# INFLUENCE OF DIGITAL COMMERCE AND MOBILE POINT-OF-SALE PAYMENTS ON BANK RISK AND PERFORMANCE IN BAHRAIN: A DYNAMIC PANEL ANALYSIS

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## Abstract

This research assesses the influence of digital payments, specifically digital commerce and mobile point-of-sale (POS) payments, on the financial performance and risk management of retail banks in Bahrain. The study covers the period from 2018 to 2023, utilizing secondary data from seven retail banks, which include both commercial and Islamic banks. The bank's performance is measured by return on assets (ROA) and return on equity (ROE). Additionally, the debt-to-capital ratio (DTC) and debt-to-equity ratio (DTE) are employed to assess risk. To analyze the impact of digital payment adoption on bank performance and risk, the Arellano-Bond generalized method of moments (GMM) dynamic panel data model was applied using Stata software. It is a similar approach used in financial technology studies examining banking performance (Irmaningtyas & Rosadi, 2014). The findings reveal that the adoption of digital commerce and mobile POS payments has an insignificant impact on traditional performance measures, such as ROA and ROE, during the study period. However, these digital payment technologies show a significant association with DTC, while these results highlight the insignificant effects of digital commerce and mobile POS payments on the DTE ratio. These findings contribute to the ongoing discussion on the role of financial technology in shaping banking performance and risk, addressing a key research gap in the literature such as Phan et al. (2020).

**Keywords:** Banks, Digital Payment, Performance, Risk, E-Commerce, Bahrain

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## 1. INTRODUCTION

Bahrain presents a very intriguing research space for digital payment dynamics, considering its proactive legislative climate and historical and economic significance in the banking and financial system in the Gulf Cooperation Council (GCC). The kingdom's aggressive push towards fintech adoption has cemented its identity as one of the most advanced digital payments in the world (Doblas & Lagaras, 2023).

On the other hand, digital commerce, a major component of digital payments, has emerged as a key driver of online transactions and economic transformation. Broadly defined as consumer transactions conducted via electronic platforms, e-commerce has become an essential pillar of modern commerce (Rigas & Riaz, 2015). Banks play a central role in facilitating e-commerce by providing the necessary digital payment infrastructure, including credit and debit cards, mobile banking, and Internet banking services (Yousafzai et al., 2003). Additionally, point-of-sale (POS) applications have significantly improved banking efficiency by simplifying and expediting service processes, enhancing customer experiences, and facilitating seamless transactions (Febrianto, 2022). As stated by Writer (2024), the kingdom is currently achieving 89% digital transformation, which leads to the rise of digital transactions, including digital commerce and POS payments. However, despite these positive developments, there remains limited empirical research examining the specific impact of digital payments on Bahrain's commercial banks' risk and performance.

Moreover, banks face various risks associated with the activities they undertake, which are often intensified by unexpected shifts in both internal and external conditions. These risks are further exacerbated when banks and their risk management frameworks struggle to adapt to such rapid changes (Shkvarchuk & Slav'yuk, 2019). With the growing use of digital payments, significant shifts have occurred in banking operations, particularly in the techniques and models used for managing these transactions. Innovation in the financial industry, especially in electronic payment systems, is impacting multiple facets of banking, including risk management and service delivery (Dong, 2019). By increasing the accuracy, speed, and resilience of risk identification and mitigation, fintech innovations — particularly in big data analytics and technology surveillance — can fortify banks' risk management models from a proactive perspective (Merani, 2023). Conventional banks are better equipped to increase service alternatives, satisfy a range of clients' wants, and increase profitability thanks to these advances (Gomber et al., 2017).

This research addressed two significant gaps in the existing literature on financial technology's impact on banking dynamics, particularly in the context of Bahrain. First, a general research gap persists concerning the effects of financial technologies (Phan et al., 2020; Almulla & Aljughaiman, 2021; Zhang et al., 2022; Varma & Nijjer, 2022; Olalere et al., 2021), with a focus on digital commerce and mobile POS payments on bank risk and performance — an area that has been underexplored in the context of Bahrain and the wider Middle East region. Although digital finance has redefined banking systems and led to substantial changes throughout the industry, there is limited scientific literature on the impacts on banks' risk metrics and performance. This research focused on these technologies, providing a crucial understanding of their impact on the financial performance of banks, thereby filling a significant gap in the existing literature.

Second, previous studies within the literature exclusively used conventional panel data models. However, the models did not, which may not fully capture the rich and evolving dynamics of bank performance and risk. Moreover, this study used the Arellano-Bond dynamic panel-data estimation method. This comprehensive methodology approach enables a more detailed examination of the temporal relationship between financial technologies, the performance of banking systems, and the associated risks (Irmaningtyas & Rosadi, 2014). By employing the Arellano-Bond dynamic panel-data estimation method, we tackled potential endogeneity, thereby establishing a more precise and reliable causal relationship. This, in turn, bolstered the trustworthiness and precision of the conclusions drawn about the effect of digital commerce and mobile POS payments on bank risk and performance. The enhancement in methodology not only improves the paper's findings but also plays a major role in explaining the roles of these technologies in banking metrics in the current highly dynamic financial sector (Mileva, 2007).

The study is structured around two key research questions:

*RQ1: How do digital payments affect the performance of banks in Bahrain?*

*RQ2: What is the effect of digital payments on bank risks?*

In addressing these questions, the research also considers broader economic trends and the evolving regulatory environment in the country. As Bahrain continues its journey toward a digital economy, the results of this study will contribute to understanding the strategic importance of digital payments and guide banks seeking to optimize their operations in this new landscape.

Ultimately, the research aims to support policymakers and banking institutions in making informed decisions about the adoption of digital payment systems. By analyzing their impact on financial performance, the study highlights the potential benefits and challenges associated with these technologies, offering a comprehensive assessment of their role in the future of banking in Bahrain.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature and develops the hypotheses that form the foundation of the study. Section 3 presents the data and methodology used for the analysis. Section 4 discusses the empirical results and findings. Finally, Section 5 concludes the study, highlighting key implications and directions for future research.

## 2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

This Section reviews the literature on digital payments, bank performance and risk management, analyzing existing research on how digital payments influence banks' risk management practices and performance.

### 2.1. Digital payment and bank performance

Assessing the impact of digital transformation on bank performance is essential, as banking institutions play a crucial role in economic stability and financial growth. According to Akuien (2023), the performance of a nation's banking sector reflects the overall effectiveness of its financial system and economic development. Traditionally, bank performance has been evaluated using key financial indicators such as return on assets (ROA), return on equity (ROE), and net interest margin (NIM), which are widely recognized in academic research (Magdalena & Widarjo, 2024; Sari & Siregar, 2024; Rehman et al., 2021; Dao, 2020).

A critical factor influencing bank performance is the successful integration of digital payments, which plays a pivotal role in enhancing operational efficiency and financial stability. The effectiveness of electronic payment systems depends on the strength of the banking infrastructure, the expertise of banking personnel, and the adoption of key technologies such as POS, automated teller machines (ATMs), mobile banking, and online banking (Adeyeye et al., 2018). In Bahrain, the banking sector serves as a key pillar of the economy, with total assets reaching USD 236.7 billion as of February 2024. The sector consists of 84 banks, spanning foreign bank branches, retail banks, and wholesale banks, with a growing emphasis on Islamic finance and FinTech innovation (Central Bank of Bahrain, 2024).

Recent performance trends reflect the resilience of Bahrain's banking sector amid economic fluctuations. According to KPMG's (2023, 2024) reports, the ROE surged from 8% in 2020 to 25.6% in 2021, signalling a strong post-pandemic recovery. However, global economic uncertainties and tighter financial conditions led to a decline to 10.8% in 2022, followed by a modest increase to 11.0% in 2023. Meanwhile, ROA remained relatively stable, increasing from 0.8% in 2020 to 1.0% in 2023, indicating consistent and effective asset utilization. These figures highlight the resilience of Bahrain's banking sector, even during economic fluctuations.

The increasing digital transformation of the financial industry has brought significant attention to the relationship between digital payments and bank performance. Numerous studies have explored how various digital payment methods impact banks, using different proxies to assess this relationship. For instance, Arilesere et al. (2021) analyzed the Nigerian banking sector and found that while POS and debit card transactions negatively affected profitability, ATMs, mobile banking, and internet banking had a positive influence on financial performance, highlighting the varying effects of different digital payment options. Moreover, another study conducted by Shaikh and Anwar (2023) demonstrates that an increase in real-time gross settlement and national electronic fund transactions positively influences banks and advances. However, credit card transactions at ATMs and POS have a negative impact. These results indicated that promoting real-time gross settlement (RTGS) can enhance bank performance, while facilitating credit-based digital payment transactions can help reduce funding costs. Also, Wang and Gunawan (2022) examine the impact of digital payments on Chinese commercial banks using data from 81 banks between 2013 and 2019. Their findings show that bank-involved digital payments boost both profitability and productivity, while third-party digital payments reduce profitability but do not affect productivity.

One major form of digital payment is digital commerce, which plays a crucial role in shaping the financial landscape by driving demand for digital banking services and influencing bank performance. As e-commerce expands, banks increasingly provide digital payment solutions to support online transactions, enhancing their operational efficiency and profitability. To exemplify, Nduji and Chris (2020) found that e-commerce improves customer satisfaction and operational efficiency, while Asiabugwa (2011) demonstrated that in Kenya, e-commerce adoption enhances market reach and bank performance. Similarly, Salami and Mercy (2014) reported that despite challenges in Nigeria, e-commerce adoption significantly improved customer satisfaction and operational processes, leading to better bank performance. Using a systematic literature review, a study carried out by Noor et al. (2023) also found that e-commerce adoption can enhance operational efficiency and profitability but these benefits may not always directly improve financial performance due to cybersecurity risks and technological integration challenges.

Additionally, Baah-Acquah and Freeman (2016) found that in Ghana, e-commerce adoption reduces paperwork and streamlines internal operations, and this could lead to an increase in the bank's profitability. This trend extends globally, as Harold et al. (2019) observed increased bank profitability in West Africa due to advancements in banking technology and internet adoption. In the Middle East and North Africa (MENA) region, Matar et al. (2024) highlighted a post-COVID-19 shift in consumer behaviour towards online purchasing, leading to higher adoption of digital wallets and financial applications.

Mobile POS payments, which are another key digital payment form, have also impacted bank performance. Mobile devices, evolving from basic communication tools to complex financial platforms, facilitate payments, transfers, and investments. Studies highlight that well-structured mobile payment systems enhance banking efficiency by reducing costs and increasing profitability. For example, Njogu (2020) explored how electronic banking channels in Kenya, such as ATMs and POS, positively impacted bank profitability. Similarly, Aduaka and Awolusi (2020) in Nigeria confirmed the positive, albeit varying, impacts of electronic banking channels on profitability.

In Bahrain, POS systems are crucial in the banking sector, where Okonkwo and Ekwueme (2022) described their role in enabling seamless fund transfers. Despite extensive research on digital payments worldwide, including studies in India (Franciska & Sahayaselvi, 2017) and Africa (Soutter et al., 2019), there remains a significant research gap in the GCC, particularly in Bahrain. While GCC studies like Niankara (2022) on digital payment adoption in financial inclusion, Khan and Al-Harby (2022) on fintech usage in Saudi Arabia, and Albastaki (2023) on e-payment adoption in Bahrain during the pandemic offer insights, the specific impacts of digital commerce and POS on banks' performance and risk management in Bahrain remain underexplored. This study aims to address this gap.

## 2.2. Digital payment and risk

The adoption of digital payment systems has increasingly influenced financial risk management, particularly in terms of debt-to-equity (DTE) and debt-to-capital (DTC) ratios. Digital payment technologies, such as mobile POS systems and online banking, can significantly impact how financial institutions manage their liabilities and capital structures. Research suggests that digital payment systems streamline transaction processes, reduce operational costs, and improve cash flow management, which may positively influence banks' capital efficiency and reduce reliance on debt. According to Xin et al. (2024), digital transformation, including digital payment adoption, can lower equity financing costs by improving future earnings and reducing risk levels. Additionally, Uddin et al. (2020) discuss the broader implications of digital finance on financial stability and risk management. The Federal Reserve Bank of Atlanta also highlights how digital payment systems can influence financial inclusion and stability, indirectly affecting financial risk management metrics like DTE and DTC (Greene & Stavins, 2021).

However, the relationship between digital payment adoption and financial risk management, particularly measured by DTE and DTC, is complex and multi-dimensional. While digital payment systems can improve capital utilization, they also introduce new risks that may require additional capital buffers, impacting these ratios. For example, Khiaonarong and Humphrey (2022) highlight that digital payment systems expose banks to increased cybersecurity threats and operational risks, which may necessitate higher capital reserves. This could lead to higher DTE ratios if banks need to rely more on debt to finance risk management infrastructure. Similarly, Chamboko (2024) emphasizes that while digital payment adoption can enhance operational efficiency, it also requires significant investments in technology and security, which might affect both DTC and DTE, depending on how these costs are financed.

Overall, while the adoption of digital payments has the potential to improve financial performance by reducing debt dependency, the associated risks require careful management to ensure that banks maintain healthy DTE and DTC ratios. Financial institutions must balance the operational benefits of digital payments with the capital requirements needed to mitigate the new risks introduced by these technologies.

## 2.3. Hypotheses development

Based on the literature review of relevant studies, the hypotheses for this research have been formulated. These hypotheses aim to explore the impact of digital payments on the performance of banks in Bahrain and are as follows:

*H1a: Digital commerce adoption does not significantly affect bank performance, measured by ROA, in Bahrain.*

*H1b: Digital commerce adoption does not significantly affect bank performance, measured by ROE, in Bahrain.*

*H2a: Mobile POS payments do not significantly affect bank performance, measured by ROA, in Bahrain.*

*H2b: Mobile POS payments do not significantly affect bank performance, measured by ROE, in Bahrain.*

*H3a: Digital commerce does not significantly affect bank risk management, measured by DTC, in Bahrain.*

*H3b: Digital commerce does not significantly affect bank risk management, measured by DTE, in Bahrain.*

*H4a: Mobile POS payments do not significantly affect bank risk management, measured by DTC, in Bahrain.*

*H4b: Mobile POS payments do not significantly affect bank risk management, measured by DTE, in Bahrain.*

# 3. RESEARCH METHODOLOGY

This Section outlines the methodology, including the overall research approach, data collection methods, analysis techniques, and model specification. It details the quantitative approach, the collection of data from secondary sources, the statistical analysis, and the regression model used to examine the impact of digital payments on bank performance and risk management.

## 3.1. Methods

To examine the influence of digital commerce and mobile POS payments on bank risk and performance in Bahrain, this study uses the Arellano-Bond generalized method of moments (GMM) dynamic panel data model. Barros et al. (2020) have noted that this method is especially applicable to studying the dynamic connections that include lagged dependent variables, along with tackling the problems of endogeneity and autocorrelation, which are typical of the financial panel data. Seo and Shin (2016) also noted that the GMM approach also deals effectively with the unobserved heterogeneity in banks, as it differs from fixed effects (FE).

Although other methods could be used for this investigation, the authors believe that the Arellano-Bond GMM is more suitable. While lagged dependent variables could cause endogeneity issues, the FE model can address time-invariant bank-specific concerns. If the unobserved effects are regarded to be uncorrelated with the regressors, the random effects (RE) model can be applied even if financial panel data may not fulfil this criterion. Especially when variables span time, the system GMM estimator variation on the Arellano-Bond method — combines equations in levels and first differences for maximum efficiency (Zhang & Zhou, 2020). Ultimately, a difference-in-difference (DiD) approach might be applied to deduce causality via treatment and control group comparisons, should a policy modification or exogenous event influence digital commerce or mobile POS payments. Notwithstanding these substitutes, the Arellano-Bond GMM was selected for its resilience in handling endogeneity, autocorrelation, and unobserved heterogeneity, which aligns with the need for analyzing the dynamic banking performance and risk data of this investigation.

In the analysis, control variables were very useful in identifying the impacts of the primary independent variables on the dependent variables. The control variables for the study were total assets (*LogTA*), inflation rate (*IR*), and gross domestic product (*GDP*).

Dávila and Walther (2017) suggested that total asset is a crucial factor that affects other performance measures like ROA and ROE. By limiting the effect of bank size, the analysis could further determine how digital commerce and mobile POS payments affect differently sized banks. GDP and Inflation were also included because both indicate economic conditions (Pabreja, 2018) and may greatly impact the spending of consumers (Scopelliti, 2016) as well as their investment (Al-Rafik, 2021).

By holding these control variables, the study addresses endogeneity issues and ensures that the relationships between digital commerce, mobile POS payments, and bank performance are effectively specified. The coefficients of regression were estimated to explain the strength and direction of these relationships, which served as valuable information in applying the findings of the study in the context of the banking systems in Bahrain.

### 3.2. Data

As of the end of September 2020, Bahrain's banking industry comprised both conventional and Islamic banks, with the financial sector consisting of 376 institutions. This included 31 retail banks, 62 wholesale banks, 17 branches of foreign banks, and eight representative offices. The retail banks are the primary focus of this study, reflecting the extensive and diverse nature of Bahrain's banking landscape, which plays a crucial role in the country's economic framework and ongoing diversification efforts (Central Bank of Bahrain, 2024).

Although the panel dataset employed in this work consists of 42 observations, which could be regarded as somewhat small for dynamic panel data approaches such as Arellano-Bond GMM, considering the specificity and concentration of Bahrain's retail banking industry, this sample size is appropriate. In addition, in line with the recommendations of Roodman (2009), the study carefully limits the number of instruments in the estimation, avoiding the proliferation of the same that would reduce the statistical power of the sample. Finally, diligent checks and diagnostics like the Sargan and Hansen tests were conducted to validate the robustness of the model.

Following a similar approach used in previous studies on Bahrain's banking sector, including research by Hawaldar et al. (2017), Daly and Frikha (2017), and Harban et al. (2021), which focused on the performance of both commercial and Islamic banks in the region. The selected sample for this research comprises seven retail banks listed on the Bahrain Bourse, excluding the Bahrain Bank of Kuwait (BBK), which is included due to its high adoption rate among users. The sample includes three conventional banks and four Islamic banks, these banks have significantly contributed to the development of digital payments solutions (see Table 1).

**Table 1.** Selected banks

| *Bank name* | *Bank type* | *Symbol* |
|---|---|---|
| Bahrain Bank of Kuwait | Conventional | BBK |
| National Bank of Bahrain | Conventional | NBB |
| Ahli United Bank | Conventional | AUB |
| Albaraka Islamic Bank | Islamic | AIB |
| Khaleeji Commercial Bank | Islamic | KHCB |
| Bahrain Islamic Bank | Islamic | BISB |
| Alsalam Islamic Bank | Islamic | AIS |

*Source: Authors' elaboration.*

To assess the influence of digital payments on both bank performance and risk management in Bahrain, this study carefully selects its variables. The primary independent variable is digital payment, operationalized through two key proxies: digital commerce and mobile POS payments. Bank performance, one of the main dependent variables, is evaluated using two financial ratios: *ROA* and *ROE*.

Additionally, risk management, the second dependent variable, is assessed via *DTC* and *DTE* ratios. To enhance the analysis, two control variables are included: bank size, indicated by *LogTA*, and the *IR*, represented by the Consumer Price Index (CPI) for Bahrain, which considers macroeconomic factors affecting both bank performance and risk management. Comprehensive descriptions of all research variables are detailed in Table A.1 in the Appendix.

### 3.3. Model specification

The analysis focuses on two types of relationships: long-term and short-term effects of the independent variables on key performance and risk metrics of banks — namely, *ROA, ROE, DTC*, and *DTE*. In the long term, the relationship between bank performance/risk and its predictors is modelled by including a lagged dependent variable, which captures the persistence of performance and risk over time. The long-term dynamic panel models for *ROA, ROE, DTC*, and *DTE* are expressed as follows:

$$ROA_{it} = \beta_0 + \beta_1 ROA_{it-1} + \beta_2 DC_{it} + \beta_3 POS_{it} + \beta_4 LogTA_{it} + \beta_5 IR_{it} + \beta_6 GDP_t + \varepsilon_{it} \tag{1}$$

$$ROE_{it} = \beta_0 + \beta_1 ROE_{it-1} + \beta_2 DC_{it} + \beta_3 POS_{it} + \beta_4 LogTA_{it} + \beta_5 IR_{it} + \beta_6 GDP_t + \varepsilon_{it} \tag{2}$$

$$DTC_{it} = \beta_0 + \beta_1 DTC_{it-1} + \beta_2 DC_{it} + \beta_3 POS_{it} + \beta_4 LogTA_{it} + \beta_5 IR_{it} + \beta_6 GDP_t + \varepsilon_{it} \tag{3}$$

$$DTE_{it} = \beta_0 + \beta_1 DTE_{it-1} + \beta_2 DC_{it} + \beta_3 POS_{it} + \beta_4 LogTA_{it} + \beta_5 IR_{it} + \beta_6 GDP_t + \varepsilon_{it} \tag{4}$$

On the other hand, the model specification to express the short-term effect of the predictors on *ROA, ROE, DTC,* and *DTE* could be, respectively, captured as:

$$\Delta ROA_{it} = \beta_0 + \beta_1 \Delta ROA_{it-1} + \beta_2 DC_{it} + \beta_3 POS_{it} + \beta_4 LogTA_{it} + \beta_5 IR_{it} + \beta_6 GDP_t + \varepsilon_{it} \tag{5}$$

$$\Delta ROE_{it} = \beta_0 + \beta_1 \Delta ROE_{it-1} + \beta_2 DC_{it} + \beta_3 POS_{it} + \beta_4 LogTA_{it} + \beta_5 IR_{it} + \beta_6 GDP_t + \varepsilon_{it} \tag{6}$$

$$\Delta DTC_{it} = \beta_0 + \beta_1 \Delta DTC_{it-1} + \beta_2 DC_{it} + \beta_3 POS_{it} + \beta_4 LogTA_{it} + \beta_5 IR_{it} + \beta_6 GDP_t + \varepsilon_{it} \quad (7)$$

$$\Delta DTE_{it} = \beta_0 + \beta_1 \Delta DTE_{it-1} + \beta_2 DC_{it} + \beta_3 POS_{it} + \beta_4 LogTA_{it} + \beta_5 IR_{it} + \beta_6 GDP_t + \varepsilon_{it} \quad (8)$$

where,

- *ROE* = return on equity;
- *ROA* = return on assets;
- *DTC* = debt-to-capital ratio;
- *DTE* = debt-to-equity ratio;
- *DC* = digital commerce;
- *POS* = mobile payment of the sales system;
- *LogTA* = log of total assets (bank size);
- *IR* = inflation rate;
- *GDP* = gross domestic product;
- $\beta_0$ = constant term;
- $\beta_1$ = coefficient for lagged DTC;
- $\beta_1$–$\beta_6$ = coefficient for *DC*, *POS*, *LogTA*, *IR*, and *GDP*, respectively;
- $\Delta$ = first difference operator (to capture short-term changes);
- $\varepsilon_{it}$ = error term.

To estimate the models, the following steps were undertaken:

1. Stationarity testing: Unit root tests (Levin-Lin-Chu and Im-Pesaran-Shin) were conducted to ensure that the variables were stationary or that the order of integration was suitable for GMM estimation.
2. Dynamic panel estimation: The Arellano-Bond GMM estimator was used to estimate the long-term and short-term models. This involved specifying appropriate lag structures for the independent variables and ensuring that the models were identified correctly.
3. Model diagnostics: Robustness checks were conducted to validate the model specifications. This included testing for serial correlation in the error terms (e.g., Arellano-Bond test for autocorrelation) and assessing the validity of the instruments used through the Sargan and Hansen test.

## 4. RESULTS AND DISCUSSIONS

This Section presents the findings from the dynamic panel data analysis assessing the influence of digital commerce (*DC*) and mobile *POS* payment on bank risk and performance in Bahrain. Descriptive statistics were conducted initially to provide a foundational understanding of the data. The analysis utilized the Arellano-Bond estimation technique to examine both static and dynamic relationships. The Section discusses the statistical significance of the results, the validity of the instruments used, and the overall robustness of the model, contributing valuable insights into the impact of digital financial technologies on banking dynamics in Bahrain.

### 4.1. Descriptive statistics and diagnostic tests for stationarity

Table 2 displays the descriptive statistics for the variables employed in this investigation, providing significant insights into the central tendencies and variability across 42 observations. The *LogTA* exhibited a mean of 6.846 (Standard deviation [SD] = 0.403), signifying a normalized distribution of bank size, with values spanning from 6.338 to 7.622. This indicates a somewhat uniform size among the banks in the sample. *IR* averaged 0.007 (SD = 0.001), indicating a steady economic climate with negligible swings, as seen by the narrow range of 0.006 to 0.009. Conversely, *ROA* displayed a mean of 0.936 (SD = 0.88), indicating significant variability with a range from -1.6 to 2.32. This broad spectrum signifies substantial disparities in bank performance, underscoring those certain institutions encountered severe losses while others realized remarkable gains.

*ROE* had a mean of 7.082 (SD = 7.428), with values spanning from -17.53 to 15.13, indicating that external influences may have significantly impacted the financial stability of the banks in the sample. This variety highlights the varied operational contexts encountered by distinct institutions. The average value for *DC* was 10.348 (SD = 2.811), with a range from 8.13 to 15.77, suggesting differing degrees of technology adoption that may influence overall performance.

Additionally, *POS* transactions averaged 49.525 (SD = 43.751), with a wide range from 9.63 to 133.14, indicating substantial variations in operational scale and client interaction among the institutions. The *GDP* variable had a mean of 0.026 (SD = 0.036), with values spanning from -0.035 to 0.061. This signifies minor economic variations pertinent to the banking sector, highlighting the necessity of considering macroeconomic aspects while evaluating bank performance. The change in total assets (*DTC*) had a mean of 0.796 (SD = 0.075), indicating consistent growth tendencies among banks, albeit with differing growth rates.

**Table 2.** Descriptive statistics of variables used in the model

| *Variable* | *Obs.* | *Mean* | *SD* | *Min* | *Max* |
|---|---|---|---|---|---|
| *LogTA* | 42 | 6.846 | 0.403 | 6.338 | 7.622 |
| *IR* | 42 | 0.007 | 0.001 | 0.006 | 0.009 |
| *ROA* | 42 | 0.936 | 0.88 | -1.6 | 2.32 |
| *ROE* | 42 | 7.082 | 7.428 | -17.53 | 15.13 |
| *DC* | 42 | 10.348 | 2.811 | 8.13 | 15.77 |
| *POS* | 42 | 49.525 | 43.751 | 9.63 | 133.14 |
| *GDP* | 42 | 0.026 | 0.036 | -0.035 | 0.061 |
| *DTC* | 42 | 0.796 | 0.075 | 0.65 | 0.89 |
| *DTE* | 42 | 4.541 | 1.871 | 1.86 | 8.31 |

*Source: Authors' elaboration*

Table 3 displays the correlation matrix for the variables in this study, emphasizing significant correlations among them. The *LogTA* exhibits robust positive associations with *ROA* (r = 0.681) and *ROE* (r = 0.629), suggesting that larger banks often attain greater profitability. *ROA* and *ROE* demonstrate a robust association (r = 0.951), underscoring their interrelation in evaluating financial performance.

*DC* exhibits negligible correlations with profitability metrics, including weak negative correlations with *ROA* (r = -0.074) and *ROE* (r = -0.060), indicating a restricted direct influence on bank profitability. *POS* transactions exhibit a moderate positive association with *IR* (r = 0.374) and mild negative correlations with *ROA* (r = -0.020) and *ROE* (r = -0.099).

The *GDP* variable demonstrates a robust positive connection with *IR* (r = 0.701) and modest associations with *ROA* (r = 0.160) and *ROE* (r = 0.221), indicating that economic growth may positively affect bank performance. The variation in total assets (*DTC*) exhibits a positive association with *LogTA* (r = 0.420) and *ROA* (r = 0.186) and demonstrates a strong link with the change in *DTE* (r = 0.960). The correlation matrix indicates significant links that will guide further analysis of the interactions between financial technologies and bank performance in Bahrain.

The Im-Pesaran-Shin test demonstrated that *ROA, ROE, DTC*, and *DTE* exhibit stationarity, as evidenced by their corresponding test statistics and p-values (p < 0.01). Conversely, *DC, POS* transactions, *IR*, *LogTA*, and *GDP* did not reject the hypotheses, indicating that these variables possess unit roots and are probably non-stationary. Hossain et al. (2019) posited that the existence of non-stationary variables in the dataset requires differencing to stabilize the series' mean and reduce the likelihood of false regression outcomes.

Thus, the Harris-Tzavalis test was performed to further assess the stationarity of the differenced variables. This test was selected as a supplementary method to the Im-Pesaran-Shin test due to its robustness with small sample sizes and its provision of an alternate evaluation of stationarity, which is especially advantageous for panel data analysis. The findings demonstrated that all differenced variables — change in total assets (*dTA*), change in digital commerce (*dDC*), change in POS transactions (*dPOS*), and change in GDP (*dGDP*) — exhibit stationarity, with statistically significant p-values (p < 0.01).

Consequently, the initial differenced values of *TA, DC, POS*, and *GDP* will be utilized in further analysis. This method not only tackles the problem of non-stationarity but also facilitates a greater comprehension of the dynamics and temporal interactions among the variables. Employing first-difference values, the study can precisely assess the impact of *DC* and mobile *POS* payment on bank risk and performance, while alleviating any biases linked to non-stationary data. This strategy strengthens the reliability of the results and aids in drawing more dependable conclusions (see Table 4).

**Table 3.** Matrix correlation of variables used in the model

| *Variables* | *(1)* | *(2)* | *(3)* | *(4)* | *(5)* | *(6)* | *(7)* | *(8)* | *(9)* |
|---|---|---|---|---|---|---|---|---|---|
| *(1) LogTA* | 1.000 | | | | | | | | |
| *(2) IR* | -0.017 | 1.000 | | | | | | | |
| *(3) ROA* | 0.681 | 0.099 | 1.000 | | | | | | |
| *(4) ROE* | 0.629 | 0.137 | 0.951 | 1.000 | | | | | |
| *(5) DC* | 0.007 | 0.011 | -0.074 | -0.060 | 1.000 | | | | |
| *(6) POS* | -0.132 | 0.374 | -0.020 | -0.099 | -0.223 | 1.000 | | | |
| *(7) GDP* | 0.045 | 0.701 | 0.160 | 0.221 | -0.015 | -0.145 | 1.000 | | |
| *(8) DTC* | 0.420 | 0.007 | 0.186 | 0.207 | -0.119 | 0.021 | 0.034 | 1.000 | |
| *(9) DTE* | 0.510 | -0.014 | 0.255 | 0.275 | -0.085 | -0.034 | 0.024 | 0.960 | 1.000 |

*Source: Authors' elaboration.*

**Table 4**. Im-Pesaran-Shin and Harris-Tzavalis unit-root tests for stationarity

| *Variable* | *Test* | *Statistic* | *p-value* | *Conclusion for the hypothesis* |
|---|---|---|---|---|
| *ROA* | Im-Pesaran-Shin | -10.3389 | 0.0000 | Reject = Variable is stationary |
| *ROE* | Im-Pesaran-Shin | -4.1554 | 0.0000 | Reject = Variable is stationary |
| *DTC* | Im-Pesaran-Shin | -7.5053 | 0.0000 | Reject = Variable is stationary |
| *DTE* | Im-Pesaran-Shin | -1.6887 | 0.0456 | Reject = Variable is stationary |
| *DC* | Im-Pesaran-Shin | -1.1906 | 0.1169 | Fail to reject = Variable contains unit roots |
| *POS* | Im-Pesaran-Shin | 1.0330 | 0.8492 | Fail to reject = Variable contains unit roots |
| *IR* | Im-Pesaran-Shin | -4.5293 | 0.0000 | Fail to reject = Variable contains unit roots |
| *LogTA* | Im-Pesaran-Shin | -1.5438 | 0.0613 | Fail to reject = Variable contains unit roots |
| *GDP* | Im-Pesaran-Shin | 0.6767 | 0.7507 | Fail to reject = Variable contains unit roots |
| *dTA* | Harris-Tzavalis | -0.1600 | 0.0002 | Reject = Variable is stationary |
| *dDC* | Harris-Tzavalis | -0.1797 | 0.0001 | Reject = Variable is stationary |
| *dPOS* | Harris-Tzavalis | -0.4738 | 0.0000 | Reject = Variable is stationary |
| *dGDP* | Harris-Tzavalis | -0.1559 | 0.0002 | Reject = Variable is stationary |

*Source: Authors' elaboration.*

## 4.2. Dynamic panel data estimations

Table 5 presents the results of the Arellano-Bond dynamic panel-data estimation for *ROA*, analysing the impact of *DC* and mobile *POS* payments on bank performance in Bahrain. The table reports the estimated coefficients, standard errors, t-values, and p-values for each independent variable, along with the 95% confidence intervals.

The Arellano-Bond dynamic panel-data estimation results for *ROA* in a sample of banks in Bahrain provide an understanding of the elements affecting financial performance. With a coefficient of -0.556 (p = 0.085), the lagged dependent variable (*L1*) suggests a negative link with historical *ROA* levels; at conventional levels, it is not statistically significant. This suggests that although the relationship is yet unknown, past *ROA* could have some impact on present performance.

With a coefficient of zero (p = 0.883), bank size exhibits, among the control factors, no significant influence on *ROA* in this sample. Though the coefficient of the *IR* is -952.424 (p = 0.410), the absence of statistical significance implies that inflation does not consistently influence *ROA*. While mobile *POS* has a coefficient of -0.001 (p = 0.692), showing no notable influence on financial performance, the variable for *DC* likewise indicates a coefficient of -0.077 ($p = 0.692$), implying that it does not significantly correlate with *ROA*.

Though it lacks a statistically significant impact on *ROA*, the *GDP* variable exhibits a positive coefficient of 2.474 ($p = 0.904$), the same as the other control factors. Although this is similarly not statistically significant, the constant term is projected at 8.277 ($p = 0.325$), suggesting the baseline level of *ROA* when other variables are kept constant.

The general model is statistically significant (Wald Chi-square = 40.551, $p < 0.01$), thereby verifying that at least one of the factors affects *ROA*. With z-values of 0.6655 ($p = 0.506$) for the first order and -1.2672 ($p = 0.205$), the Arellano-Bond test for zero autocorrelation also shows no evidence of autocorrelation in the first-differenced errors. This helps the dynamic model to be more resilient.

Though the model generally shows statistical significance, individual predictors do not exhibit notable effects on *ROA*, implying that other elements not included in this model may be affecting financial success. The results highlight the need for more research on the factors influencing *ROA*, especially about bank-specific elements or other economic variables possibly very important in determining financial results.

**Table 5**. Arellano-Bond dynamic panel-data estimation results — Return on assets

| *Panel A: Panel-data estimation results* | | | | | |
|---|---|---|---|---|---|
| ***ROA*** | ***Coef.*** | ***Std. error*** | ***t-value*** | ***p-value*** | ***[95% conf. interval]*** |
| *L1* | -0.556 | 0.385 | -0.05 | 0.085 | [-1.212, 0.113] |
| *LogTA* | 0 | 0 | 0.15 | 0.883 | [-1.53e-07, 1.78e-07] |
| *IR* | -952.423 | 1155.997 | -0.82 | 0.41 | [-3218.135, 1313.289] |
| *DC* | -0.077 | 0.194 | -0.40 | 0.692 | [-0.4560948, 0.302] |
| *POS* | -0.001 | 0.01 | -0.06 | 0.953 | [-0.020, 0.019] |
| *GDP* | 2.474 | 20.594 | 0.12 | 0.904 | [-37.890, 42.838] |
| Constant | 8.277 | 8.408 | 0.98 | 0.325 | [-8.203, 24.757] |
| Mean dependent var | | 0.912 | SD dependent var | | 0.839 |
| Number of observations | | 28 | Wald Chi-square | | 40.551*** |
| *Panel B: Arellano-Bond test for zero autocorrelation in first-differenced errors* | | | | | |
| ***Order*** | | ***z*** | | ***Prob > z*** | |
| 1 | | 6655 | | 0.5057 | |
| 2 | | -1.2672 | | 0.2051 | |

*Note: *** p < 0.01, ** p < 0.05, * p < 0.1.*
*Source: Authors' elaboration.*

Table 6 shows the dynamic panel-data estimates of *ROE*. Although the lagged dependent variable (*L1*) displays a coefficient of -0.581, its significance or impact on current *ROE* is difficult to evaluate without standard error, t-value, or p-value. The confidence interval, which runs from -1.310 to 0.199, indicates doubt on the link between previous and present *ROE* levels.

With a coefficient of zero ($p = 0.797$), bank size is among the control variables and has not much effect on *ROE*. Though this result is not statistically significant, meaning that inflation does not have a consistent impact on *ROE*, the *IR* shows a coefficient of -7458.896 ($p = 0.777$). Comparably, the *DC* variable exhibits a coefficient of -0.523 ($p = 0.891$), implying no notable relationship with *ROE*. Further underlining a lack of notable impact on financial performance, the mobile *POS* variable has a coefficient of -0.012 ($p = 0.942$). Though it does not show a statistically significant impact on *ROE*, the *GDP* variable displays a positive coefficient of 5.93 ($p = 0.984$), the same as the other control factors. Although the constant term is stated as zero, its interpretation is nevertheless unknown without more data.

At least one of the factors influences *ROE*; the total model is statistically significant (Wald Chi-square = 21.325, $p < 0.05$). The Arellano-Bond test for zero autocorrelation reveals evidence of first-order autocorrelation ($z = -2.1745$, $p = 0.035$) and second-order autocorrelation ($z = -3.5751$, $p = 0.013$), therefore, casting questions on the validity of the dynamic model used.

Thus, although the model is statistically significant, individual predictors show no appreciable impact on *ROE*. This led to no appreciable correlation between *DC* and Mobile *POS* concerning the evaluation of both bank performance indicators (*ROA* and *ROE*). This would imply that the integration of digital technologies in banking operations would not directly or immediately affect financial performance measures such as *ROE*.

**Table 6**. Arellano-Bond dynamic panel-data estimation results — Return on equity

| *Panel A: Panel-data estimation results* | | | | | |
|---|---|---|---|---|---|
| ***ROE*** | ***Coef.*** | ***Std. error*** | ***t-value*** | ***p-value*** | ***[95% conf. interval]*** |
| *L1* | -0.581 | | | | [-1.310, 0.199] |
| *LogTA* | 0 | 0 | 0.26 | 0.797 | [-1.21e-06, 1.58e-06] |
| *IR* | -7458.896 | 26284.49 | -0.28 | 0.777 | [-58975.55, 44057.76] |
| *DC* | -0.523 | 3.217 | -0.16 | 0.871 | [-6.828, 5.781] |
| *POS* | -0.012 | 0.161 | -0.07 | 0.942 | [-0.326, 0.303] |
| *GDP* | 5.93 | 304.333 | 0.02 | 0.984 | [-590.55, 602.412] |
| Constant | 0 | | | | |
| Mean dependent var | | 7.006 | SD dependent var | | 7.348 |
| Number of observations | | 28 | Wald Chi-square | | 21.325** |
| *Panel B: Arellano-Bond test for zero autocorrelation in first-differenced errors* | | | | | |
| ***Order*** | | ***z*** | | ***Prob > z*** | |
| 1 | | -2.1745 | | 0.0346 | |
| 2 | | -3.5751 | | 0.0132 | |

*Note: *** p < 0.01, ** p < 0.05, * p < 0.1.*
*Source: Authors' elaboration.*

Table 7 offers a similar estimation for the *DTC*. With a substantial positive correlation of 4.125 ($p = 0.032$), the lagged dependent variable (*L1*) indicates that past debt levels significantly affect current *DTC*, therefore, implying a trend for companies to either keep or raise their debt over time. Among the control variables, bank size (-2.29e-08, $p = 0.263$), *IR* (-95.756, $p = 0.147$), and *GDP* (0.322, $p = 0.414$), none show statistically significant effects on *DTC*, suggesting that external economic forces may not be the main drivers of capital structure decisions in this sample.

While the mobile *POS* correlates -0.002 ($p = 0.010$), demonstrating that higher involvement with these technologies is associated with lowered *DTC*, *DC* has a substantial negative coefficient of -0.015 ($p = 0.001$). This implies that companies using mobile payments and *DC* could have better cash flow control and less dependence on debt funding.

Supporting the validity of the dynamic model used, the model is statistically significant (Wald Chi-square = 32.495, $p = 0.01$) and exhibits no indication of first-order autocorrelation ($z = -0.333$, $p = 0.739$; $z = -1.182$, $p = 0.923$ for second order). Overall, the results illustrate the need for technological integration in optimizing capital structure and underline that, although conventional economic considerations are taken into account, new financial practices may be more crucial in determining the capital decisions of companies.

The risk indicator, *DTE*, is much influenced by both *DC* and mobile *POS*, so the Sargan and Hansen tests are justified to validate the instruments in the dynamic panel data model. With a Chi-square result of 5.86 (14 degrees of freedom, Prob > $Chi^2 = 0.970$), the Sargan test indicated suitable instruments since the null hypothesis of valid overidentifying limits cannot be refuted. Conversely, the Hansen test produced a chi-squared result of 0.00 (Prob > $Chi^2 = 1.000$), so supporting instrument validity even more.

Exogeneity of particular instrument groups was verified using difference-in-Hansen tests. The Hansen test produced a chi-squared statistic of 0.00 (Prob > $Chi^2 = 1.000$) for the first group (*L.DTC*), and similarly for the second group (*dTA, dIR, dDC, dGDP*), therefore, supporting instrument validity. With instruments not connected to the error term, the Sargan and Hansen test findings thus confirm the dependability of the model and validate the negative effect of *DC* and mobile *POS* on the *DTE*. This emphasizes the need for contemporary financial methods for choices on capital structure.

**Table 7.** Arellano-Bond dynamic panel-data estimation results — Debt-to-capital ratio

| ***Panel A: Panel-data estimation results*** | | | | | |
|---|---|---|---|---|---|
| ***DTC*** | ***Coef.*** | ***Std. error*** | ***t-value*** | ***p-value*** | ***[95% conf. interval]*** |
| *L1* | 4.125** | 2.345 | 2.18 | 0.032 | [8.000, 1.250] |
| *LogTA* | -2.29e-08 | 2.05e-08 | -1.12 | 0.263 | [-6.31e-08, 1.72e-08] |
| *IR* | -95.756 | 63.18 | -1.99 | 0.147 | [-221.586, 30.074] |
| *DC* | -0.015*** | 0.004 | -3.75 | 0.001 | [-0.025, -0.005] |
| *POS* | -0.002*** | 0.001 | -2.56 | 0.010 | [-0.004, -0.0001] |
| *GDP* | 0.322 | 0.393 | 0.82 | 0.414 | [-1.215, 1.859] |
| Constant | 7.959* | 4.015 | 1.73 | 0.083 | [0.053, 15.865] |
| Mean dependent var | | 0.794 | SD dependent var | | 0.077 |
| Number of observations | | 28 | Wald Chi-square | | 32.495*** |
| ***Panel B: Arellano-Bond test for zero autocorrelation in first-differenced errors*** | | | | | |
| ***Order*** | | ***z*** | | ***Prob > z*** | |
| 1 | | 0.333 | | 0.739 | |
| 2 | | 1.182 | | 0.237 | |

*Note: *** p < 0.01, ** p < 0.05, * p < 0.1.*
*Source: Authors' elaboration.*

**Table 8.** Arellano-Bond dynamic panel-data estimation Results — Debt-to-equity ratio

| ***Panel A: Panel-data estimation results*** | | | | | |
|---|---|---|---|---|---|
| ***DTE*** | ***Coef.*** | ***Std. error*** | ***t-value*** | ***p-value*** | ***[95% conf. interval]*** |
| *L1* | 1.904 | 1.315 | 1.45 | 0.147 | [-0.672, 4.480] |
| *LogTA* | 0 | 0 | 1.46 | 0.144 | [-1.08e-07, 7.44e-07] |
| *IR* | 63.321 | 1260.946 | 0.05 | 0.96 | [-2408.087, 2534.728] |
| *DC* | -0.009 | 0.139 | -0.07 | 0.947 | [-0.281, 0.262] |
| *POS* | 0.008 | 0.006 | 1.29 | 0.198 | [-0.004, 0.020] |
| *GDP* | -2.721 | 16.165 | -0.17 | 0.866 | [-34.403, 28.961] |
| Constant | -4.359 | 13.842 | -0.31 | 0.753 | [-31.488, 22.769] |
| Mean dependent var | | 4.540 | SD dependent var | | 1.950 |
| Number of observations | | 28 | Wald Chi-square | | 30.262*** |
| ***Panel B: Arellano-Bond test for zero autocorrelation in first-differenced errors*** | | | | | |
| ***Order*** | | ***z*** | | ***Prob > z*** | |
| 1 | | | | | |
| 2 | | -2.292 | | 0.022 | |

*Note: *** p < 0.01, ** p < 0.05, * p < 0.1.*
*Source: Authors' elaboration.*

Table 8 ultimately offers the dynamic panel-data estimate results for the *DTE*. Though it is not statistically significant, demonstrating ambiguity in the impact of prior *DTE* decisions on current ratios, the lagged dependent variable (*L1*) has a coefficient of 1.904 ($p = 0.147$). This suggests a positive association between past and present *DTE* levels.

With a coefficient of zero ($p = 0.144$), bank size among the control variables indicates no appreciable impact on *DTE*. With a coefficient of 63.321 ($p = 0.960$), the *IR* shows that, based on its lack of statistical significance, changes in inflation have little effect on *DTE*. With a coefficient of -0.009 ($p = 0.947$), *DC* indicates no appreciable relationship with *DTE*. With a coefficient of 0.008 (p = 0.198), the mobile *POS* variable was shown to have also negligible influence on *DTE*. At last, the *GDP* variable exhibits a correlation of -2.721 (p = 0.866), implying that variations in economic development have little bearing on the *DTE*.

With a p-value of 0.753, the constant term — estimated as -4.359 — indicates, even more, a lack of notable baseline effect on the *DTE* when all other predictors are kept constant. The general model is statistically significant (Wald Chi-square = 30.262, p < 0.01), thereby verifying that the *DTE* is much influenced by at least one predictor. Concerning the validity of the model, the Arellano-Bond test for zero autocorrelation reveals notable first-order autocorrelation (z = -2.292, p = 0.222), which causes worries. Therefore, even if the *DTE* model exhibits general statistical relevance, the individual predictors do not have a notable influence on the ratio.

## 5. CONCLUSION

The study findings' implications are significant to practitioners and academics alike, as this would provide an evidence-based approach to digital transformation plans and activities within the context of banking institutions. Interestingly, the study found no association between digital commerce and mobile POS and traditional performance measures like ROA and ROE. While several explanations could be available, one feasible reason is that substantial investments in financial technologies, like those explored in this study, are not captured by these accounting-based traditional metrics. Sura et al. (2022) explained that traditional accounting-based metrics, such as ROA and ROE, may be unable, if not unsuitable, to reflect the rewards of digital investments, particularly when such investments aim to enhance long-term capabilities, customer engagement, and risk management. Looking at this perspective, the non-significant influence of the tested financial technologies could suggest that the problem might be more with the metrics traditionally used to evaluate these initiatives than with the initiatives themselves. These challenges make it important for banking institutions to shift their focus from short-term measures of financial performance and look at other strategic measures of performance.

On the DTC, however, the significant influence of digital commerce and mobile POS exposes a fundamental element of risk management. This result shows that although efforts in digital commerce might not raise profitability measures, they are absolutely important in strengthening banks' capital structures and control of financial leverage. Here, the inference is that digital platforms help banks to maximize their funding sources and lower their dependence on debt, therefore improving their whole risk profile. Better financial decision-making is made possible by these digital solutions, which could have helped to improve the DTC through enhanced accessibility and efficiency (Carlin et al., 2022).

However, why only the DTC was found to have a statistically significant relationship with the digital commerce metrics may be explained by the nature of this risk metric. Other financial performance measures, to some extent, reflect operational efficiency and profitability, and the DTC is more directly associated with financial management decisions that are enabled by digital strategies. For example, digital commerce and mobile POS may enhance transaction procedures and contribute to the optimization of cash flows, which in turn, may help the banks to better control their debt levels and capital structure (Palazzo, 2019). ROA and ROE, on the other hand, are factors that can be influenced by other variables such as the management of assets (Wijaya, 2019) and general market conditions (Al-Homaidi et al., 2020) that may overrule the impacts of financial technology applications and strategies.

However, the fact that the coefficients for digital commerce and mobile POS variables were not significantly related to the DTE, even though it is another measure of financial risk like the DTC, should be further explained. It may be that the reason for this lies in the very nature of these ratios (what they measure). The DTC shows the extent of debt in a bank's balance sheet and thus depends on the financing policies and the cash flow from operations (Samryn et al., 2023). Financial technology structures like digital commerce and mobile POS can help in the financial process and cash flow management and thereby increase capital productivity. These aspects help financial institutions, like banks, to control their debt conditions, hence influencing the DTC in a positive manner.

By comparison, the DTE gauges the relative share of debt financing to shareholder equity. This ratio is more sensitive to variations in the equity component, which can be affected by retained earnings, dividend policies, and market circumstances (Nukala & Rao, 2021), among others. Digital commerce and mobile POS platforms have probably more indirect effects on equity, which can be eclipsed by changes in the larger financial market or strategic choices on equity financing. Therefore, even if financial technologies can increase operational efficiency and risk management, their effect on the DTE could be less noticeable because of these more general influencing elements.

Furthermore, the negative coefficient linked with *L1* highlights the necessity of time in the link between financial technological activity and bank performance. This result suggests that since the immediate effects of the same on financial performance are not as simple as it may seem, a longer time horizon could be needed to fully enjoy the benefits of such activities. Therefore, companies such as banks should create long-term plans and strategies allowing more time for the technical investment to grow rather than expecting instantaneous benefits. Muttai et al. (2023) already highlighted those investments in financial innovation take time to mature, especially since infrastructure building, personnel training, and system integration with conventional operations during the early phases of their deployment are costly. This reduces the short-term profitability of companies, stifling any quick pay-off.

Not to be subdued, the theoretical implications of the study findings should be emphasized twofold. First, the study aligns with philosophies of organizational change and change management, which asserts that immediate payoffs are unlikely compared to consistent long-term benefits when it comes to operational adjustments that involve processes, market, people, and technology. Consequently, there may be a need to further investigate traditional frameworks of performance, such as ROA and ROE, and how they link to digital transformations. Modifying metrics of performance may be needed to capture elements of modern business and banking operations that could appropriately reflect the value and true standing of the organization.

Second, the study findings contribute to contemporary theories of risk management, particularly in financial institutions like banks. The varying influence of digital commerce and mobile POS opens the argument that different risk mitigation and response measures involving technology cannot address all aspects or similar components of financial and operational risk. As the results show, technological investments could only be effective if they address the distinctive nature of the risk. Put differently, the mitigating effects of investment in financial technology may be more pronounced in addressing risk exposures that are primarily due to internal and operational factors rather than those that are more attributable to external market and economic conditions.

Our analysis acknowledges several limitations that provide directions for future research. First of all, the scope of digital payments examined is confined to digital commerce and mobile POS payments such as blockchain-based systems, cryptocurrency, digital wallets, or peer-to-peer lending platforms, which may also affect bank performance and risk (Agarwal et al., 2019; Kumar & Bird, 2020). Moreover, the six-year timeframe of the research analyzed might not be adequate to fully capture long-term impacts. Additionally, external factors such as economic fluctuations, regulatory shifts, and competition from non-bank fintech firms were not explicitly controlled. Lastly, the focus on retail banks in Bahrain limits the generalizability of findings to other banking sectors, financial institutions, or jurisdictions with differing regulatory frameworks and digital payment adoption rates.

For future studies, researchers could explore the use of other comprehensive measures of risk and performance, such as economic value added or risk-adjusted return on capital, which could further the suitability of findings for financial institutions. A larger sample size, controlling for varying countries or economy-specific characteristics, could also enhance the conclusiveness of future explorations within a similar theme. It is further suggested that other methods of model specification correcting for small finite-sample biases and over-fitting could be utilized to generate more robust results.

## REFERENCES


Adeyeye, O. P., Fapetu, O., & Adefolu, I. T. (2018). Does quality of bank services lead to customer satisfaction in the Nigerian banking sector? *Journal of Humanities, Social Science and Creative Arts, 13*, 52–74. https://journal.funaab.edu.ng/index.php/JHSSCA/article/view/1929/1582

Aduaka, U., & Awolusi, O. D. (2020). Electronic banking and profitability in the Nigerian banking industry. *Information Management and Business Review, 12*(2(I)), 20–37. https://doi.org/10.22610/imbr.v12i2(I).3086

Agarwal, A., Gupta, A., Kumar, A., & Tamilselvam, S. G. (2019). Learning risk culture of banks using news analytics. *European Journal of Operational Research, 277*(2), 770–783. https://doi.org/10.1016/j.ejor.2019.02.045

Akuien, A. D. (2023). The importance of banking sector in the growth of nation economy: A case study of Stanbic Bank in South Sudan. *International Journal of Science and Business*, *28*(1), 1–20. https://doi.org/10.58970/IJSB.2201

Albastaki, Y. (2023a). E-payment acceptance factors in Bahrain: Neutrosophic perspective. *Information Sciences Letters, 12*(11), 3087–3099. https://doi.org/10.18576/isl/121119

Albastaki, Y. A. (2024). Toward a cashless society: Assessing the acceptance of Bahrain BenefitPay using TAM and SEM. *Competitiveness Review: An International Business Journal, 34*(1), 193–207. https://doi.org/10.1108/CR-12-2022-0184

Al-Homaidi, E. A., Almaqtari, F., Yahya, A., & Khaled, A. (2020). Internal and external determinants of listed commercial banks' profitability in India: Dynamic GMM approach. *International Journal of Monetary Economics and Finance, 13*, 34–67. https://doi.org/10.1504/IJMEF.2020.105333

Almulla, D., & Aljughaiman, A. A. (2021). Does financial technology matter? Evidence from an alternative banking system. *Cogent Economics & Finance, 9*(1), Article 1934978. https://doi.org/10.1080/23322039.2021.1934978

Al-Rafik, M. (2021). The effect of investment, exports, and interest rates on the gross domestic product of the Republic of Yemen: An econometric analysis. *Journal of Advanced Research in Economics and Administrative Sciences, 2*(2), 112–129. https://doi.org/10.47631/JAREAS.V2I3.325

Arilesere, M. S., Olaleye, B. R., Asaolu, A. A., & Akienabor, E. (2021). Digital electronic payment and bank performance in Nigeria. *Annals of Spiru Haret University Economic Studies, 21*(4), 327–340. https://www.researchgate.net/publication/357680801

Asiabugwa, M. A. (2011). *E-commerce strategy and performance of commercial banks in Kenya* [Master's thesis, University of Nairobi]. University of Nairobi Repository. https://erepository.uonbi.ac.ke/bitstream/handle/11295/95710/Asiabugwa_E-commerce%20strategy%20and%20performance%20of%20commercial%20banks%20in%20Kenya.pdf?sequence=1

Baah-Acquah, P., & Freeman, E. (2016). E-commerce in the banking industry of Ghana: An innovative approach to maximize banking profit and market share. *The International Journal of Business & Management, 4*(10), 335–345. https://www.internationaljournalcorner.com/index.php/theijbm/article/view/127043

Bahrain Economic Development Board. (2020, October 7). *Bahrain's journey to digitization*. https://www.bahrainedb.com/bahrain-pulse/bahrains-journey-to-digitisation

Barros, L., Castro, F., Silveira, A., & Bergmann, D. (2020). Endogeneity in panel data regressions: Methodological guidance for corporate finance researchers. *Review of Business Management, 22*, 437–461. https://doi.org/10.7819/rbgn.v22i0.4059

Carlin, B., Olafsson, A., & Pagel, M. (2022). Mobile apps and financial decision-making. *Review of Finance, 27*(3), 977–996. https://doi.org/10.1093/rof/rfac040

Central Bank of Bahrain. (2024). *Banking sector overview*. https://www.cbb.gov.bh/banking

Chamboko, R. (2024). Digital financial services adoption: A retrospective time-to-event analysis approach. *Financial Innovation, 10*(1), Article 46. https://doi.org/10.1186/s40854-023-00568-1

Daly, S., & Frikha, M. (2017). Determinants of bank performance: Comparative study between conventional and Islamic banking in Bahrain. *Journal of the Knowledge Economy, 8*, 471–488. https://doi.org/10.1007/s13132-015-0261-8

Dao, B. (2020). Bank capital adequacy ratio and bank performance in Vietnam: A simultaneous equations framework. *Journal of Asian Finance, Economics and Business, 7*(6), 039–046. https://doi.org/10.13106/jafeb.2020.vol7.no6.039

Dávila, E., & Walther, A. (2017). *Does size matter? Bailouts with large and small banks* (NBER Working Paper No. 24132). National Bureau of Economic Research (NBER). https://doi.org/10.3386/w24132

Doblas, M. P., & Lagaras, M. C. (2023). The granger causality of Bahrain stocks, Bitcoin, and other commodity asset returns: evidence of short-term return Spillover before and during the COVID-19 pandemic. *International Journal of Business Analytics, 10*(1), 1–20. https://doi.org/10.4018/IJBAN.322304

Dong, X. (2019). *Performance expectancy, effort expectancy, social influence, facilitating conditions, and relative advantage affecting Chinese customers' decision to use mobile payment in Bangkok* [Master's thesis, Graduate School of Bangkok University]. https://dspace.bu.ac.th/handle/123456789/3779

Febrianto, A. (2022). Mplementation of POS (point of sale) applications in improving services at Kopersi Induk Pondok Pesantren Nurul Jadid Paiton Probolinggo. *Profit: Jurnal Kajian Ekonomi dan Perbankan Syariah, 6*(1), 32–50. https://doi.org/10.33650/profit.v6i1.3594

Franciska, A. M., & Sahayaselvi, S. (2017). An overview on digital payments. *International Journal of Research, 4*(13), 2101–2111. https://shorturl.at/JkA0J

Gomber, P., Koch, J. A., & Siering, M. (2017). Digital finance and FinTech: Current research and future research directions. *Journal of Business Economics, 87*, 537–580. https://doi.org/10.1007/s11573-017-0852-x

Greene, C., & Stavins, J. (2021). *The 2020 diary of consumer payment choice* (Research Data Report No. 21-2). Federal Reserve Bank of Atlanta. https://doi.org/10.29338/rdr2021-02

Harban, F. J. M. J., Ali, B. J. A., & Oudat, M. S. (2021). The effect of financial risks on the financial performance of banks listed on Bahrain Bourse: An empirical study. *Information Sciences Letters, 10*(S1), 71–89. https://www.naturalspublishing.com/Article.asp?ArtcID=24076

Harold, A. G., Wen, L. Z., & Ruth, I. A. E. (2019). Website dimensions and e-trust, disposition, perceived risk, and online self-efficacy: Technology acceptance model in China and Ivory Coast context. *Journal of Entrepreneurship & Organization Management, 8*(1), 1–8. https://pdfs.semanticscholar.org/91b0/6b91e29874d6172e52e064f357489a476dda.pdf

Hawaldar, I. T., Rohith, B., Pinto, P., & Rajesha, T. M. (2017). The impact of oil price crisis on financial performance of commercial banks in Bahrain. *Banks and Bank Systems, 12*(4), 4–16. https://doi.org/10.21511/bbs.12(4).2017.01

Hossain, Z., Rahman, A., Hossain, M., & Karami, J. (2019). Over-differencing and forecasting with non-stationary time series data. *Dhaka University Journal of Science. 67*(1), 21–26. https://doi.org/10.3329/dujs.v67i1.54568

Irmaningtyas, W., & Rosadi, D. (2014). Estimating the parameter of dynamic panel data model using Arellano-Bond method. *International Journal of Applied Mathematics and Statistics, 53*, 206–211. https://www.ceser.in/ceserp/index.php/ijamas/article/view/3727

Khan, S., & Al-Harby, A. S. A. (2022). The use of FinTech and its impact on financial intermediation: A comparison of Saudi Arabia with other GCC economies. *Intellectual Economics, 16*(2), 26–43. https://doi.org/10.13165/IE-22-16-2-02

Khiaonarong, M. T., & Humphrey, D. (2022). *Falling use of cash and demand for retail central bank digital currency* (IMF Working Paper No. WP/22/27). International Monetary Fund (IMF). https://doi.org/10.5089/9798400200861.001

KPMG. (2023). *GCC listed banks' results 2023.* https://assets.kpmg.com/content/dam/kpmg/bh/pdf/2023/04/gcc-listed-banks-results-report-fy23-web-bh.pdf

KPMG. (2024). *GCC listed banks' results 2024.* https://assets.kpmg.com/content/dam/kpmg/qa/pdf/2024/03/gcc-listed-banks-results-report-fy23-web-version.pdf

Kumar, V., & Bird, R. (2020). Do profitable banks make a positive contribution to the economy? *Journal of Risk and Financial Management, 13*(8), Article 159. https://doi.org/10.3390/jrfm13080159

Magdalena, T., & Widarjo, W. (2024). Bibliometric analysis: The research development of return on equity (ROE) in commercial banks during 2021–2023. *Navigating the Blue Economy: Sustainable Development Goals and Trends in Economics, Business, Management, and Information Technology, 3*, 852–861. https://e-conf.usd.ac.id/index.php/icebmr/icebmr2024/paper/viewFile/3711/670

Matar, A., Abdeldayem, M. M., & Aldulaimi, S. H. (2024). The growing digitalization of e-commerce in the MENA region: Consumer behavior and shift towards digital payment methods. In *2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)* (pp. 1–5). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/ICETSIS61505.2024.10459416

McKinsey & Company. (2023). *The 2023 McKinsey global payments report: On the cusp of the next payments era: Future opportunities for banks.* https://www.mckinsey.com/industries/financial-services/our-insights/the-2023-mckinsey-global-payments-report

Merani, A. (2023). *Impact of FinTech on risk management for commercial banks in the digital era* [Doctoral dissertation, Goa University]. https://iqac.unigoa.ac.in/criterion1/1.3.4-22-23-INT-MBAFS-28.pdf

Mileva, E. (2007). *Using Arellano-Bond dynamic panel GMM estimators in Stata.* https://www.researchgate.net/file.PostFileLoader.html?id=575fcb0a217e200cb31d2f1f&assetKey=AS%3A372807700631552%401465895690276

Muttai, S., Njoka, C., & Muchira, B. (2023). Effect of financial technology on the financial performance of commercial banks in Kenya. *Journal of Finance and Accounting, 7*(3). https://doi.org/10.53819/81018102t6063

Nduji, R., & Chris, O. (2020). Effect of e-commerce on performance of commercial banks in Nigeria (A case study of First Bank Plc, Bwari Area Council, Abuja). *Journal of African Studies and Sustainable Development, 3*(10), 1–30. https://acjol.org/index.php/jassd/article/view/721

Niankara, I. (2022). The impact of financial inclusion on digital payment solution uptake within the Gulf Cooperation Council. *International Journal of Innovation Studies, 7*(3), 1–17. https://doi.org/10.1016/j.ijis.2022.09.004

Njogu, J. (2020). *Effect of financial technology on financial development in Kenya* [Master's thesis, University of Nairobi]. University of Nairobi Repository. https://erepository.uonbi.ac.ke/bitstream/handle/11295/153996/Njogu_Effect%20of%20financial%20technology%20on%20financial%20development%20in%20Kenya.pdf?sequence=1

Noor, L. S., Deriawan, D., & Oktrivina, A. (2023). E-commerce and financial performance: Identification on trends, benefits and challenges. *Atestasi: Jurnal Ilmiah Akuntansi, 6*(1), 528–543. https://doi.org/10.57178/atestasi.v6i1.931

Nukala, V., & Rao, S. (2021). Role of debt-to-equity ratio in project investment valuation, assessing risk and return in capital markets. *Future Business Journal, 7*, 1–14. https://doi.org/10.1186/s43093-021-00058-9

Okonkwo, A., & Ekwueme, C. (2022). Effect of electronic payment on financial performance of Nigerian deposit money banks. *International Journal of Advanced Academic Research, 8*(3), 2488–9849. https://www.ijaar.org/articles/v8n3/sms/ijaar-v8n3-Mar22-p83119.pdf

Olalere, O. E., Kes, M. S., Islam, M. A., & Rahman, S. (2021). The effect of financial innovation and bank competition on firm value: A comparative study of Malaysian and Nigerian banks. *The Journal of Asian Finance, Economics and Business, 8*(6), 245–253. https://doi.org/10.13106/jafeb.2021.vol8.no6.0245

Pabreja, K. (2018). Anticipation of gross domestic product using world development indicators. In A. K. Saini, A. K. Nayak, & R. K. Vyas (Eds.), *ICT based innovations: Proceedings of CSI 2015* (pp. 141–151). Springer. https://doi.org/10.1007/978-981-10-6602-3_14

Palazzo, B. (2019). Cash flows risk, capital structure, and corporate bond yields. *Annals of Finance, 15*, 401–420. https://doi.org/10.1007/S10436-018-00342-9

Phan, D. H. B., Narayan, P. K., Rahman, R. E., & Hutabarat, A. R. (2020). Do financial technology firms influence bank performance? *Pacific-Basin Finance Journal, 62,* Article 101210. https://doi.org/10.1016/j.pacfin.2019.101210

Rahmad, N. N., Zullzaidi, N. S. M., Azmi, N. D. F., & Khairudin, N. M. (2024). *Mobile payment security: A critical analysis of vulnerabilities & emerging threats.* TechRxiv. https://doi.org/10.36227/techrxiv.170620372.22051414/v1

Rehman, A., Aslam, E., & Iqbal, A. (2021). Intellectual capital efficiency and bank performance: Evidence from Islamic banks. *Borsa Istanbul Review, 22*(1), 113–121. https://doi.org/10.1016/j.bir.2021.02.004

Rigas, D., & Riaz, N. (2015) E-commerce purchase intention in emerging markets: The influence of gender and culture. In P. L. P. Rau (Ed.), *Cross-cultural design: Applications in mobile interaction, education, health, transport and cultural heritage* (pp. 90–100). Springer. https://doi.org/10.1007/978-3-319-20934-0_9

Roodman, D. (2009). How to do Xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal, 9*(1), 86–136. https://doi.org/10.1177/1536867X0900900106

Salami, C. G. E., & Mercy, O. (2014). E-commerce and banking performance in Nigeria. *Information Engineering and Applications, 4*(5). https://www.iiste.org/Journals/index.php/JIEA/article/view/13167#google_vignette

Samryn, L. M., Ismail, I. b., Sudarmadji, & Kasmir. (2023). Cash flows and capital adequacy ratio of Indonesian commercial banks. *European Journal of Business and Management Research. 8*(6), 147–154. https://doi.org/10.24018/ejbmr.2023.8.6.2143

Sari, I., & Siregar, F. A. (2024). Analysis of the influence of mobile banking on the profitability level of Sharia banks in Indonesia in 2019–2023. *Journal of Islamic Financial Technology, 3*(1), 1–8. https://doi.org/10.24952/jiftech.v3i1.11687

Scopelliti, D. (2016). Consumer spending: Past and present. *Monthly Labor Review.* https://www.bls.gov/opub/mlr/2016/beyond-bls/pdf/consumer-spending-past-and-present.pdf

Seo, M., & Shin, Y. (2016). Dynamic panels with threshold effect and endogeneity. *Journal of Econometrics, 195*, 169–186. https://doi.org/10.1016/J.JECONOM.2016.03.005

Shaikh, I., & Anwar, M. (2023). Digital bank transactions and performance of the Indian banking sector. *Applied Economics, 55*(8), 839–852. https://doi.org/10.1080/00036846.2022.2094880

Shkvarchuk, L., & Slav'yuk, R. (2019). The financial behavior of households in Ukraine. *Journal of Competitiveness, 11*(3), 144–159. https://doi.org/10.7441/joc.2019.03.09

Soutter, L., Ferguson, K., & Neubert, M. (2019). Digital payments: Impact factors and mass adoption in Sub-Saharan Africa. *Technology Innovation Management Review, 7*(10), 41–55. https://doi.org/10.22215/timreview/1254

Sura, J., Panchal, R., & Lather, A. (2022). Economic value-added (EVA) myths and realities: Evidence from the Indian manufacturing sector. *IIM Ranchi Journal of Management Studies, 2*(1), 82–96. https://doi.org/10.1108/irjms-03-2022-0037

Uddin, M. H., Ali, M. H., & Hassan, M. K. (2020). Cybersecurity hazards and financial system vulnerability: A synthesis of literature. *Risk Management, 22*(4), 239–309. https://doi.org/10.1057/s41283-020-00063-2

Varma, P., & Nijjer, S. (2022). Examining the role of fintech in the future of retail banking. *ECS Transactions, 107*(1), Article 9855. https://doi.org/10.1149/10701.9855ecst

Wang, H., & Gunawan, A. (2022). Analyzing the impact of digital payment on efficiency and productivity of commercial banks: A case study in China. In *12th Annual International Conference on Industrial Engineering and Operations Management* (pp. 1649–1659). IEOM Society International. https://index.ieomsociety.org/index.cfm/article/view/ID/181

Wijaya, R. (2019). Analisis perkembangan return on assets (ROA) dan return on equity (ROE) untuk mengukur kinerja keuangan [Analysis of the development of return on assets (ROA) and return on equity (ROE) to measure financial performance]. *Jurnal Ilmiah Manajemen, 9*, 40–51. https://doi.org/10.32502/jimn.v9i1.2115

Writer, S. (2024, August 7). Bahrain achieves 89% digital transformation rate. *ZAWYA.* https://www.zawya.com/en/business/technology-and-telecom/bahrain-achieves-89-digital-transformation-rate-kbt691bw

Xin, X., Zhu, R., & Ou, G. (2024). Does digital transformation lower equity financing costs? An explanation based on the "return-risk-expectation" framework. *Economic Change and Restructuring, 57*(2), Article 88. https://doi.org/10.1007/s10644-024-09682-1

Yousafzai, S. Y., Pallister, J. G., & Foxall, G. R. (2003). A proposed model of e-trust for electronic banking. *Technovation, 23*(11), 847–860. https://doi.org/10.1016/S0166-4972(03)00130-5

Zhang, X., Zhao, T., Wang, L., & Dong, Z. (2022). Does Fintech benefit financial disintermediation? Evidence based on provinces in China from 2013 to 2018. *Journal of Asian Economics, 82*, Article 101516. https://doi.org/10.1016/j.asieco.2022.101516

Zhang, Y., & Zhou, Q. (2020). Correction for the asymptotical bias of the Arellano-Bond type GMM estimation of dynamic panel models. In T. Li, M. H. Pesaran, & D. Terrell (Eds.), *Essays in honor of Cheng Hsiao* (Vol. 41: Advances in Econometrics, pp. 1–24). Emerald Publishing Limited. https://doi.org/10.1108/s0731-905320200000041001

# APPENDIX

**Table A.1.** Variables description

| *Variables* | *Measurement* | *Symbol* |
|---|---|---|
| | ***Dependent variables*** | |
| Bank performance | Return on assets (%) = Net income / Total assets | *ROA* |
| | Return on equity (%) = Net income / Owner's equity | *ROE* |
| Bank risk | Debt-to-capital (%) = Total debt / Total debt + Total equity | *DTC* |
| | Debt-to-equity (%) = Total debt / Total equity | *DTE* |
| | ***Independent variables*** | |
| Digital commerce | Payments for products and services made over the Internet, including credit card and online payment providers (%) | *DC* |
| Mobile POS payment | Payments processed through mobile devices at the point of sale using smartphone applications (%) | *POS* |
| | ***Control variables*** | |
| Bank size | Total assets of each bank (USD, $) | *TA* |
| Inflation rate | Consumer Price Index (CPI, %) | *IR* |

*Source: Authors' elaboration.*