratio, leverage ratio, and operational efficiency, as determinants of ROE. Apart from firm-specific factors, Ozili and Arun [18] considered country-specific factors as determinants of ROE. Their findings revealed that high economic policy uncertainty positively impacts bank profitability in Asia and the Americas, leading to higher return on equity during periods of elevated economic policy uncertainty. These findings underscore the necessity of assessing specific components of the DuPont model, relevant financial ratios, and country-specific factors when analyzing and interpreting ROE across diverse industries and sectors. The magnitude of these factors varies, and comprehending their influence on ROE can yield valuable insights for financial analysis and decision-making.

Despite several studies of ROE determinants as aforementioned, they have not incorporated any temporal variables into their models [16,17,19,24]. On the other hand, parallel studies including Jin [44] and Konstantakis et al. [45] indirectly integrated time-related elements by utilizing lagged values of financial variables as predictors for future values. The primary objective of these papers revolves around short-term and long-term forecasting. Sinha and Samanta [46] stand as an exception within this category, employing time dummies to capture temporal effects on firm leverage. Nonetheless, the direct incorporation of temporal measures as determinants of financial variables, especially ROE, remains limited in the existing literature. The present study bridges this gap by introducing time variables as covariates in the determination of ROE.

3. Dataset

The data utilized for this study was sourced from the financial statements of banks in Uganda over the period spanning from 2010 to 2020. While the financial reports were publicly accessible online, a significant data constraint arose due to the absence of financial reports for certain years. Particularly, a conspicuous absence of financial reports for years preceding 2010 was observed among many Ugandan banks. This phenomenon primarily stems from the fact that a considerable portion of banks operating in Uganda are subsidiaries of foreign-owned banks. Before 2010, the majority of these institutions had yet to establish a presence in the Ugandan market. The primary focus of this research centers on unraveling the variabilities inherent in banks' ROE. The decision to exclude time series data for the years 2008 and 2009 arises from a prudent consideration of the tumultuous financial crisis spanning 2008–2009, which profoundly impacted banks globally, including those within Uganda. The inclusion of these years would introduce erratic shifts in volatilities, potentially magnifying the variance component at the time level. As a consequence of these considerations, the resultant dataset comprises a total of 92 firm-year observations. It is imperative to acknowledge that this sample size is limited due to pragmatic constraints stemming from data availability. To address the challenge posed by the modest sample size, a range of measures have been implemented within the analytical model. Specifically, restricted maximum likelihood estimation and Kenward-Roger adjustment, as elucidated by McNeish [47], have been deployed to counteract this concern.

The dataset used in this study is characterized by its unbalanced nature, implying that certain banks lack complete data coverage throughout the entire examined period. The selected sample encompasses banks with available data, including Centenary Bank Uganda, Stanbic Bank Uganda, Bank of Baroda Uganda, Housing Finance Bank, DFCU Bank, Pride Microfinance Bank, ABC Bank Uganda, Absa Bank, Bank of Africa Uganda, and Diamond Trust Bank Uganda. The financial reports of these banks are available online on their respective websites, providing essential information about operating income, net profits, total equity, total assets, and ROE. To calculate key financial metrics, such as profit margins, total asset turnover, and equity multiplier, the formulae outlined in equation (2) were employed. Consequently, the variables utilized at the bank level comprise income, net profit, assets, equity, profit margin, total asset turnover, and equity multiplier.

At the time level, the study employed methodologies to capture time-related effects. Initially, drawing from the frameworks proposed by Bajari et al. [48] and Sinha and Samanta [46], the study employed time-varying factors, encompassing macroeconomic indicators and other banking institutional variables, as proxy variables to represent time. Given the singular country focus of this analysis, the incorporation of these macroeconomic and institutional variables is both pertinent and suitable. Specifically, data encompassing variables such as GDP growth rate, inflation rate, policy uncertainty, the density of bank branches per 1000 individuals, the prevalence of borrowers per 1000 individuals, and the incidence of non-performing loans in Uganda were obtained from the World Bank database (https://data.worldbank.org/).

Data for the policy uncertainty index of Uganda were gathered from the World Uncertainty Index (WUI) database (https://worlduncertaintyindex.com/data/). Policy uncertainty creates a climate of uncertainty and caution, which can affect banks' willingness to lend and invest, impacting their overall profitability [18,26,27,49]. This negative effect on ROE results from the diverse ways in which uncertainty shapes the broader economic landscape and the functioning of financial institutions. Previous research on the effect of policy uncertainty on corporate financial performance typically employs the Economic Policy Uncertainty (EPU) index as an indicator of policy uncertainty [18,28,29]. However, limitations exist within the EPU index. It solely addresses uncertainty linked to economic policies—specifically, monetary, trade, and fiscal policies—without considering uncertainty related to political events. Additionally, the calculation of the EPU index for different nations lacks a unified foundation, raising concerns about precision, reliability, and potential ideological bias [50]. To overcome these limitations, this study utilizes Uganda's policy uncertainty of the WUI proposed by Ahir et al. [30].

The WUI index incorporates both economic and political developments for 143 countries. This index has gained widespread recognition in recent times, with numerous studies referencing it as a measure of policy uncertainty [30,50–53]. With reference to Ahir et al. [30], the WUI index is constructed from Economist Intelligence Unit (EIU) country reports. Notably, the WUI surpasses the Economic Policy Uncertain (EPU) index by deriving computations from a unified source—the EIU reports—and by incorporating both economic and political developments within nations [54]. The WUI is quarterly calculated by tallying the percentage of the word "uncertain" (or its variations) in the EIU country reports. Subsequently, the WUI is rescaled by multiplication with 1,000,000. A higher numerical value corresponds to greater uncertainty, while a lower value signifies the opposite. For instance, an index of 200 indicates that the term "uncertainty" constitutes 0.02% of all words. Given that the EIU reports are generally around 10,000 words long, this translates to approximately 2 occurrences of the word per report. To derive an annual WUI, the sum of quarterly WUI values is divided by the number of quarters.

Adopting a commonly employed approach in time-series analyses, the study embraced a time-trend strategy to encapsulate the temporal dimension. Here, numerical codes were attributed to each year, commencing from the baseline year 2010 and extending through the final year 2020. The appeal of this technique rests on its theoretical alignment with the inherent irreversibility of time, as deliberated within domains like physics and economics [55]. Practically, organizational decision-making often leverages the current year's experiences to inform future-year choices, which may give rise to incremental behaviors like incremental budgeting. These practices potentially influence the overall performance trajectory of a firm in subsequent periods. Moreover, this approach aligns cohesively with various banking practices, including compounding, loan amortization, and depreciation, which inherently involve the sequencing of time in ascending order. As such, the allocation of numeric codes to denote time (year) within a time-trend structure emerges as a judicious and sound choice.

4. Analytical framework

The present study employs the hierarchical linear model (HLM) to explore the multilevel impacts of time and firm-specific variables on ROE. This estimation approach has been widely employed in prior research focused on elucidating the variability of financial variables, including the profitability and capital structure of corporations [46,56]. The analytical methodology of variance decomposition, realized through the utilization of hierarchical linear modeling, is particularly endorsed due to the inherent nesting structure of the data. At the foundational modeling level, temporal variables are introduced as independent factors influencing the dependent variable, ROE, with the added dimension of being nested within the level-two variable, representing the bank. This hierarchical arrangement mirrors the interdependence between time-based factors and bank-specific operating and investment variables, validating the utilization of hierarchical linear modeling to capture the complexities involved in modeling the bank's ROE. A comprehensive understanding of the underlying rationale, conceptual framework, and procedural intricacies inherent to this model can be derived from seminal works such as those authored by Raudenbush and Bryk [57] and Woltman et al. [58].

HLM, constituting a mixed-effects model, incorporates both fixed effects and random effects components. Both the fixed and random parts of the model are assumed to be linearly related to the outcome. A comprehensive blueprint of the model's structure and the associated estimation procedures is available in the Stata documentation [39], excerpted and detailed in equation (5) below.

$$y = X\beta + Zu + \epsilon \tag{5}$$

where y is a $n \times 1$ vector of the outcome variable (response), X is $n \times p$ design matrix of covariates for fixed effects β, Z is a $n \times q$ matrix of covariates for random effects u, and ϵ is a $n \times 1$ matrix of error terms. The fixed effects Xβ are analogous to linear covariates in ordinary least squares regression. For the random effect, $Zu + \epsilon$, u is assumed to be orthogonal to ϵ. For clustered data, as in this case, the n observations are grouped or clustered. It is not necessary for the clusters to have the same size. Therefore, in a clustered situation, equation (5) can be written as shown in equation (6).

$$y_i = X_i\beta + Z_iu_i + \epsilon_i \tag{6}$$

The subscript $i = 1, \ldots, M$ represents the clusters, with cluster i consisting of n_i observations. The response y_i comprises the rows of y corresponding to the i^{th} cluster, X_i and ϵ_i are defined as before. The random effect u_i can be thought of as M realizations of a $q \times 1$ vector that is normally distributed with mean 0 and a $q \times q$ variance matrix.

In this case, there are two mixed levels, with level one being time and level two being bank. In such a case, the random effects can only be specified at level two, the bank. In Stata, the multilevel mixed effects model in equation (5) above is fitted either directly using the "mixed" command or by choosing a statistic for multilevel mixed effects models, followed by the regression technique used. Then, the estimation method is chosen. The two methods available in Stata are maximum likelihood and restricted maximum likelihood. We employed the restricted maximum likelihood method because of its power to correct small sample bias in the estimation. Usually, with small samples, restricted maximum likelihood provides accurate estimates [38,59].

The problem arises with the maximum likelihood method when the level-two sample size is small because this method estimates fixed effects and variance components simultaneously, leading to an inflation of type I error. Restricted maximum likelihood minimizes this problem by estimating fixed effects and variance components separately [47]. The fixed effect component is fitted where the dependent variable, ROE, was entered, followed by level-one covariates. As noted earlier, this part is analogous to ordinary least squares regression. The random effect component was included by creating the random effect equation in the next dialogue box. As mentioned earlier, the yearly ROEs of banks were clustered among banks, so at level two, bank ID was used to identify level-two variables. The degrees of freedom were determined using the Kenward-Roger adjustment to minimize errors due to the small sample size [47]. Our full modeling strategies are as follows, starting with the specification of an empty model.

4.1. The empty model

The starting point in hierarchical linear modeling is to specify an empty model, shown in equation (7), which does not contain any independent variables. This helps to assess the relative importance of higher-level variables on variability in ROE.

$$ROE_{ist} = \beta_{ist} + \varepsilon_{ist} \tag{7}$$

where ROE_{its} is the return on equity for bank i in the banking sector s in year t, β_{ist} is the intercept that measures the mean ROE for bank i in the banking sector s over the time period t, and ε_{ist} is the random error assumed to be normally distributed with zero mean and variance, representing the variance of ROE over time.

The mean ROE over time (β_{ist}) for a given bank is a function of the grand mean (μ_{st}) of ROE for all the banks plus the random error, which can be expressed as in equation (8).

$$\beta_{ist} = \mu_{st} + \varnothing_{ist} \tag{8}$$

where μ_{st} is the grand mean of all banks in the sample, and $\varnothing_{ist}$ is the residual for the mean ROE for banks over the period t. Therefore, in a reduced form, equations (7) and (8) can be combined to give equation (9).

$$ROE_{ist} = \mu_{st} + \varnothing_{ist} + \varepsilon_{ist} \tag{9}$$

Equation (9) is the empty model made up of the fixed component (μ_{st}) and two random components ($\varnothing_{ist}$ and ε_{ist}). The values of the random components connote the relative importance of bank and time in the variance partitioning. The model in equation (9) is first estimated without including any independent variables. This helps to show the random variation in intercepts (mean ROE) across banks.

4.2. The random intercept model with fixed level-one covariates

Commencing with the null model presented in equation (9), we proceeded to incorporate independent variables in a sequential manner, commencing with level-one (time) variables, and subsequently, bank-related variables. The time-level variables encompass three distinct categories: time-trend, country-specific variables (GDP growth, inflation, and policy uncertainty), and industry-specific variables (non-performing loans, the number of bank branches per 1000 individuals, and the number of borrowers per 1000 individuals). We introduced them into the model sequentially to ascertain their impact on ROE. We then evaluated their cumulative influence by estimating a random intercept model with fixed coefficients that encompassed time-trend, GDP growth, inflation, and the policy uncertain index, in conjunction with the bank-level variables. However, for the third category of time-level variables (non-performing loans, the number of bank branches per 1000 individuals, and the number of borrowers per 1000 individuals), we exclusively integrated them into the random intercept and random coefficient models, owing to the rationale expounded in the ensuing section. The model containing only the time trend is depicted in equation (10).

$$ROE_{ist} = \mu_{st} + \delta T + \varnothing_{ist} + \varepsilon_{ist} \tag{10}$$

Equation (10) represents a random intercept model encompassing a single covariate (T), the coefficient of which captures the influence of the time trend on ROE. The intercept denotes the grand mean ROE for all banks within the sample. The model incorporating time-varying macroeconomic variables is presented as equation (11).

$$ROE_{ist} = \mu_{st} + \theta_1 INF + \theta_2 GDP + \theta_3 PUI + \varnothing_{ist} + \varepsilon_{ist} \tag{11}$$

Equation (11) includes inflation (INF), GDP growth rate (GDP), and the policy uncertainty index (PUI) as time-varying macroeconomic variables at the time level. Building upon equations (10) and (11), we formulated the model integrating time-trend, inflation, GDP growth rate, and the policy uncertainty index in equation (12).

$$ROE_{ist} = \mu_{st} + \beta_1 T + \beta_2 INF + \beta_3 GDP + \beta_4 PUI + \varnothing_{ist} + \varepsilon_{ist} \tag{12}$$

Expanding on equation (12), we incorporated the influence of bank-level variables, yielding equation (13).

$$ROE_{ist} = \mu_{st} + \beta_1 T + \beta_2 INF + \beta_3 GDP + \beta_4 PUI + \beta_5 Assets + \beta_6 Equity + \beta_7 Incomes + \beta_8 Profits + \beta_9 PM + \beta_{10} TAT + \beta_{11} EM + \varnothing_{ist} + \varepsilon_{ist} \tag{13}$$

Apart from time trend, GDP growth rate (GDP), inflation rate (INF), and the policy uncertainty index (PUI), the explanatory variables at the bank level include assets (Assets), equity (Equity), incomes (Incomes), profits (Profits), profit margin (PM), total asset turnover (TAT), and equity multiplier (EM). Characterized by covariates capturing fixed effects and residuals ($\varnothing_{ist}$ and ε_{ist}) encompassing the two hierarchical levels, this model is classified as a mixed-effects model.

4.3. The random intercept and random coefficient model with additional level-one variable

In this context, we operate under the assumption that certain level-one (time-level) variables are not only influenced by bank-level variables, but are also subject to changes in their slope coefficients concurrent with shifts in their intercepts. Specifically, the activities of banks hold the potential to impact select time-level variables, thereby engendering fluctuations in their slope coefficients that align with shifts in intercepts. The theoretical explication of the intricate links connects GDP growth, inflation, and policy uncertainty to bank credit, encompassing avenues such as investment, savings, monetary policy transmission, business cycles, and asset price misalignment [18,60]. From an empirical perspective, numerous studies have robustly identified causal linkages between indicators of banking sector development and macroeconomic variables [61,62]. Consequently, it is judicious to posit the coefficients associated with GDP growth, inflation, and policy uncertainty (time-level variables) as random coefficients, their values susceptible to influence by banking activities.

Within this model, we have also incorporated certain banking institutional variables at the time level, namely: non-performing loans (NPL), the number of borrowers per 1000 individuals (Borrowers), and the number of bank branches per 1000 individuals (Branches). While these variables exhibit temporal fluctuations, they equally represent direct consequences of decisions undertaken by banks. For instance, earlier literature, particularly Rajan [63], has elucidated the theoretical framework underpinning bank loan borrowers and credit policies, demonstrating that the tally of borrowers at any given point is contingent upon dynamic credit policies of the bank. In essence, credit policies shift once the bank has ascertained the true creditworthiness of borrowers, a determination reached after a certain interval. Non-performing loans, in addition, bear links to operational efficiency, capital adequacy, and the financial health of banks [64]. Furthermore, these non-performing loans are influenced by the oscillations of business cycle shocks (time) and other pertinent banking variables [65].

Our model incorporating random intercepts and random slope coefficients resonates with the structure outlined in equation (10), albeit distinguished by the inclusion, at the time level (level one), of variables such as NPL, Borrowers, and Branches. Moreover, we have accounted for the variability in the slope coefficients of these variables, alongside those associated with inflation, GDP growth, and the policy uncertainty index in alignment with the rationale explained earlier. The comprehensive specification of this model is presented in equation (14).

$$\begin{aligned} ROE_{ist} &= \mu_{st} + \beta_1 T + \beta_2\, INF + \beta_3 GDP + \beta_4 PUI + \beta_5 Assets + \beta_6 Equity \\ &+ \beta_7 Incomes + \beta_8 Profits + \beta_9 PM + \beta_{10} TAT + \beta_{11} EM \\ &+ \beta_{12}\, NPL + \beta_{13}\, Borrowers + \beta_{14}\, Branches + \varphi_{its} + \epsilon_{its} \end{aligned} \tag{14}$$

5. Empirical results

5.1. Variability in ROE

Table 1 presents a summary of ROE statistics. Column (a) provides the mean ROE for each bank during the study duration. Notably, Stanbic Bank exhibited the highest mean ROE (29.5%), followed by Centenary Bank (24.8%). Conversely, ABC Capital Bank Uganda reported the lowest ROE at −0.16%. The variability within ROE across all banks is evident from the substantial standard deviations presented in column (b) and coefficients of variation in column (c). DFCU Bank displayed the greatest variability, evidenced by its standard deviation of 7.9%, whereas Bank of Baroda Uganda demonstrated relative stability with a standard deviation of 2.6%.

When the standard deviations are normalized by dividing them by their respective means to derive coefficients of variation, the observed ROE variabilities span from medium to very high, aligning with classification criterion proposed by Gomes [66]. This criterion, widely employed in various studies, designates coefficients of variation below 10% as low, between 10% and 20% as medium, between 20% and 30% as high, and surpassing 30% as very high [67]. Applying this classification unveils that none of the bank's ROE coefficients of variation can be characterized as low. Bank of Baroda Uganda's coefficient of variation (15%) qualifies as medium, while those of Centenary Bank and Absa Bank can be categorized as high. Remarkably, the coefficients of variation for Bank of Africa Uganda (104%) and ABC Capital Bank Uganda (−1562%) indicate an extreme degree of instability in ROE values. Notably, the coefficient of variation for ABC Capital Bank Uganda is not only very high but also negative due to a negative mean profit (loss) reported.

Furthermore, as depicted in Table 1, the standard deviation of means of ROE for all banks in column (f) reveals interbank variations in mean ROE (8.7%, between-bank variation) exceeding variations within individual banks (standard deviation). This high interbank variation in mean ROE (8.7%) suggests disparities in banking practices, operational processes, and strategic approaches adopted by each bank to generate ROE. Conversely, variations in ROE from one period to the subsequent period within a specific bank, attributed to time-related macro environmental factors influencing the entire industry, appear to be relatively subdued. In essence, the descriptive statistics suggest that interbank variations (standard deviation of mean ROE of 8.7%) eclipse variations at the time level. Lastly, an examination of Table 1 reveals that the mean ROE for Stanbic Bank, Centenary Bank, DFCU Bank, Pride Microfinance Bank,

Table 1
Summary statistics of banks' ROE.

Bank	Mean ROE for each bank (a) %	Std dev ROE for each bank (b)%	CV (c)%	Grand mean of means of ROE (d)%	Deviation of mean ROE from grand mean (e) %	Std dev of means of ROE for all banks (f) %
Stanbic Bank	29.5	7.3	25	15.2	14.3	8.7
Centenary Bank	24.8	5.3	21	15.2	9.6	8.7
DFCU Bank	20.6	7.9	38	15.2	5.4	8.7
Pride Microfinance Bank	18.2	6.8	37	15.2	3.0	8.7
Bank of Baroda Uganda	17.3	2.6	15	15.2	2.1	8.7
Absa Bank	14.6	3.1	21	15.2	−0.6	8.7
Housing Finance Bank	9.6	4.3	45	15.2	−5.6	8.7
Bank of Africa Uganda	9.2	9.6	104	15.2	−6.0	8.7
DTB Uganda	8.5	3.6	42	15.2	−6.7	8.7
ABC Capital Bank Uganda	−0.16	2.5	−1562	15.2	−15.36	8.7

Notes: This table reports summary statistics of return on equity (ROE) for banks in Uganda. The coefficient of variation (CV) is calculated by dividing column (b) by column (a).

and Bank of Baroda Uganda exceeds the industry average of 15.2% (the grand mean in column (d)). This implies that their mean ROE over time mirrors the overall mean (the grand mean) of all banks across time, supplemented by a positive random residual value. Conversely, Absa Bank, Housing Finance Bank, Bank of Africa Uganda, DTB Uganda, and ABC Capital Bank Uganda register mean ROE beneath the industry average (the grand mean in column (d)), their values influenced by a negative residual. These residual values are reflected in the deviations of mean ROE for the respective bank from the grand mean in column (e) of Table 1.

Table 2 presents descriptive statistics for key variables that are integral to the DuPont model's consideration of major determinants of ROE. These variables include banks' assets, income, equity, and profits. The descriptive statistics highlighted in Table 2 substantiate the observed trends within ROE as delineated in Table 1. As an illustration, Stanbic Bank Uganda, possessing the highest mean assets (UGX 4,482,366 million), the highest mean equity (UGX 660,638 million), the highest mean income (UGX 566,420 million), and the highest mean profits (UGX 165,431 million), accordingly exhibits the highest mean ROE of 29.5%. The coherence in variability patterns among these bank-level variables, reflected in Table 2, corresponds to the variability pattern observed within ROE as demonstrated in Table 1. For instance, DFCU Bank, characterized by the most pronounced variability in ROE (standard deviation of 7.9% and coefficient of variation of 38%) as depicted in Table 1, similarly registers one of the most notable variabilities in assets (coefficient of variation of 52%), the highest variability in equity (coefficient of variation of 70%), and among the highest variabilities in income (coefficient of variation of 51%) and profit (coefficient of variation of 64%) as indicated in Table 2. This analogous propensity of heightened variability in ROE (Table 1) aligned with corresponding amplified variabilities in the bank-level variables (Table 2) is also observable for Bank of Africa Uganda and other institutions, including ABC Capital Bank. These consistent relationships between variability trends in bank-level variables and those within ROE suggest the potential of bank-level variables to substantially elucidate ROE variability. It underscores the significance of upholding stability within a bank's profitability, income, equity, and assets to ensure a steady ROE.

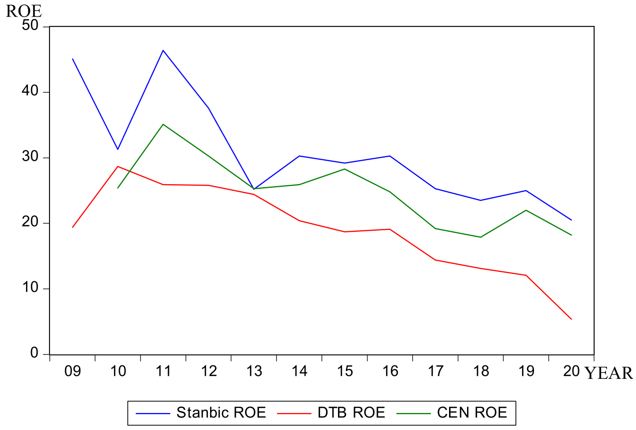
For some Ugandan banks, despite growth in incomes and profits, there is an apparent ROE decline, suggesting an inverse relationship between ROE and either net profit or income. Panels A and B of Fig. 1 illustrate this problematic situation, based on data extracted from Stanbic Bank Uganda. A careful examination of financial results for other banks in Uganda, such as Centenary Bank, Diamond Trust Bank, and Equity Bank, also confirms this inverse relationship between net profits and ROE. Generally, as shown in Fig. 2, graphs of ROE for some Ugandan banks are declining over time.

The fluctuations evident in the values of the bank-level variables, as delineated in Table 2, possess ramifications not only for the banks' ROE but also for their overall stability. These results in Table 2 proffer valuable insights for broader research on firm stability. For instance, Ando et al. [68] discerned the pronounced influence of the relationship between growth rates of income, asset growth

Table 2
Summary statistics of the bank-level variables.

Bank	Asset			Equity		
	Mean asset (UGX million)	Std dev asset (UGX million)	CV (%)	Mean equity (UGX million)	Std dev equity (UGX million)	CV (%)
Stanbic Bank	4,482,366	1,887,091	42	660,638	343,255	52
Centenary Bank	2,201,033	1,185,253	54	435,705	256,420	59
DFCU Bank	1,911,899	988,017	52	291,031	204,735	70
Pride Microfinance Bank	209,649	97,605	47	76,088	42,978	56
Bank of Baroda Uganda	1,503,300	400,379	47	300,566	103,865	35
Absa Bank	2,462,325	838,294	34	410,618	86,492	21
Housing Finance Bank	666,486	211,239	32	137,146	49,903	36
Bank of Africa Uganda	605,407	193,779	32	82,637	34,943	42
DTB Uganda	1,566,344	170,994	11	240,970	64,998	27
ABC Capital Bank Uganda	57,947	4,747	8	30,627	1,346	4
Bank	**Income**			**Profit**		
	Mean income (UGX million)	Std dev income (UGX million)	CV (%)	Mean profit (UGX million)	Std dev profit (UGX million)	CV (%)
Stanbic Bank	566,420	168,361	30	165,431	59,963	36
Centenary Bank	408,018	196,851	48	91,018	42,895	47
DFCU Bank	275,214	140,335	51	48,168	30,604	64
Pride Microfinance Bank	74,061	58,868	79	11,835	3,941	33
Bank of Baroda Uganda	151,110	38,185	25	51,190	18,102	35
Absa Bank	280,198	119,345	43	58,768	14,773	25
Housing Finance Bank	73,329	25,525	35	13,121	7,645	58
Bank of Africa Uganda	53,462	28,464	53	8,371	8,149	97
DTB Uganda	172,476	10,479	6	18,470	2,243	12
ABC Capital Bank Uganda	7,694	193	2	−48.6	771	−1,586

Notes: This table reports summary statistics of the bank-level variables for banks in Uganda. The coefficient of variation (CV) is computed for all bank-level variables including asset, equity, income, and profit.



Notes: This figure plots return on equity (ROE) obtained from financial reports of Stanbic Bank Uganda (Stanbic), Diamond Trust Bank (DTB), and Centenary Bank (CEN) over the period of 2009 to 2020.

Fig. 2. Trends in ROE for banks in Uganda
Notes: This figure plots return on equity (ROE) obtained from financial reports of Stanbic Bank Uganda (Stanbic), Diamond Trust Bank (DTB), and Centenary Bank (CEN) over the period of 2009–2020.

rates, and debt ratios on firm stability. They interpreted low profitability as a potential marker of instability. Equally, the equity ratio, denoting shareholders' equity divided by assets, serves as a proxy for financial stability [69]. More recently, Kyissima et al. [70] underscored profitability's substantial impact on the stability of capital structure. In the ensuing analysis, we will elaborate on the segmentation of these variations into time-driven and bank-driven components.

5.2. Variance partitioning of ROE

Table 3 reports descriptive statistics of all variables for HLM estimations. Table 4 depicts the outcomes of variance partitioning analysis derived from HLM estimations. The derived intraclass correlation coefficient (ICC), ranging between 0% and 100%, substantiates the justification for data clustering within this investigation. If the ICC approaches 100%, this indicates that the bank-level factor predominantly influences the variation in ROE, overshadowing the time-level factor. Conversely, if the ICC is near 0%, it suggests that the time-level factor is the primary contributor to the variation in ROE, rather than the bank-level factor. Within the context of the empty model, the ICC of 64.4% signifies that 64.4% of the observed variations in ROE can be explicated by the inherent clustering tendencies of ROE exhibited across diverse banks. Notably, the "between bank" variation (70.66) surpasses the corresponding "within bank" variation (39.03), denoting that the bank-level factor accounts for 64.4% of the comprehensive variations witnessed within ROE. This emphasizes that the bank-level influence on ROE holds greater sway compared to the temporal impact on ROE. This prevailing pattern is consistently manifested across all models illustrated in Table 4. In fact, as discerned across all models, both the clustering effect and the bank-level effect burgeon with the incorporation of additional control variables.

Upon the introduction of inflation, GDP growth, and policy uncertainty as control variables at the time level, the intraclass correlation coefficient (ICC) escalates to 69.3%, indicative of an amplified variance between banks. This phenomenon might imply that

Table 3
Summary statistics of variables in the hierarchical linear model.

Variable	Mean	Median	Std Dev	Min.	Max.
ROE	16.52	16.25	9.91	−12.50	46.40
Time trend	6.61	7.00	3.06	1.00	11.00
Inflation	5.46	4.90	3.49	2.62	15.13
GDP growth	5.02	5.11	1.68	2.95	9.39
Policy uncertainty	0.13	0.12	0.09	0.02	0.30
Assets	1,628,214.00	1,166,286.00	1,558,703.00	49,941.00	8,578,898.00
Equity	276,016.70	192,686.50	253,883.10	17,947.00	1,243,439.00
Incomes	217,798.20	147,370.50	205,763.20	7,380.00	831,390.00
Profits	50,531.45	26,737.00	57,696.51	−6,780.00	259,094.00
Profit margin	0.19	0.21	0.12	−0.41	0.46
Total asset turnover	0.15	0.12	0.07	0.04	0.35
Equity multiplier	5.72	5.58	2.00	1.70	10.43
NPL	4.99	4.94	2.23	1.86	10.40
Borrowers	38.27	30.95	20.73	17.41	70.72
Branches	2.72	2.67	0.22	2.45	3.05

Notes: This table reports summary statistics of variables used in the hierarchical linear model (HLM) estimations.

Table 4
Variance partitioning of banks' ROE.

Model				Conclusion
Level	Amount	Percentage	ICC	
Model 1: Empty model				
Time Level	39.03 (6.10)	35.6		
Bank Level	70.66 (35.73)	64.4	64.4 (0.12)	Bank effects > Time effects
Model 2: Level-one covariate: time trend				
Time Level	33.47 (5.26)	35.2		
Bank Level	61.57 (31.10)	64.8	64.8 (0.12)	Bank effects > Time effects
Model 3: Level-one covariates: inflation, GDP growth, and policy uncertainty				
Time Level	28.89 (4.60)	30.7		
Bank Level	65.13 (32.48)	69.3	69.3 (0.11)	Bank effects > Time effects
Model 4: All level-one covariate				
Time Level	28.76 (4.52)	31.4		
Bank Level	62.83 (31.42)	68.6	68.6 (0.11)	Bank effects > Time effects
Model 5: All level-one and level-two covariates				
Time Level	3.40 (0.59)	14.8		
Bank Level	19.53 (12.30)	85.2	85.2 (0.08)	Bank effects > Time effects
Model 6: Random intercept and random coefficients with additional level-one variables				
Time Level	3.27 (0.59)	14.2		
Bank Level	19.72 (12.59)	85.8	85.8 (0.08)	Bank effects > Time effects

Notes: This table reports the estimated variance components of hierarchical linear model (HLM) estimations. ICC denotes the intraclass correlation coefficients. The standard errors are in parenthesis.

the influence of these time-level variables (inflation, GDP growth, and policy uncertainty) on banks' ROE could vary. In line with the perspectives of Hamadi and Awdeh [71], the asymmetrical impacts of inflation and GDP growth on banks' ROE could be attributed to the heterogeneity within the sample banks. For instance, foreign banks may experience less vulnerability to fluctuations in the country's GDP growth and inflation rates compared to their local counterparts [71,72].

It is noteworthy that the incorporation of the time-trend variable in isolation within the initial model yielded a marginal alteration in the "between bank" variation. Specifically, the proportion of between bank variation increased modestly from 64.4% to 64.8%. This suggests a near-equitable influence of the time-trend variable on all banks in the sample. However, upon integrating all level-one and level-two variables into the model with fixed slope coefficients, a pronounced clustering effect emerges, characterized by an ICC of 85.2%. Consequently, the between bank variation significantly surpasses the within bank variation, which is grounded in temporal dynamics. This conspicuous shift underscores the substantial contributions of the bank-level variables integrated into the model, positing them as pivotal drivers of the between-bank variations observed in ROE.

Anticipatedly, Table 4 discloses a substantial residual component within the empty model, measuring 39.03. This value diminishes significantly to 3.40 upon the incorporation of all time-level and bank-level covariates into the model. This reduction underscores the efficacy of the independent variables introduced to the model in explaining the observed variability in ROE. However, in the context of the random intercept and random coefficient model, the incorporation of additional time-level variables (specifically, non-performing loans, the number of borrowers per 1000 individuals, and the number of branches per 1000 individuals) and their coefficients, along with the coefficients of inflation, GDP growth, and policy uncertainty allowed to vary, engendered a further amplification of the bank-level effect. The proportion of variation in ROE attributed to the bank level escalated to 85.8%. This augmentation in the bank-level effect implies that when the slopes of these variables are allowed to exhibit variability, the disparities in ROE across banks intensify, surpassing the intrinsically time-driven variations within banks. Essentially, this underscores that the rate at which these variables evolve contributes differentially to the changes in banks' ROE.

These findings resonate with prior research outcomes [56,73–75], which underscore the pivotal role of firms in shaping their own performance outcomes. A study by Sur and Cordeiro [76] dissected CEO compensation into its time, firm, and industry effects, revealing that 60.91% of the variation in CEO compensation was ascribed to the firm level, 19.88% to the time level, and 19.21% to the industry level. In congruence with these insights, the current study identifies the bank level as the primary source of variation in ROE, a revelation aligned with the tenets of the resource-based view theory. This theoretical framework posits that a firm's competitive advantage is rooted in its resource endowments. This perspective, in line with Certo et al. [77], elucidates that the observed situation can be rationalized by the influence of resource disparities among banks. A scrutiny of the descriptive statistics depicted in Table 2 underscores substantial divergences in the assets held by distinct banks, which may potentially extend to significant discrepancies in their performance, as underscored by the values of ROE.

5.3. Determinants of ROE

Although Table 4 displays the distribution of variability in ROE attributed to time-level and bank-level variables, it does not confirm the statistical significance of these variables. In contrast, Table 5 offers parameter estimates for HLM, their corresponding significance levels, and model fit statistics. We initially focus on the model fit statistics to assess the adequacy of HLM estimations for the data. The likelihood ratio (LR) test, which compares the HLM estimation to a one-level ordinary linear regression, is highly significant for Models 1 to 6. These significant LR test results suggest that the data's multilevel structure cannot be overlooked. Put differently, there is evidence suggesting that the single-level model (ordinary linear regression) does not sufficiently capture the data's structure. Hence, HLM estimations provide a good fit for the data. The intraclass correlation coefficient (ICC) values across Models 1 to 6 range between 64.4% and 85.8%. This suggests that a substantial proportion of the total variance in ROE is attributable to between-bank variance. Although ICC is not a direct measure of model fit, it offers insights into the variance proportion at each hierarchical level, which is pivotal for grasping the significance and relevance of the multilevel model.

In Model 1, the constant value of 15.31 represents the grand mean ROE for all banks throughout the study period. Model 2 introduces the time-trend coefficient, which is significantly negative at the 1% level. This finding, as depicted in Figs. 1 and 2, hints the possibility of time-reversed generating processes influencing banks' ROE. In Model 3, the coefficient on inflation is positive and statistically significant at the 1% level. Conversely, the coefficient on policy uncertainty has a negative and significant effect at the 10%

Table 5
Determinants of banks' ROE.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	15.31***	21.05***	8.10**	11.27***	−12.87***	−6.60
	(2.74)	(2.93)	(3.41)	(4.17)	(3.45)	(6.23)
Time trend		−0.84***		−0.64***	0.50***	0.71***
		(0.21)		(0.24)	(0.13)	(0.25)
Inflation			0.85***	0.72***	0.40***	0.35***
			(0.17)	(0.20)	(0.07)	(0.10)
GDP growth			0.50	0.43	0.16	0.08
			(0.36)	(0.37)	(0.13)	(0.17)
Policy uncertainty			−7.57*	−6.92*	−6.75*	−6.65*
			(3.90)	(3.79)	(3.62)	(3.54)
Assets					2.50e-06**	2.58e-06**
					(1.19e-06)	(1.18e-06)
Equity					−4.20e-05***	−4.64e-05***
					(8.49e-06)	(8.65e-06)
Incomes					2.94e-07	2.86e-06
					(7.05e-06)	(7.04e-06)
Profits					1.05e-04***	1.16e-04***
					(1.88e-05)	(1.92e-05)
Profit margin					36.57***	36.64***
					(2.97)	(2.94)
Total asset turnover					76.04***	75.63***
					(11.94)	(11.78)
Equity multiplier					1.23***	1.06***
					(0.34)	(0.34)
NPL						−0.31*
						(0.16)
Borrowers						−0.03
						(0.04)
Branches						−0.95
						(1.55)
Chibar2(01)	56.6***	59.9***	68.7***	66.6***	22.1***	21.2***
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ICC	64.4	64.8	69.3	68.6	85.2	85.8
(Std Err)	(0.12)	(0.12)	(0.11)	(0.11)	(0.09)	(0.08)

Notes: This table reports the hierarchical linear model (HLM) estimations. The parameter estimates are provided together with respective standard errors in parenthesis. The HLM model was estimated using the method of restricted maximum likelihood estimator. Chibar2(01) of the likelihood ratio (LR) test comparing the model with one-level ordinary linear regression is reported with respective p-value. The intraclass correlation coefficient (ICC) is reported with respective standard errors in parenthesis. *, **, *** show the significance level of 10, 5 and 1% level, respectively.

level. The negative relationship between policy uncertainty and banks' ROE contrasts with the finding of Ozili and Arun [18], who documented that high policy uncertainty positively affects banks profitability in Asia and America. The coefficient on GDP growth remains insignificant. Prior research, exemplified by Căpraru and Ihnatov [78] and Riaz and Mehar [79], has similarly reported insignificant effects of GDP growth on banks' ROE. A possible explanation for the impact of country-specific factors (inflation, GDP growth, and policy uncertainty) on banks' ROE is as follows.

Firstly, inflation and banks' ROE can be positively related due to several factors. Rising inflation often prompts central banks to raise interest rates, allowing banks to earn more from the spread between deposit and loan rates, thereby enhancing interest income and ROE [21,71]. Inflation-driven loan demand can also lead to increased interest income. Additionally, asset values, like real estate, tend to rise during inflation, potentially boosting banks' equity and ROE [80,81]. Secondly, policy uncertainty creates an environment of ambiguity and risk aversion, which can influence banks' lending, investment, and overall profitability [18,82,83]. The negative impact on return on equity results from the various ways in which uncertainty affects the broader economic landscape and the functioning of financial institutions. For instance, when banks are uncertain about the regulatory and economic landscape, they may become more cautious in their lending and investment activities, potentially reducing revenue-generating opportunities and overall profitability [84]. Finally, while GDP growth is often considered an indicator of economic health, its direct translation into bank profitability is not always straightforward. The impact of GDP growth on banks' profitability might not be immediate because there can be time lags between changes in the overall economy and their effects on banks' financial performance [78,79]. The absence of a significant relationship might suggest that other internal and external factors play a more dominant role in determining banks' ROE. For example, banks engage in various financial activities beyond traditional lending, such as investment banking, wealth management, and trading. These activities can generate income that is not directly tied to the overall GDP growth, leading to less correlation between GDP and ROE.

When a time trend is incorporated into Model 3, the consistency in signs and significance of all explanatory variables is retained in Model 4. In Model 5, where both time-level and bank-level variables are included with fixed coefficients, the coefficient for the time trend becomes positive and significant. This change in the sign of the time-trend coefficient, upon the inclusion of more bank-level covariates, suggests that the time-reversed generating processes for banks' ROE, as previously described, can be altered by enhancements in bank-level variables. For instance, improvements in banks' operational efficiency (e.g., profit margin and asset turnover), investment decisions (e.g., equity multiplier), profit growth, and asset investments can align the time trend and ROE in the same direction. The coefficients on equity multiplier, asset turnover, profit margin, profits, and inflation exhibit statistical significance with positive signs. The negative coefficient on equity, substantively significant at the 1% level, aligns with theoretical expectations since equity serves as a denominator variable in ROE computations. This negative coefficient's persistence across Model 6 (the random intercept and random coefficient model) is noteworthy. The coefficient on policy uncertainty remains negative and significant at the 10% level. Incomes and GDP growth, conversely, exhibit insignificance.

The attainment of stability and advancement in ROE is potentially attainable through the enhancement of operational efficiency in banks, marked by stable profit margins and the effective utilization of assets for generating incomes (denoted by total asset turnover). Notably, over the past 15 years, Ugandan commercial banks have witnessed substantial asset growth. For instance, the assets of 14 regulated banks in Uganda have surged from UGX 5,116 billion to UGX 33,380 billion, averaging UGX 370 billion per bank. The proficient utilization of this augmented assets base could potentially bolster ROE, a phenomenon underscored by Bunea et al. [36], highlighting the pivotal role of efficient asset turnover in ROE enhancement.

Model 6 extends Model 5 by incorporating non-performing loans, the number of branches, and the number of borrowers as additional explanatory variables. As anticipated, non-performing loans are negatively correlated with the banks' ROE at the 10% significance level. This relationship is quite intuitive, given that non-performing loans have negative implications for a bank's profitability, asset quality, operational efficiency, and overall financial health. These factors collectively contribute to the negative impact on return on equity, making it imperative for banks to manage credit risk and maintain a healthy loan portfolio to safeguard their profitability and stability [8,27,64]. Conversely, the coefficients for the number of borrowers and branches per 1000 individuals are characterized by insignificance, accompanied by negative coefficients. This trend marks a potential shift from prior literature, exemplified by Liang et al. [85], which postulated that an increased number of bank branches augments bank performance. However, given the contemporary expansion strategies adopted by banks to reach customers through digital platforms, mobile banking, and agency banking, an elevated number of physical branches could potentially lead to a decline in ROE due to escalated operational costs.

6. Discussions and policy implications

The unstable and declining nature of ROE sends adverse signals to stock markets about a bank's performance. Consistent high and stable ROE is an indicator shareholders use to gauge the health of their investment. A decreasing ROE trajectory in Ugandan banking sector risks shareholder investments and jeopardizes the sector's stability. Our study has highlighted three primary concerns necessitating immediate managerial and regulatory action: (1) Volatility in ROE and its core determinants, such as assets, profits, equity, and income; (2) Greater variability in "between bank" ROE compared to "within bank" ROE, emphasizing the dominant role of bank-level variables in influencing ROE fluctuations; (3) Identification of significant variables affecting ROE.

The study implies not just instability in banks' ROE but also in their operational efficiency, asset management, and investment strategies in Uganda. While time-driven shocks contribute to ROE's volatile trend, they do so minimally. Hoelscher and Quintyn [86] and Segoviano and Goodhart [87] posited that banking instability arises either from idiosyncratic factors associated with individual banks' practices or systemic factors resulting from macroeconomic shocks. In our study, the former influences the "between bank" ROE variation, whereas the latter determines the "within bank" variation. Notably, "between banks" variation surpasses "within bank" variation, signifying that banks wield a more substantial influence on their performance than time-driven fluctuations.

A significant and positive relationship between DuPont variables and a bank's ROE has crucial policy implications. Banks should prioritize operational efficiency and cost reduction to safeguard their profit margins. This can be achieved through investments in cost-saving technologies, which have the potential to enhance both profit margins and asset turnover. Notably, the automation levels in many banks across Uganda and Sub-Saharan Africa remain limited. For instance, prominent Indian banks such as ICICI Bank, HDFC Bank, and Axis Bank have embraced Robotic Process Automation (RPA), shown by Vijai et al. [88] to significantly decrease operational costs, including labor expenses by up to 70%. In contrast, technologies like Robotic Process Automation are yet to be widely adopted in Uganda. Furthermore, many banks have a scarcity of Automated Teller Machines (ATMs) in bustling commercial areas. According to the Bank of Uganda [89], the average annual operational cost for Ugandan banks–equating to 11% of their income-earning assets–is remarkably high in comparison to international standards. This elevated cost could potentially lead to a decline in banks' ROE through reduced profitability. Therefore, management should focus on internal factors under their control, such as provisioning policies, capital adequacy policies, expense management, and bank size. Aligning these policies could bolster operational efficiency and equity management.

Beyond the DuPont components, the significant impact of macroeconomic and industry variables holds important policy implications. The inflation rate's positive impact on a bank's ROE demands careful policy implications [60,61]. Policymakers should prudently manage interest rates to balance increased income from moderate inflation against stability during high inflation. Moreover, effective risk management, loan pricing, consumer protection, and financial literacy are vital, especially in inflationary contexts. The uncertainty of policies negatively affecting banks' ROE underscores the need for a stable regulatory environment [18,25,26]. Clear, consistent rules and transparent communication of policy shifts are essential [90]. Furthermore, fostering strong risk management practices, such as stress testing and scenario analysis, helps banks navigate uncertainties. The adverse effect of non-performing loans on banks' ROE points to the necessity for enhanced loan quality assessments and risk management [8,27,64]. Implementing stringent loan standards, comprehensive due diligence, and advanced risk evaluation techniques can prevent non-performing loans. Moreover, policymakers should promote an economy conducive to growth to indirectly reduce non-performing loans and enhance banks' ROE by mitigating credit risks.

In conclusion, an integrated effort is imperative to address the evident declining ROE trend among Ugandan banks. The prevalent pattern of ROE generation, seen across banks, requires urgent intervention. Through systematic inclusion of covariates in our model, we have charted a path to address this trend. The findings from our model support the potential of targeted interventions that focus on enhancing banks' operational efficiency, especially regarding profit margins and asset turnover. Thoughtful investment decisions, especially about equity multipliers, are crucial for improving profitability and effective asset management. Adopting this strategic approach may reverse the current negative ROE trend in Ugandan banks.

7. Concluding remarks

This study examined ROE variations in Ugandan banking sector using a hierarchical linear modeling approach. The analytical framework partitioned ROE variance into two primary components: influences from time-driven dynamics and individual bank practices. The temporal dimension, our first level of analysis, focused on time-related variables, including the time trend and other macroeconomic indicators known for random fluctuations. Conversely, the bank-level variables, grounded in the DuPont model, emphasized crucial banking performance determinants. The analysis began with the empty model, which set the baseline variance by excluding covariates. Covariates were then sequentially integrated: starting with the time-trend variable, followed by macroeconomic indicators, and finally combining both time-level and bank-level attributes in our variable intercept model with fixed covariates. This methodical approach illuminated the variance contributions from time and bank levels, and also highlighted shifts in the explanatory power of the covariates. Intriguingly, introducing covariates step-by-step revealed variables that could offset the initial negative correlation between time trend and ROE.

From the analysis, a consistent theme emerged: the "between bank" variance consistently outweighed the "within bank" variance. This suggests individual banks exert a stronger influence on their performance than time-driven factors do on ROE variability. At the time-level, the time trend was only significant but with negative coefficient before more variables were added to the model. It became significant and positive, after the addition of more bank-level variables in the model. While the inflation rate showed positive significance across models, GDP growth was not significant in any. Policy uncertainty and non-performing loans negatively influenced ROE. Yet, metrics like the number of borrowers and branches per 1000 individuals remained insignificant. In essence, our research unveiled a clear pattern: banks in Uganda hold more sway over their individual performance compared to time-driven influences on ROE fluctuations. The interplay of variables demonstrated nuanced shifts in significance and changes in covariate coefficients. This study elucidates the multifaceted dynamics of banking performance in Uganda, urging deeper probes into the intricate factors shaping ROE and the wider financial landscape.

One of the main insights from our study is the positive impact of improved operational efficiency and wise investment choices on ROE. This underscores the importance for banking leaders to consistently refine processes and rigorously assess investments. For policymakers, it might be worth considering incentives to encourage these practices, potentially via regulatory reliefs or by promoting standards for operational efficiency. Collectively, this research enriches the existing body of literature on ROE determinants by integrating temporal effects, expands the discourse on ROE dynamics through the lens of HLM, deepens insights into volatility by assessing ROE fluctuations on both temporal and bank-specific planes, and offers actionable strategies to counteract the declining trend in ROE.

This study has inherent limitations. It is exclusively centered on Ugandan banking sector, which may limit the generalizability of results to broader contexts. Extrapolating these findings to other nations requires caution due to potential differences in regulatory structures, economic conditions, and market dynamics. Another constraint is the selection of variables. Despite a rigorous focus on key determinants of ROE, other impactful factors might have been overlooked. Future research could expand on this by incorporating more variables for a richer analysis. The study's concentration on a specific time frame might also narrow insights into long-term ROE dynamics. A more extended analysis would offer a comprehensive view of ROE trends across economic cycles. Future investigations could further delve into the interplay between ROE and other pivotal financial metrics, such as return on assets or return on investment, to provide a holistic perspective on banking performance.

Data availability statement

Data will be made available on request.

Additional information

No additional information is available for this paper.

CRediT authorship contribution statement

Boonlert Jitmaneeroj: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **John Ogwang:** Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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