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Financial Technology Adoption and Bank Financial Performance: Evidence from Jordan

Yahia Alhadab[1]*, Roslan Ali[2], Resul Sapar[3], & Murad Mohammad Mujahed[4]

[1,2,3,4] Putra Business School (PBS), Universiti Putra Malaysia, 43400. Serdang, Selangor. Malaysia.

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ABSTRACT

This paper investigates the relationship between FinTech adoption and bank financial performance in Jordanian commercial banks over the period 2010–2023. The analysis will focus on accounting-based performance, market-based performance, and the timing of performance effects as the main channels for considering the potential impact of FinTech, using fixed-effects panel regressions and dynamic-lead specification. The findings indicate that FinTech adoption has an insignificant immediate impact on bank profitability and market valuation. However, the dynamic analysis shows that FinTech adoption contributes positively to future financial performance. The findings indicate that operational performance, as measured by ROA, improves after a lag of two to three years, while shareholder returns (ROE) show positive responses at longer horizons. By contrast, the response of market-based performance, measured as Tobin's Q, to FinTech adoption is tenuous and statistically insignificant, even in the long run. At a broader level, the results suggest that the FinTech adoption effect is time-structured and sequential, thereby rendering digital transformation as a long-run strategic investment rather than a short-run driver of profitability or market valuation. The study adds to the literature by providing dynamic evidence on the performance implication of FinTech adoption in an emerging economy banking market.

JEL Classification: G21; O33; C23; G32.

1. Introduction

The rapid diffusion of FinTech has totally changed the anatomy and operations of the banking industry worldwide. The digital payments, mobile and online banking, data analytics, blockchain, and artificial intelligence have shaped the ways banks deliver services of finance, processing information, and relating with customers. Digital finance technologies are heavily promoted as means to enhance operational efficiency, reduce transaction costs, improve service quality, and finally strengthen financial performance. Due to these reasons, the adoption of FinTech has become a strategic priority for banks to sustain competitiveness within the increasingly digitized financial markets. Despite the large-scale adoption of FinTech, empirical evidence of its impact on bank financial performance is still mixed. On one hand, some

* Corresponding author.
E-mail address: yehea.m.89@gmail.com
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studies evidence that digital transformation can enhance profitability and efficiency through cutting operating costs and increasing customers touched [1, 2, 3]. Other studies, however, find weak, insignificant, or even adverse impacts, particularly within emerging and developing economies themselves [4, 5]. Therefore, the question of whether adoption of FinTech improves the financial performance of banks in emerging economies has emerged as a research gap. An interesting and educational backdrop in which to review this dynamic is presented by Jordan. The past decade has seen significant investment by commercial banks in Jordan in FinTech-enabled digital banking technologies such as real-time payment solutions, mobile channels, and online billing payment systems. These projects have been facilitated by supportive regulatory policies and plans at the national level that intend to enhance digital financial solutions and minimize dependence on cash-based payment systems. Notably, however, key financial performance ratios such as return on assets and return on equity have reflected fluctuations in financial performance as FinTech adoption has accelerated.

Previous empirical studies that explored FinTech and bank performance mainly targeted developed countries that enjoy well-organized technology frameworks and institutional settings in which financial institutions operate. FinTech-related studies in developing markets and their effects in emerging markets conducted by Bashayreh and Wadi (2021) used proxy variables in measuring FinTech adoption that took into consideration simple ATM and online capabilities. Further, most studies on the topic treat FinTech as a 'homogeneous innovation.' This overlooks the multifaceted phenomenon associated with the digitalization of the financial services industry. As such, there seems to be an existing knowledge gap when more sophisticated forms of FinTech adoption are linked to financial performance in emerging markets. This research aims to fill the research gap by focusing on the direct impact of FinTech adoption on the financial performance of commercial banks operating in the emerging market setting. The research employs a panel dataset for the period 2010 to 2023 for commercial banks operating in Jordan, where a comprehensive FinTech adoption index has been built using the self-reported use of major FinTech by the respective banks. The financial performance of the banks has been evaluated using the accounting and market approaches.

In contemporary era of globalization, economies and companies must adapt their approaches towards technology for growth. In similar regards, there exists a significant body of research related to digital banking. However, not all studies cover emerging economies or analyze dimensions of the adoption of these technologies. In these regards, the current thesis aims to add to existing bodies of knowledge related to digital banking through its focus on a different approach related to performance and technology that helps banks adapt. The rest of the paper is organized as follows. Section 2 presents a literature review and the formulation of the hypotheses. Section 3 describes the data and the methodology that was used. Section 4 presents the results, and Section 5 provides a discussion related to the implications of the results. Section 6 presents the conclusions and directions for further research.

2. Literature Review

2.1 Financial Technology in the Banking Sector

FinTech can be defined as the application of digital innovations in financial services provision with the view to enhance efficiency, accessibility, and quality of services. Banking includes a broad selection of technologies, such as digital payments systems, mobile and internet banking channels, big data analytics, cloud computing, artificial intelligence, and blockchain-based solutions. These technologies have disrupted long-standing banking models because of the process automation they enable, the speed increase in execution, and data-based decision-making. FinTech adoption has taken a strategic turn in the rising tide of competition that banks generally face from non-bank financial service providers and FinTech startups. In light of this, traditional banks are increasingly integrating digital technologies into core operations and shifting away from branch-centered models toward platform-based service delivery. Previous research indicates that adoption of FinTech will ultimately enhance the operational flexibility of banks in responding to the now-changing customer preferences [4, 7]. Theoretical frameworks that are relevant to the subject matter include the Technology Acceptance Model (TAM). The TAM theory argues that the main predictions in determining the model of technology adoption and sustained usage lie in perceived usefulness and perceived ease of use [8]. By applying it to the subject at hand, FinTech services that are seen as efficient, dependable, and easy to use can be adopted at a wider scale; hence, performance and productivity are affected at the organizational level [9].

2.2 FinTech Adoption and Bank Financial Performance

A growing number of empirical studies have investigated the impact of FinTech adoption on bank financial performance. Proponents argue that FinTech adoption enhances bank performance in several ways: it helps to reduce operating costs, improve asset utilization, increase customer reach, and speed transactions more quickly [3, 5]. Digital platforms can lower personnel and branch-related expenses while enabling banks to scale services more efficiently, which is expected to improve profitability indicators such as return on assets (ROA) and return on equity (ROE). Empirical evidence from most developed economies generally supports the positive relationship that exists between FinTech adoption and bank performance. For example, Gomber et al. (2018) and Thakor (2020) find that digital transformation improves efficiency and competitiveness in the banking system within mature technological infrastructures. This is corroborated by Campanella et al. (2017), who report higher productivity and cost efficiency in banks with the adoption of advanced digital technologies. However, results from emerging and developing economies are not conclusive. While there are studies that show positive outcomes of FinTech adoption for banks based on increased efficiency and inclusiveness [10, 11], others conclude there are insignificant or lagged outcomes owing to the cost of adoption and the degree of technology adoption readiness, among others [4, 12]. Within emerging markets in particular, FinTech adoption could have additional performance implications in terms of dynamic rather than direct influence. Upfront investment in FinTech technology entails high fixed costs that could negatively affect financial performance in the short term. By virtue of learning curve economies and process improvements in addition to user adoption in due course, performance could improve in the long term [13, 3]. The two have particular significance regarding performance impact.

2.3 Measuring FinTech Adoption in Banking

One of the challenges in the literature of FinTech-performance association deals with the quantification of FinTech adoption. In the earlier literature, the FinTech adoption metric was limited to the extent of the usage of automation technology or the development of online banking services. These proxies are less appropriate in the sense that digital transformation is a complex process [6]. More recent research uses a range of indices that rely upon the usage of various digital technologies utilized in the bank [14]. Disclosure-based FinTech indices, which have been derived from annual reports, have also been recognized as more transparent and comparable across institutions over time. Disclosure-based FinTech indices better identify banks' strategic focus regarding FinTech, rather than technological specifics. In emerging markets, FinTech usage data is difficult to standardize, making disclosure data the only reliable source of constant information regarding FinTech adoption.

3. Hypotheses Development

Grounded in the Technology Acceptance Model (TAM) and the digital efficiency literature, the adoption of FinTech is hypothesized to improve the financial performance of banks in several related ways. Under the TAM, technologies that are seen as valuable and easy to use are more enthusiastically adopted and embedded within the organization, leading to improvements in their productivity and performance [8, 9]. For the banking sector, FinTech technologies such as digital payments, online and mobile banking, data analytics, and process automation make transactions less costly, increase the efficiency of their processing, and increase the speed and accuracy of the resulting transactions [1, 2]. From an efficiency viewpoint, the implementation of FinTech enables banking institutions to enhance the efficiency of asset management, reduce costs of operation, and incur lower administrative costs, as compared to the costs involved in the conventional branch banking model, while using this opportunity to increase customer engagement channels through digital means. The increased efficiencies are projected to translate into increased profitability, as indicated by specific financial performance ratios such as return on asset (ROA) and return on equity (ROE) [7, 3]. Furthermore, the availability of information technology allows banking institutions to tap into alternative revenue streams, hence increasing the capacity for risk assessment, consequently promoting financial sustainability [5, 10]. Besides accounting-based results, the impact of FinTech adoption can extend to market-based outcomes, including the demonstration of innovation capability and adaptability for investors. Those banking institutions that invest actively in and report about their efforts in digital transformation can be viewed as more competitive and effective in dealing with technological changes, thus improving the market valuation vis-à-vis the costs of replacing assets [4, 12]. Consequently, the implications of adopting FinTech on performance are presumed not only for current profitability ratios but also for future market estimates, such as those of Tobin's Q Ratio. Based on these theoretical arguments and prior empirical evidence, the following hypotheses are proposed:

H1: Financial technology adoption has a positive effect on banks’ return on assets (ROA).

H2: Financial technology adoption has a positive effect on banks’ return on equity (ROE).

H3: Financial technology adoption has a positive effect on banks’ market valuation, as measured by Tobin’s Q.

4. Methodology

This research uses an equal weighted panel dataset, which includes 12 conventionally operating for-profit commercial banks listed in the public markets of Jordan, observed from 2010 until 2023, generating 168 observations for each bank-year observation. The dataset consists of all for-profit commercial banks listed within the Amman Stock Exchange, for which comprehensive financial reports and compliance data are accessible for the duration of the research period. The research does not include Islamic banks because of their differing business paradigms, Sharia-supervised management structures, and principles associated with profit and loss-sharing, which might introduce structural heterogeneity affecting the distinctness of adopting financial technology and financial performances. The financial information employed in creating the variables for both dependent and control variables is obtained from the audited financial reports presented by each bank in annual audited accounts as published in both the Amman Stock Exchange and specific bank announcements. The details regarding financial technology adoption are obtained by carefully examining annual financial reports as presented in bank announcements. The sources are accurate in documenting digital bank innovations. In particular, the return measures, such as ROA, ROE, and Tobin’s Q, are calculated from the audited financial reports. The FinTech adoption is treated as an index, which is built based on the qualitative disclosures in the annual reports about digital payment systems, mobile and internet banking, blockchain, artificial intelligence, and data analytics technologies. The control variables, established by the size, leverage, and age of the banks, are collected from the annual financial reports and the banks' official records. The unit of observation is the bank-year, which enables the research to take advantage of both cross-section and time-series variation existing within the dataset. The timeframe chosen encompasses the crucial phases of digital revolution, regulation, and economic cycles that have occurred within the banking sector of the emerging country of Jordan. The final sample consists of 12 commercial banks in Jordan that are studied over the period of 2010–2023, generating a total of 168 bank-years. The study selects all the commercial banks that provided consistent disclosures of annual reports and financial information during the period of the study.

4.1 Measurement of Variables

4.1.1 Dependent Variable: Financial Performance

In this research, bank financial performance is the dependent variable, which is operationalized using accounting-based and market-based indicators together. The use of multiple performance measures allows a better grasp of the performances of banks by capturing both internal profitability and external market valuation. Return on Assets is obtained by dividing net income by total assets. ROA indicates the efficiency of bank management in exploiting available assets for earnings generation. The measure is widely applied in banking studies because of its capability to capture operational performance independent of capital structure. ROE is defined as the ratio between net income and shareholders' equity. ROE shows the return achieved for equity holders and reflects managerial decisions on how effectively equity capital is deployed. It is usually applied when the profitability needs to be analyzed from the perspective of bank owners or investors (Athanasoglou et al., 2008; Saleh et al., 2021). The use of Tobin’s Q (TQ) ratio acts as a performance metric that is obtained using the formula: Market value of equity plus the book value of total liabilities divided by the book value of total assets. The use of Tobin’s Q ratio is applicable in measuring investors’ views of a bank's potential growth or value that is not captured in the accounting statement. Market-based ratios are ideal in estimating the extent to which markets value banks’ strategic moves, such as digital transformation (Claessens et al., 2018; Wei, 2023). The use of accounting metrics (ROA and ROE) and market metrics (Tobin's Q) will allow the research to facilitate a more comprehensive assessment of bank performance between realized outcomes and market valuation as it relates to the overall effect of FinTech adoption.

4.1.2 Independent Variable: Financial Technology Adoption (Final)

The adoption rate of FinTech is scored utilizing the FinTech Adoption Index, which is derived based on the disclosures method suggested by Abu Alim and Mansour (2024). This method is used to identify the extent of banking involvement within the sector of FinTech by examining the disclosures within the annual reports, and it has been used in recent studies investigating the digital transformation of the banking sector, especially within the emerging economies. In line with Abu Alim and Mansour (2024), the FinTech Adoption Index is constructed from a keyword-based content analysis of the annual reports published by the banks. The FinTech score captures the degree of disclosures made by the banks with regard to FinTech usage such as digital payment systems, mobile and internet banking, blockchain technology, artificial intelligence, and data-driven financial services. Each of the FinTech-related keywords extracted will feed into the overall FinTech score for a particular bank-year. It is designed on a bank-by-year basis to ensure comparison across banks and across time. This measure, emphasizing the need to disclose, according to Abu Alim and Mansour (2024), is very much a Strategic Orientation to the adoption of Financial Technology, rather than any Transaction Volume or Usage, which would presumably remain unavailable in a secondary source. Using the original approach, the FinTech Adoption Index can be normalized to maintain consistency in the scale and to properly align with the principles for econometric testing. Moreover, higher values on the FinTech Adoption Index represent higher levels of FinTech adoption. Such an approach towards measuring will ensure that results are transparent, replicable, and aligned with existing methodologies used in past studies, yet still consistent with data availability conditions common in emerging markets for banking.

4.1.3 Control Variables

In order to control the isolated effect of FinTech adoption on the financial performance of banks, the research project encompasses a group of control variables specific to the banking sector that were formerly used in studies related to banking research. These control variables capture the underlying bank structure or financial traits that can affect profitability or values irrespective of the effect of FinTech adoption. Bank Size

(SIZE) is calculated by natural logs of total assets. Bank size is used to account for economies of scale, where larger banks have better scale economies, investment capabilities, or technological infrastructure, thus influencing bank financial performance. The prior body of research has also documented a positive correlation between bank size and bank profitability across both developed markets and emerging markets [15, 18, 19]. Leverage ratio (LEV) is calculated by dividing total liabilities by total assets. As indicated above, the leverage ratio measures the level of risk associated with the financial performance of the bank. Moreover, the leverage ratio can have both negative and positive effects on profitability. However, including the leverage ratio as a control variable aligns with prior banking studies, which use the ratio as an aspect that influences the risk–reward spectrum for banks [20, 21]. Bank Age (AGE) is calculated as the number of years since a bank's founding date. Older or younger banks can have different experience, reputation, or learning capabilities, and different banks can benefit or suffer from these aspects. Older banks can benefit from long-term experience and established customer networks, while younger banks can enjoy greater flexibility and lower adaptation costs. The empirical literature uses bank age as a control variable for studying financial performance differences among banks [22, 23].

4.2 Econometric Model Specification

These are included to account for time-specific effects, which can affect the performance of all banks in a certain year, for example, macroeconomic conditions, government legislation, or technology shocks. Including year fixed effects is generally considered standard procedure in panel data analysis as it helps control for omitted variable bias caused by time-specific effects [24]. These variables together improve the robustness of the empirical models by incorporating important features that might affect the relationship between FinTech use and financial performance. In order to test the impact of financial technology adoption on the financial performance of banks, the study uses the panel data regression approach, which utilizes the cross-sectional and time-series features of the data. Panel data analysis is particularly appropriate in banking studies due to its ability to control for individual effects and track changes over time, as noted in the literature [25, 24]. The base empirical model takes the following form:

$$FP_{it}=\alpha+\beta_1 FinTech_{it}+\sum\gamma_k Control_{kit}+\mu_i+\lambda_t+\varepsilon_{it} \qquad (1)$$

where FP denotes the financial performance of bank i in year t, measured alternatively by return on assets (ROA), return on equity (ROE), and Tobin's Q. FinTech represents the FinTech Adoption Index constructed following Abu Alim and Mansour (2024). Control is a vector of bank-specific control variables, including bank size, leverage, and bank age. μ(i) captures unobserved time-invariant bank-specific effects, λ(_t) represents year fixed effects, and ε is the idiosyncratic error term.

The inclusion of bank-specific fixed effects controls for unobservable characteristics such as managerial culture, business model orientation, and risk appetite that may influence financial performance but remain constant over time. Year fixed effects are incorporated to account for macroeconomic shocks, regulatory changes, and industry-wide developments affecting all banks in a given year [25, 24]. To assess whether FinTech adoption influences not only contemporaneous performance but also future financial outcomes, the model is extended by incorporating lead values of financial performance. This dynamic specification allows the analysis to capture potential delayed effects arising from learning costs, adjustment periods, and gradual efficiency gains associated with digital investment [13, 3]. The extended model is specified as:

$$FP_{i,t+1}=\alpha+\beta_1 FinTech_{it}+\sum\gamma_k Control_{kit}+\mu_i+\lambda_t+\varepsilon_{it} \qquad (2)$$

This will enable the study to assess whether present FinTech adoption affects better future bank performance, as it will offer additional insights regarding the passage of time incorporating digitization within the banking sector. A separate regression for each financial performance indicator is estimated to reflect the distinction between accounting-based measures and market-based valuation. This overcomes the aggregation bias problem and facilitates a more refined view of the financial performance implications of FinTech use.

4.3 Estimation

The analysis utilizes panel data techniques to examine the impact of financial technology adoption on the financial performance of banks. The use of panel data analysis in banking research has the advantage of accounting for unobserved heterogeneity across banks as well as capturing both cross-sectional and time-series variation in the dataset [25, 24]. The main estimation method employed in the study is the fixed-effects estimator. The fixed-effects estimator controls for unobserved and time-invariant bank characteristics, such as management style, organizational culture, and risk attitude, which may affect banks' financial performance and are correlated with the use of FinTech. This way, the fixed-effects estimator provides unbiased estimates of the relationship between FinTech use and banks' financial performance [26]. The choice between the fixed-effects estimator and the random-effects estimator follows the conventional specification test between the two estimators. Following traditional banking literature, the preferred model is the fixed-effects model if the bank-specific unobservable effects are correlated with the explanatory variables, which is expected in the context of digital transformation [25, 24]. The separate estimations are conducted for each financial performance measure (ROA, ROE, and Tobin’s Q) taking into account the differences between accounting-based and market-based valuation measures of profitability. This enhances the robustness of the results and provides deeper insights into the extent of FinTech’s influence on various banking performance measures.

The current research adopts a quantitative panel data approach to investigate the direct impact of financial technology adoption on the financial performance of banks in emerging markets. By employing a balanced panel of 12 commercial banks operating in Jordan over the period 2010–2023, the study exploits both cross-sectional and time-series variations. A set of accounting ratios (ROA, ROE, and Tobin’s Q) along with a market-based ratio, Tobin’s Q, facilitates a comprehensive evaluation of financial and market performance. The FinTech Adoption Index is constructed using a disclosure-based methodology following Abu Alim and Mansour (2024), ensuring methodological consistency in measuring financial technology adoption. Control variables including bank size, leverage, and age are incorporated to account for structural differences across banks. Empirical analysis is conducted using fixed-effects panel regression models to control for unobserved time-invariant bank characteristics, along with year fixed effects. Robust standard errors are employed to address potential heteroscedasticity and serial correlation issues. In addition to contemporaneous specifications, lead models are estimated to examine the dynamic impact of FinTech adoption on future financial performance. Thus, the methodological framework adopted in this study provides a rigorous and reliable basis for assessing the performance implications of FinTech adoption within the banking sector, particularly in the context of emerging economies.

5. Empirical Results

This section elaborates on the empirical results of the relationship between the adoption of financial technology and bank financial performance. The succeeding analytical treatment in this section has been done based on the methodological framework followed in Section 3, wherein panel data has been accessed over Jordanian commercial banks from 2010 to 2023. The results were reported in a structured way, starting with descriptive statistics and follow-up analysis of correlation analysis, after which multivariate regression estimates assess the impact of FinTech adoption on accounting-based and market-based performance measures. Descriptive statistics are first reported, consistent with prior empirical banking studies, to summarize the main characteristics of the sample and to provide preliminary insights into the distribution and variability of the main variables. Then, correlation analysis is conducted in order to check for bivariate associations and to assess potential multicollinearity concerns. Afterwards, the main regression results are presented using fixed-effects panel estimations, estimating separate models for ROA, ROE, and Tobin's Q, respectively. Additional specifications that use lead values of financial performance are reported to assess the dynamic effects of FinTech adoption.

5.1 Descriptive Statistics

Table 1: This table highlights the descriptive statistics of the key variables employed in the analysis, which are the financial performance variables, the FinTech Adoption Index, and the control variables, and was obtained using a sample of 168 bank-years. The table reveals the mean, standard deviation, lowest, and highest values of the variables during the period of 2010 to 2023.

Table 1: Descriptive Statistics of Financial Performance, FinTech Adoption, and Control Variables

Variable	Mean	Std. Dev.	Min	Max
Return on Assets (ROA)	1.108	0.507	-0.160	2.050
Return on Equity (ROE)	8.234	3.554	-0.990	16.870
Tobin'sQ	1.051	0.534	0.200	7.706
FinTech Index	4.703	0.822	0.693	5.820
Leverage	0.924	0.535	0.065	7.626
Size	21.704	0.906	20.334	24.049
Age	45.416	17.415	15.000	93.00

Note: This table presents descriptive statistics for financial performance measures, the FinTech Adoption Index, and control variables for Jordanian commercial banks over the period 2010–2023. N denotes the total number of bank-year observations.

The FinTech Adoption Index has a mean of 4.703, a standard deviation of 0.822, and a range of 0.693 to 5.820. This standard deviation reflects the variation of the level of FinTech adoption exhibited by the Jordanian commercial banks, and the variation observed is a good setting to test the implications of the adoption of FinTech on the performance of the banks. Concerning financial performance, the average return on assets (ROA) stands at 1.108%, while it varies between -0.160% and 2.050%. Likewise, the average return on equity (ROE) is 8.234%, while it varies between -0.990% and 16.870%. Both show moderate and high variability, respectively, in profitability and shareholder returns, consistent with the volatility of profitability in the emerging banking market environment. Table 2 presents the result for the model M2 and indicates the insignificance of the coefficients for lagged return on equity, return on equity, return on assets, and return on equity volatility, while the coefficients for return. The market-oriented performance indicator, which is the Tobin Q, has a mean of 1.051, implying a wide range that lies between 0.200 and 7.706, which shows variances in bank valuation across the market and market expectations of potential bank growth for the future. Turning to the control variables, the mean for bank size, using the natural logarithm of total assets, is 21.704, which has little dispersion, implying that the banking sector is very homogeneous in terms of the size of the banks. The leverage has a mean of 0.924, which reflects the high use of liabilities common among banks, but the standard deviation shows a high degree of risk differentiation among the firms. The bank age has a mean of 45.416 years, which ranges from 15 to 93 years and ensures that old and younger banks are well represented in the study.

5.2 Correlation Analysis

Presented in Table 2 are the results of the Pearson's correlation coefficients between the key variables employed in the study: financial performance metrics, the FinTech Adoption Index, as well as the control variables.The results of the correlation analysis can provide initial clues about the nature and intensity of the association between each pair of variables considered in the study, as well as help diagnose any multicollinearity problems.The correlation coefficient on the accounting performance measures is high and significant. This is because return on assets (ROA) and return on equity (ROE) have a high correlation coefficient of 0.903 with $p < 0.01$. This clearly shows that both performance measures are similar. On the other hand, the correlation coefficient for Tobin's Q with ROA and ROE measures is weak and insignificant.

The values are -0.011 and -0.016 respectively. This indicates that market value and short-term profitability measures are not similar.

Table 2: Correlation Matrix for Study Variables

	ROA	ROE	Tobin's Q	FinTech Index	Leverage	Size	Age
ROE	0.903***	1					
Tobin's Q	-0.0113	-0.016	1				
FinTech index	-0.114	-0.067	0.004	1			
Leverage	-0.0697	-0.059	0.994***	0.034	1		
Size	-0.001	0.026	-0.006	0.495***	-0.026	1	
Age	-0.0762	-0.0609	0.176*	0.397***	0.178*	0.710***	1

Note: This table presents Pearson correlation coefficients among the study variables. Statistical significance is denoted as follows: $p < 0.10$ (*), $p < 0.05$ (**), and $p < 0.01$ (***).

FinTech Adoption Index correlation coefficients show very low and statistically insignificant correlation coefficients for ROA (–0.114) and ROE (–0.067), and approximately zero correlation for Tobin's Q (0.004). All of these findings indicate that there is nothing immediate and straightforward in terms of correlation between FinTech and financial performance of banks in their bivariate framework. All these will instead be explored in regression analyses. Concerning the control variables, there is a very strong positive correlation between Leverage and Tobin's Q (0.994, $p < 0.01$), which confirms strong mechanics linking the stock market value and balance sheet management in banking institutions. Leverage has a weak and insignificant correlation with ROA (–0.0697) and ROE (–0.059). Bank size has a positive and significant correlation with the FinTech Adoption Index (0.495, $p < 0.01$), which confirms that larger banks have a greater adoption rate of financial technology. Bank age also has a positive and significant correlation with the FinTech Adoption Index (0.397, $p < 0.01$), which confirms that older banks experience a greater adoption rate of financial technology.

Notably, notwithstanding that most of the pairwise correlations among the variables incorporated into the model are below the generally accepted cut-offs, a very high correlation exists between the variables LEVERAGE and Tobin's Q. The closeness of the relationship between leverage ratios and market valuation ratios, as characterized by Tobin's Q vis-à-vis banking firms, can be attributed to the fact that these variables are more closely aligned from a mechanical and balance sheet perspective. Consequently, the outcome of the Tobin's Q regression analysis ought to be used cautiously, especially where the variable leverage is concerned. Except for that particular aspect, the correlation matrix does not indicate the presence of multicollinearity among the principal variables.

5.3 Regression Results: FinTech Adoption and Financial Performance.

The following table shows the fixed-effects regression model results for the relationship between financial technology and bank financial performance. Different regression models have been used for each financial performance indicator, which include return on assets, return on equity, and Tobin's Q to distinguish between accounting profitability and market returns.

5.3.1 FinTech Adoption and Accounting-Based Financial Performance (ROA and ROE)

Table 3 reports fixed-effects regression results for the relationship between financial technology adoption and accounting-based measures of bank profitability, that is ROA and ROE. All models include bank- and year-fixed effects; robust standard errors are clustered at the bank level.

Table 3: Fixed-Effects Panel Regression Results: FinTech Adoption and Accounting-Based Financial Performance

VARIABLES	(1) ROA	(2) ROE
FinTech Index	0.054	0.320
	(0.911)	(0.879)
Leverage	0.024	1.364*
	(0.306)	(1.988)
Size	0.140	4.161**
	(0.634)	(2.267)
Age	-0.029	-0.378
	(-1.223)	(-1.751)
Constant	-0.833	-67.008*
	(-0.194)	(-1.966)
Observations	168	168
R-squared	0.365	0.351
Number of Bank	12	12
Bank FE	Yes	Yes
Year FE	Yes	Yes
SEs	Clustered by bank	Clustered by bank
R^2 (within)	0.365	0.351
R^2 (between)	0.00303	0.00386
R^2 (overall)	0.0769	0.0473
N	168	168

This table displays the fixed-effect regression analysis of the effect of financial technology (FinTech) adoption on the bank Return on Assets (ROA) and Return on Equity (ROE). The FinTech Adoption Index utilizes the disclosure-based approach using the keywords frequency method proposed by Abu Alim and Mansour (2024). The frequency of the keywords is aggregated and calculated through the natural logarithm of the keyword's frequency. The results are controlled by the bank size, leverage, and age variables, while bank and year fixed effects are also included. The standard errors are also bank-level robust, and the t-statistics are presented inside the parentheses. The symbols ***p<0.01, **p<0.05, and *p<0.10 represent the respective significance of the results.

In both specifications, the coefficient on the FinTech Adoption Index is positive but statistically insignificant. More precisely, the estimated coefficient for ROA is 0.054 (t = 0.911), while for ROE it is 0.320 (t = 0.879). These findings imply that, after considering bank-specific characteristics and unobserved heterogeneity, no statistically significant direct effect of FinTech adoption on the accounting-based profitability of banks exists for the period under investigation. Consequently, this may indicate that financial gains from FinTech adoption are not immediately captured by conventional measures of profitability or that costs of adjustment, implementation lags, and/or the long-term nature of digital investments impede its current financial gains. Among the control variables, the result shows that leverage has a positive and marginal significant correlation with ROE, and its coefficient is 1.364 (t=1.988, p<0.10), which indicates that highly leveraged banks have the tendency to yield higher return on equity. Leverage does not have a statistical significant impact on return on assets. Bank size has a positive and statistical significant impact on return on equity because its coefficient is 4.161 (t=2.267, p<0.05), which indicates that banks following the economies of scale theory yield higher return on equity because they get the benefit of economies of scale. The impact of size on return on assets is positive and statistical insignificant. Bank age is negatively correlated with both ROA and ROE; however, in both cases, the coefficients are not statistically significant. It indicates that age is not a definitive factor in profitability. Thus, the results suggest that although FinTech adoption is positively related to profitability for banks, this positive relationship lacks statistical significance in the fixed effect models. Conversely, the more traditional structural factors—itself or size and/or capital—

seem to carry relatively greater importance in explaining the variations in accounting performance in the Jordanian commercial banks.

5.3.2 FinTech Adoption and Market-Based Financial Performance (Tobin's Q)

Table 4 presents results from fixed-effect regression analyses testing the link between adoption of financial technology and market-based performance of banks, which is captured by the measure of Tobin's Q. The regression includes bank effects as well as year effects, employing robust standard errors clustered for banks. It is worth highlighting that, within banks, the measure of Tobin's Q is fundamentally connected to balance-sheet characteristics, especially leverage, that overtakes its explanation power. The coefficient for the FinTech Adoption Index is positive but statistically insignificant, and the estimated coefficient is 0.003 (t = 0.390). This indicates that FinTech adoption does not have any statistically significant, contemporaneous impact on the valuation of banks, after accounting for the bank-specific factors and the time factors. This is an intriguing finding and raises the question of whether the capital markets are immediately responsive to banks' efforts in their digital makeover, especially in an emerging economy, where the challenges of asymmetry of information, regulatory barriers, and the uncertainties of returns on digital investments might impinge on their responsiveness.

Table 4: Fixed-Effects Panel Regression Results: FinTech Adoption and Market-Based Performance (Tobin's Q)

VARIABLES	(1) Tobin's Q
FinTech Index	0.003
	(0.390)
Leverage	0.992***
	(95.152)
Size	-0.003
	(-0.128)
Age	-0.007**
	(-2.325)
Constant	0.508
	(1.143)
Observations	168
R-squared	0.998
Number of Bank	12
Bank FE	Yes
Year FE	Yes
SEs	Clustered by bank
R^2 (within)	0.998
R^2 (between)	0.119
R^2 (overall)	0.936
N	168

Note: This table reports fixed-effects regression estimates on the effect of financial technology (FinTech) adoption on bank profitability, which was measured by Tobin Q. The FinTech Adoption Index was constructed using a disclosure keyword frequency method, following the approach by Abu Alim and Mansour (2024). The index was calculated by taking the natural log of the total frequency of FinTech keywords discovered on each bank's annual reports. The standard errors are clustered at the bank level. Statistical significance was determined by the presence of *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.10$. The references to the parentheses contain the t-statistic.

Among control variables, leverage is strongly positively and highly significantly associated with Tobin's Q. The magnitude of the leverage coefficient and the exceptionally high within R^2 suggests that market-based valuation in the sample is to a great extent driven by balance-sheet dynamics rather than incremental differences in digital transformation. As a consequence, the specification of Tobin's Q leaves little room for FinTech adoption to create an independently significant effect once leverage and fixed effects are controlled. In contrast, bank size exerts a negative though statistically insignificant impact on Tobin's Q, revealing that scale alone has little significant effect on market valuation once other factors are accounted for. Bank age is negatively related to Tobin's Q with a coefficient of –0.007 ($t = –2.325$, $p < 0.05$). This result indicates that older banks have relatively lower market valuations compared to asset replacement costs than growth expectations and/or less aggressive business models.

The model shows a very high within R^2 at 0.998, revealing that the greater part of the variation in Tobin's Q is explained by within-bank changes over time when fixed effects are incorporated. This agrees with the nature of market-based measures in banking performance studies, which have strong roots in balance-sheet structure and persistent bank-specific characteristics. Thus, the results suggest that FinTech adoption is positively related to market-based performance, but its effect is not statistically significant in the fixed-effects specification. This reinforces the view that the valuation effects of digital transformation may materialize only over longer horizons or through indirect channels rather than through immediate market revaluation. Accordingly, the Tobin's Q results should be interpreted as reflecting structural valuation mechanisms in banking rather than as a direct test of the market's responsiveness to FinTech adoption.

5.3.3 Model Diagnostics and Goodness of Fit

The results for all regression models presented in Tables 3 and 4 are obtained through the use of fixed-effect panel models, which include the effect of both bank fixed effects and year fixed effects. Using this method, the estimates obtained for the coefficients are able to control for any unobserved variables that are not changing over time. The overall goodness-of-fit measures of the accounting-based performance models appear to be satisfactory. The within R^2 statistics of the ROA and ROE models are 0.365 and 0.351 respectively. This implies that the variation in the profitability of banks over time, explained by the explanatory variables and the fixed effects in the ROA and ROE models, represents a substantial part of the overall variation in the profitability of banks over time. This compares well with the findings of other empirical banking studies conducted earlier.

In the case of the market-based performance measure, the R^2 of the Tobin's Q formula is very high at 0.998. This is because of the explanatory power of the fixed effects of banks and the leverage variable in the model. First of all, the nature of the variable of interest in banking organizations (Tobin's Q) being balance sheet-oriented does not appear surprising to have high explanatory power in the empirical results when leverage and fixed effects have a prominent influence in the determination of the value. Robust standard errors clustered by bank are used in each of the models to account for possible het-eroskedasticity or correlation of the errors.

Robust standard errors clustered at the bank level are used in all models in order to account for possible problems of heteroscedasticity and correlation. It is found in correlation tests that multicollinearity in general is not prevalent in the variables. Still, it is found that the high correlation between leverage and Tobin's Q represents a structural relationship in and of itself in banking balance sheets. It is thus concluded that although unobserved heterogeneity is accounted for in the fixed-effects model, results from the Tobin's Q model should be analyzed in terms of balance sheet mechanisms and that there is little additional explanatory force of FinTech adoption in particular. First and foremost, the very high explanatory force of variables in the Tobin's Q model will be attributed not to model misspecification in particular but to its relevance in terms of balance sheets.

5.4 Dynamic (Lead) Effects of Financial Technology Adoption

In the adoption of financial technology, there are high initial costs of technology adoption or organization change, which could delay the effect of the financial performance of the organization. Thus, the benefits derived from the adoption of financial technology may not be seen immediately in the financial performance indicators of the organization. To address these delays in the process of financial performance generated by the adoption of financial technology in a bank, the study will use the lead specifications of the dependent variables. Particularly, the empirical models are re-estimated by replacing the contemporaneous financial performance indicators with one-period-ahead indicators, thereby enabling the examination of whether FinTech adoption has contributed to better performance results in the next period. This is based on existing studies proposing that performance improvements are realized over time, as banks optimize their operations, thereby deriving scale benefits, and engraining customers with technological adoption.

The results of the lead-effect estimations indicate that FinTech adoption has a stronger association with future financial performance relative to contemporaneous outcomes. Although the immediate effects of FinTech adoption on accounting-based and market-based performance are statistically insignificant, dynamic specifications suggest that the benefits of digital investment in terms of performance may materialize over time rather than instantaneously. This finding supports the view that FinTech adoption should be regarded as a long-term strategic investment rather than a short-term profitability driver. These dynamic results help to explain why statistically significant contemporaneous effects are absent in Section 4.4 and provide reason for the importance of adopting longer time horizons when assessing the financial implications of digital transformation in banking. Indeed, in emerging market settings, where improvements in technological infrastructure, customer readiness, and regulatory frameworks may be relatively gradual, such lagged performance effects are particularly plausible. In summing up the results from the analysis based on the Lead Effect approach, there are indications that the adoption of FinTech influences the future financial performance of banks, thereby ensuring the continued relevance of digital transformation as an investment area.

5.5 Dynamic (Lead) Effects of Financial Technology Adoption

Although the results from regression analyses in Section 4.4 show that in the currentmodel and period of time considered, there is no statistically significant direct relationship between financial technology adoption and bank financial performance, digital investments in their very nature and applications take time before their benefits can actually materialize. In this regard, this proposed study will therefore investigate and examine the relationship between financial technology adoption and future bank performance.

5.5.1 Dynamic Effects on Accounting-Based Performance: ROA

Table 5 reports fixed-effects regression results of the predictive power of FinTech adoption on future return on assets (ROA) up to one to four years ahead. All models include bank and year fixed effects, standard errors clustered at the bank level.

Table 5: Predictive Effect of Financial Technology Adoption on Future Bank Profitability (Lead ROA Models)

VARIABLES	**(1)** **ROA_{t+1}**	**(2)** **ROA_{t+2}**	**(3)** **ROA_{t+3}**	**(4)** **ROA_{t+4}**
FinTech Index	0.061	0.070*	0.097**	0.120*
	(1.355)	(1.876)	(2.467)	(2.034)
Leverage	0.157**	0.075	-0.111*	-0.131*
	(2.690)	(1.323)	(-1.994)	(-2.137)
Size	0.091	-0.139	-0.063	-0.227
	(0.615)	(-0.885)	(-0.256)	(-0.963)
Age	-0.016	-0.020	-0.037*	-0.045*
	(-0.836)	(-1.114)	(-1.852)	(-1.907)
Constant	-0.533	4.708	3.859	7.685
	(-0.177)	(1.597)	(0.827)	(1.786)
Observations	156	144	132	120
R-squared	0.408	0.464	0.460	0.450

Number of Banks	12	12	12	12
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs	Clustered by bank	Clustered by bank	Clustered by bank	Clustered by bank
R^2 (within)	0.408	0.464	0.460	0.450
R^2 (between)	0.00408	0.000488	0.00311	0.000654
R^2 (overall)	0.174	0.0930	0.0551	0.0265
N	156	144	132	120

This table shows the results of the fixed-effects regression analysis of the effect of FinTech development on the future profitability of banks in Jordan. The dependent variable is the Return On Asset (ROA) ratio that is observed from year +1 to year +4 after the current year's FinTech development. All the regressions conducted will control for the size of the banks, their Leverage, and their Age. In addition to that, there would be Fixed Effects of banks and Fixed Effects of Year. Standard errors will be clustered for banks. Control variables: Size of banks, Leverage of banks, and Age of banks. p < 0.10, **p < 0.05, ***p < 0.01

The findings indicate a strong and meaningful dynamic relationship. The FinTech Adoption Index coefficient is positive in all lead models and gains significance with longer leads. In particular, a positive, albeit insignificant, effect of FinTech adoption on ROA can be observed in the one-year-ahead model (ROAt+1_{t+1}t+1: coefficient of 0.061, t-statistic of 1.355). Nevertheless, significance can first be obtained in two years ahead (ROAt+2_{t+2}t+2: coefficient of 0.070, t-statistic of 1.876, p-value less than 0.10), with further strengthened levels in the three years ahead (ROAt+3_{t+3}t+3: coefficient of 0.097, t-statistic of 2.467, p-value less than 0.05). The positive effect retains statistical significance in the four years ahead (ROAt+4_{t+4}t+4: coefficient of 0.120, t-statistic

These findings suggest that the profitability benefits of FinTech adoption materialize gradually over time, rather than immediately. Indeed, an increase in the magnitude and statistical significance of the FinTech coefficient at longer horizons may indicate that banks require several years to absorb implementation costs and restructure internal processes in order to then translate digital investments into improved efficiency of operations. Such dynamic evidence is, therefore, a very strong explanation for the absence of statistically significant contemporaneous effects and highlights the importance of adopting a longer time horizon when assessing the financial impact of digital transformation.

With respect to the control variables, leverage has an overall positive and statistically significant impact on ROA for the short horizon, that is, ROAt+1_{t+1}t+1, while for ROAt+3_{t+3}t+3 and ROAt+4_{t+4}t+4, the effect of leverage turns negative and statistically significant, reflecting the evolving risk-return trade-offs over time. Bank size does not have a statistically significant effect on future ROA, while bank age evidences a negative and weakly significant relationship at the longer horizons, suggesting slower profitability growth among more mature banks.

5.5.2 Dynamic Effects on Accounting-Based Performance: ROE

To better understand the dynamic effect of FinTech adoption, this study will now explore the predictive role of FinTech adoption in determining the return on equity in a lead specification. This will require estimation of the model presented in Equation (3) with ROE predicted one to four years forward, while the FinTech Adoption Index and control variables measured contemporaneously. This study will be estimated with fixed effects, including bank and year dummies and robust to clustering by bank, as presented in "Table 6".

Table 6: Predictive Effect of Financial Technology Adoption on Future Return on Equity (Lead ROE Models)

VARIABLES	(1) ROE $_{t+1}$	(2) ROE $_{t+2}$	(3) ROE $_{t+3}$	(4) ROE $_{t+4}$
FinTech Index	0.171	0.182	0.588**	0.902**
	(0.494)	(0.447)	(2.235)	(2.440)
Leverage	2.000***	1.183**	-0.488	-0.790*
	(4.012)	(2.935)	(-1.171)	(-1.914)
Size	3.174**	0.910	0.116	-0.638
	(2.589)	(0.765)	(0.077)	(-0.421)
Age	-0.182	-0.147	-0.206	-0.338*
	(-1.004)	(-0.899)	(-1.362)	(-2.139)
Constant	-54.991**	-6.299	13.285	34.566
	(-2.322)	(-0.292)	(0.476)	(1.202)
Observations	156	144	132	120
R-squared	0.334	0.359	0.364	0.376
Number of Banks	12	12	12	12
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs	Clustered by bank	Clustered by bank	Clustered by bank	Clustered by bank
R^2 (within)	0.334	0.359	0.364	0.376
R^2 (between)	0.0294	0.0404	0.0451	0.0318
R^2 (overall)	0.146	0.181	0.114	0.0563
N	156	144	132	120

Fixed-effects regression estimates of how FinTech development will affect Jordanian banks' future return on equity (ROE) are shown in this table. ROE, which is measured in years t+1 to t+4 after the current year's FinTech index, is the dependent variable. Each model accounts for age, leverage, and bank size. Included are year and bank fixed effects. Parentheses surround standard errors. SEs are grouped by bank; bank FE and year FE are included. Size, leverage, and firm age are the controls. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results show that the dynamic effects of FinTech adoption on ROE are lagged but economically important. In the one-year- and two-year-ahead models, the FinTech Adoption Index coefficient is positively but statistically insignificant (ROE t+1: coefficient = 0.171, t = 0.494; ROE t+2: coefficient = 0.182, t = 0.447). Yet the result is statistically significant and larger in magnitude in the longer-term models. For instance, FinTech adoption exerts a positively significant effect on ROE in the three-year-ahead model (ROE t+3: coefficient = 0.588, t = 2.235, $p < 0.05$) and in the four-year-ahead model (ROE t+4: coefficient = 0.902, t = 2.440, $p < 0.05$).

The above results indicate that the advantages associated with FinTech implementation go beyond the aspect of operating efficiency and, in the end, result in better performance for shareholders, although the adjustment period differs compared to the ROA model. The rising magnitude of the FinTech coefficient as the time horizon lengthens shows that shareholders derive gains only after the initial implementation costs are absorbed and digital technology has been fully integrated into business processes by the banks. Concerning the control variables, while leverage positively affects ROE in the short horizon (ROEt+1: Coefficient = 2.000, $p < 0.01$, ROE t+2: Coefficient = 1.183, $p < 0.05$), this impact lessens and turns negative for longer terms, evidencing a marginally significant effect in the four-year model (ROE t+4: Coefficient = -0.790, $p < 0.10$), signifying an increased risk sensitivity for longer terms. The size of the bank positively impacts ROE for shorter terms but turns insignificant for further terms, while the age of the bank presents a weakly significant, negative impact on ROE for longer terms, signifying lower equity return growth for mature banks. The dynamic ROE provides further evidence for the findings related to ROA in such a way that the adoption of FinTech leads to superior long-term returns for shareholders, although such returns emerge more slowly than improvements in ROA. This pattern confirms the assertion that the digital transformation of the banking sector is an evolutionary process, first improving ROI and later increasing returns on equity.

5.5.3 Dynamic Effects on Market-Based Performance: Tobin's Q

To test whether the dynamic benefits from FinTech adoption carry over into market-based performance, this work investigates the predictive power of FinTech adoption on future market valuation, as captured by the logarithm of Tobin's Q. The fixed-effects regression results reported in Table 7 measure Tobin's Q one to four years ahead of the current period, while FinTech adoption and all control variables are measured contemporaneously. All models contain bank and year fixed effects, with standard errors clustered at the bank level. Results suggest that the dynamic relationship between FinTech adoption and market-based performance is very weak and statistically insignificant across all lead horizons. The coefficient on the FinTech Adoption Index is positive in the one-, two-, and three-year-ahead specifications but none of these coefficients are statistically significant. For the four-year-ahead model, the coefficient is zero for FinTech, thereby rendering evidence of no delayed valuation effect.

Empirical results indicate that, contrary to accounting-based profits, market value does not systematically react to FinTech adoption, even over longer-term periods. Such observations might be driven by persistent information asymmetries, a lack of disclosures regarding digital investment returns, or market doubts about FinTech initiatives' capacity to create sustainable competitive differentials within the banking sector. Emerging market-specific environments might be driven by market actors' emphasis on traditional balance-sheet ratios over technological innovations. Among the control variables, bank age is shown to have a negative and weakly significant correlation with respect to Tobin's Q in the two-year and four-year ahead models (Tobin's Q t+2: coefficient = -0.031, $p < 0.10$; Tobin's Q t+4: coefficient = -0.035, $p < 0.10$), indicating a lower valuation of the stock for older banks. In contrast, bank size is positive but statistically insignificant in the regression results, whereas leverage does not have a significant association in the lead specifications.

Thus, the dynamic Tobin's Q results suggest that the market-based valuation channel is the weakest link in the FinTech–performance relationship. Whereas FinTech adoption does contribute to future improvements in operational efficiency, as proxied by ROA and, with longer lags, shareholder returns proxied by ROE, these advantages are only partly reflected in market valuations. This corroborates the perspective that the financial consequence of FinTech adoption is sequential, where internal performance improvements precede and may not necessarily translate into market revaluation.

Table 7: Predictive Effect of Financial Technology Adoption on Future Market Valuation (Lead Tobin's Q Models)

VARIABLES	(1) Tobin'sQ t+1	(2) Tobin'sQ t+2	(3) Tobin'sQ t+3	(4) Tobin'sQ t+4
FinTech Index	0.086	0.058	0.161	-0.000
	(1.042)	(0.780)	(0.996)	(-0.000)
Leverage	-0.070	-0.058	-0.044	-0.006
	(-1.423)	(-1.258)	(-0.980)	(-0.103)
Size	0.010	0.070	0.154	0.280
	(0.072)	(0.510)	(1.148)	(1.658)
Age	-0.019	-0.031*	-0.040	-0.035*
	(-1.481)	(-2.040)	(-1.682)	(-2.100)
Constant	1.262	0.643	-1.326	-3.534
	(0.473)	(0.228)	(-0.548)	(-1.085)
Observations	156	144	132	120
R-squared	0.101	0.099	0.118	0.109
Number of Banks	12	12	12	12

Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
SEs	Clustered by bank	Clustered by bank	Clustered by bank	Clustered by bank
R^2 (within)	0.101	0.0995	0.118	0.109
R^2 (between)	0.598	0.557	0.596	0.469
R^2 (overall)	0.000970	0.00687	0.0109	0.00394
N	156	144	132	120

This table reports fixed-effects regression results assessing whether current-year FinTech adoption predicts future market-based valuation of Jordanian banks, measured via Tobin's Q from year t+1 to t+4. All models include control variables and fixed effects. *Standard errors in parentheses. Bank FE and Year FE included; SEs clustered by bankControls: Size, Leverage, Age. * p < 0.10, ** p < 0.05, *** p < 0.01*

6. Conclusion

This study examines the association of corporate governance with bank performance in Jordanian commercial banks during 2010–2023 adopting both accounting-based performance (ROA and ROE) and market-based valuation measurement (Tobin's Q), but also between overall governance quality and separate board-level mechanisms. Based on fixed-effects panel regressions, the study offers new insights into governance in a developing banking market. The results suggest that overall corporate governance quality, as measured by composite Corporate Governance Index, has no statistical impact on bank profit performance and market valuation. This implies that 'one size fits all' governance codes may not immediately lead to better financial performance in the Jordanian banking industry even when important for regulatory fetish. The findings for individual governance mechanisms indicate that board gender diversity has a positive and statistically significant effect on both ROA and ROE providing evidence of the influence of specific board characteristics as opposed to overall strength in control. This study investigates the relationship between FinTech adoption and bank financial performance in Jordanian commercial banks over the period 2010–2023, applying fixed-effects panel regressions and dynamic lead specifications. The analysis differentiates between accounting-based performance, market-based performance, and time relative to how FinTech adoption influences financial performance. The estimates indicate that FinTech adoption does not have a statistically significant immediate impact on the profitability of banks or their market valuation. However, the dynamic analysis reveals that FinTech adoption adds value to future financial performance, most strongly with regard to accounting-based measures. In particular, ROA operational performance shows improvement with a delay of two to three years, whereas ROE shareholder returns react positively at longer horizons. In contrast, market-based valuation (Tobin's Q) reacts weakly and statistically insignificantly to FinTech adoption, even in the long term. The results demonstrate that the financial effects of FinTech adoption are both time-dependent and sequential. Digital transformation improves internal efficiency first, next checks the shareholder box, and the effect on market valuation is weak. The findings emphasize the critical consideration of treating FinTech adoption as a longer-term investment proposition rather than a short-term way to boost financial prosperity or revalue the stock price. Policy/Management wise implication of the results is that in the evaluation of FinTech projects, a long-term orientation in light of the lagged effect of performance should be used. For research purposes, the implication is that dynamic specifications are essential in research into the financial sector impact of digital change in emerging markets

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