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DETERMINANTS OF FINTECH ADOPTION: PANEL DATA EVIDENCE FROM DEVELOPING COUNTRIES

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ABSTRACT

FinTech adoption has expanded rapidly, but its development remains uneven across developing countries because digital infrastructure, economic capacity, institutional conditions, and macroeconomic environments differ substantially. This study investigates the determinants of FinTech adoption using annual panel data for selected developing countries over 2010–2023. The analysis examines GDP per capita, internet penetration, regulatory quality, and interest rates using static and dynamic panel-data methods. Static specifications are evaluated through pooled ordinary least squares, random effects, and fixed effects, followed by diagnostic tests and Driscoll–Kraay robust standard errors. Dynamic specifications are estimated using difference and system Generalized Method of Moments (GMM), with the Two-Step System GMM model selected on the basis of the reported Hansen test. The static results indicate that GDP per capita and internet penetration are positively associated with FinTech adoption, while regulatory quality and interest rates are not statistically significant in the preferred Driscoll–Kraay fixed-effects specification. The dynamic results show strong persistence in FinTech adoption, a positive and significant effect of GDP per capita, and negative and significant effects of regulatory quality and interest rates, while internet penetration is positive but statistically insignificant. The findings indicate that FinTech adoption is shaped by economic capacity and technological access, while institutional and macroeconomic effects become more evident when persistence and potential endogeneity are considered.

Keywords: developing countries, digital finance, financial technology, FinTech adoption, panel data

INTRODUCTION

Financial technology (FinTech) has transformed the delivery of financial services through mobile banking, electronic payments, digital lending, online investment, and other technology-enabled financial solutions. Its expansion has increased the speed, accessibility, and convenience of financial transactions and has created new opportunities

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for financial inclusion. However, adoption is not uniform across developing countries because countries differ in income, technological infrastructure, institutional capacity, and financial-market development.

Previous FinTech research has frequently examined individual-level adoption through behavioral constructs such as perceived usefulness, perceived ease of use, trust, perceived risk, and behavioral intention. These studies provide important explanations of user behaviors, but many rely on cross-sectional surveys or single-country settings. Such designs provide limited evidence about how country-level conditions and changes over time shape FinTech adoption across developing economies.

The cross-country perspective is important because FinTech adoption depends not only on individual willingness to use technology but also on the environment in which digital financial services operate. Internet access provides the infrastructure required for many digital financial services, while income affects consumers' and firms' ability to access digital devices and formal financial services. Institutional and regulatory conditions can influence market confidence and the costs of operating FinTech services, whereas interest rates can affect borrowing, investment, liquidity, and the demand for financial products. Existing cross-country evidence also suggests that economic development and technological progress are important drivers of FinTech development (Haddad & Hornuf, 2019; Lee & Shin, 2018).

Despite this literature, an empirical gap remains in the joint examination of technological, economic, institutional, and macroeconomic determinants using panel data for developing countries. A panel approach can account for unobserved country-specific characteristics while also identifying changes over time. In addition, a dynamic specification can capture persistence in adoption and reduce concerns arising from potential endogeneity. This study therefore shifts the emphasis from predominantly individual-level explanations toward a country-level panel perspective.

The novelty of this study lies in combining static and dynamic panel approaches in a single empirical framework. The static analysis identifies the relationship between current country characteristics and FinTech adoption after controlling for country-specific effects, while the dynamic analysis incorporates lagged FinTech adoption and uses GMM estimation to account for persistence and potential endogeneity. The study consequently provides an integrated assessment of the factors associated with FinTech adoption across developing economies.

The objective of this study is to examine the effects of GDP per capita, internet penetration, regulatory quality, and interest rates on FinTech adoption in selected developing countries during 2010–2023. The study also examines whether the relationships identified in the static panel remain consistent when persistence in FinTech adoption is incorporated into a dynamic panel framework.

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METHODS

The study uses annual panel data for selected developing countries covering 2010–2023. The final dataset contains 285 country-year observations. The dependent variable is the FinTech Adoption Index (FINTECH). The explanatory variables are GDP per capita (GDP), internet penetration (IP), regulatory quality (RQ), and interest rate (IR). The variable set is kept identical across the conceptual framework, hypotheses, and empirical specifications; financial literacy is not included because it is not part of the reported dataset or regression models.

The empirical strategy has two stages. First, pooled ordinary least squares (POLS), random effects (RE), and fixed effects (FE) models are estimated as static specifications. The Breusch–Pagan Lagrange Multiplier test is used to compare pooled estimation with a model containing panel effects, while the Hausman test is used to select between RE and FE. Diagnostic tests are then used to assess multicollinearity, heteroskedasticity, serial correlation, and cross-sectional dependence. Because the reported diagnostics indicate heteroskedasticity, serial correlation, and cross-sectional dependence, the preferred static specification is the FE model with Driscoll–Kraay robust standard errors.

Second, dynamic panel models are estimated using one-step and two-step difference GMM and one-step and two-step system GMM. A lagged FinTech Adoption Index is included to capture persistence in adoption. The Hansen J-test is used to assess instrument validity. The reported results identify the Two-Step System GMM specification as the preferred dynamic model because its Hansen test does not reject the validity of the instruments.

The primary evidence is therefore based on the Driscoll–Kraay fixed-effects model for the static analysis and the Two-Step System GMM model for the dynamic analysis. These specifications are not expected to produce identical coefficients because they answer related but different empirical questions: the static model estimates contemporaneous associations after controlling for time-invariant country effects, whereas the dynamic model additionally accounts for persistence and potential endogeneity. The dynamic specification is used as a complementary robustness perspective rather than as a direct substitute for the static model.

The main static model is specified as:

$$FINTECH_{it} = \beta_0 + \beta_1 GDP_{it} + \beta_2 IP_{it} + \beta_3 RQ_{it} + \beta_4 IR_{it} + \mu_i + \varepsilon_{it}$$

where FINTECH is the FinTech Adoption Index; GDP is GDP per capita; IP is internet penetration; RQ is regulatory quality; IR is interest rate; μ_i represents country-specific effects; and ε_{it} is the idiosyncratic error term.

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The dynamic specification extends the model by including lagged FinTech adoption:

$$FINTECH_{it} = \alpha FINTECH_{i,t-1} + \beta_1 GDP_{it} + \beta_2 IP_{it} + \beta_3 RQ_{it} + \beta_4 IR_{it} + \mu_i + \varepsilon_{it}$$

The hypotheses are formulated as follows. H1: GDP per capita has a significant effect on FinTech adoption. H2: Internet penetration has a significant effect on FinTech adoption. H3: Regulatory quality has a significant effect on FinTech adoption. H4: Interest rates have a significant effect on FinTech adoption. The hypotheses are tested through the reported static and dynamic panel specifications.

RESULTS AND DISCUSSION

The model-selection and diagnostic results establish the basis for interpreting the regression coefficients. Table 1 summarizes the static panel estimates and specification tests. The Breusch–Pagan LM statistic is 777.78 ($p < 0.001$), indicating the presence of panel effects and supporting a panel estimator over pooled OLS. The Hausman statistic is 16.51 ($p = 0.0024$), leading to rejection of the random-effects specification in favor of fixed effects. The reported VIF value is 1.64, indicating no serious multicollinearity. The heteroskedasticity and serial-correlation tests are statistically significant, supporting robust inference. Together with the reported cross-sectional dependence, these diagnostics motivate the use of Driscoll–Kraay standard errors for the preferred static model.

Table 1 shows Static panel estimates of FinTech adoption. Note: Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

Variables	Pooled OLS	Random Effects	Fixed Effects	Driscoll–Kraay FE
GDP	0.211*** (0.0747)	0.8515*** (0.0846)	1.0517*** (0.0942)	1.0517*** (0.1522)
Internet penetration	0.0455 (0.0395)	0.0357* (0.0209)	0.0445** (0.0203)	0.0445** (0.0192)
Regulatory quality	0.3855*** (0.1244)	−0.1716 (0.1294)	−0.1320 (0.1334)	−0.1320 (0.1364)
Interest rate	0.0121*** (0.0198)	−0.0007 (0.0030)	0.0004 (0.0030)	0.0004 (0.0019)
Constant	1.6561*** (0.654)	−3.8596*** (0.6988)	−5.5290*** (0.7666)	−5.5289*** (1.3110)
Observations	285	285	285	285
R-squared	0.1885	0.1293	0.1470	0.3460

Table 1 shows that GDP per capita has a positive and statistically significant coefficient of 1.0517 in the preferred Driscoll–Kraay FE specification. This indicates that higher income levels are associated with greater FinTech adoption. A plausible interpretation is that higher income increases purchasing power and the ability to access smartphones, internet services, bank accounts, and digital financial products. The result

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is consistent with evidence linking economic development and technological progress to FinTech development (Haddad & Hornuf, 2019; Lee & Shin, 2018).

Internet penetration is also positive and statistically significant in the preferred static specification, with a coefficient of 0.0445. This result supports the role of digital infrastructure as an enabling condition for mobile banking, digital payments, online lending, and other internet-based financial services. It is consistent with the FinTech ecosystem perspective, in which technological infrastructure forms an important foundation for digital financial activity (Gomber et al., 2017; Lee & Shin, 2018).

Regulatory quality has a negative coefficient of -0.1320 in the preferred static model, but the coefficient is not statistically significant. Therefore, the static results do not provide sufficient evidence that regulatory quality has a direct contemporaneous effect on FinTech adoption in the sample. This does not imply that regulation is unimportant; rather, the effect may depend on the design, timing, and implementation of regulation.

Interest rate has a small positive coefficient of 0.0004 in the preferred static specification and is not statistically significant. The result suggests that short-run variation in interest rates is not strongly associated with aggregate FinTech adoption in the static model. This may reflect the broad nature of the FinTech index, which includes services such as payments and mobile banking that are not necessarily interest-sensitive. The dynamic estimates in Table 2 provide a complementary perspective. The lagged dependent variable is positive and highly significant in the preferred Two-Step System GMM specification (0.7040 , $p < 0.01$), indicating substantial persistence in FinTech adoption. This means that existing FinTech development is associated with subsequent adoption, consistent with technological learning, network effects, user familiarity, and ecosystem development.

Table 2 shows Dynamic panel estimates of FinTech adoption. Note: Standard errors are in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively

Variables	1-Step GMM	Difference GMM	2-Step GMM	Difference GMM	1-Step GMM	System GMM	2-Step GMM	System GMM
Lagged FINTECH	0.6361*** (0.0920)		0.6376*** (0.0161)		0.6997*** (0.0773)		0.7040*** (0.0149)	
GDP	0.4938*** (0.1453)		0.4715*** (0.0332)		0.3185*** (0.1070)		0.3017*** (0.0276)	
Internet penetration	0.0111 (0.0193)		0.0113 (0.0085)		0.0093 (0.0199)		0.0101 (0.0099)	
Regulatory quality	-0.3063^* (0.1614)		-0.3168^{***} (0.0699)		-0.3921^{**} (0.1568)		-0.3845^{***} (0.0288)	
Interest rate	-0.0013 (0.0027)		-0.0013^{***} (0.0003)		-0.0014 (0.0027)		-0.0016^{***} (0.0005)	
Constant	-2.9087^{***} (0.9736)		-2.7307^{***} (0.2389)		-1.7144^{**} (0.7216)		-1.5890^{***} (0.1908)	
Observations	237		237		261		261	
Hansen J-test p-value	0.6680		0.8104		0.0000		0.8104	

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GDP per capita remains positive and statistically significant in the preferred Two-Step System GMM model, with a coefficient of 0.3017 ($p < 0.01$). The consistency of the positive GDP effect across the static and dynamic specifications strengthens the interpretation that economic capacity is an important country-level condition associated with FinTech adoption. Higher income can facilitate access to digital devices and financial services while supporting investment in digital and financial infrastructure.

Internet penetration remains positive in the dynamic model but is not statistically significant in the preferred Two-Step System GMM specification. This differs from the significant positive static estimate. The difference is informative rather than contradictory: the static estimate captures the contemporaneous relationship after controlling for country-specific effects, whereas the dynamic model also accounts for past FinTech adoption and potential endogeneity. Once the strong persistence of adoption is included, the independent contribution of internet penetration is less precisely estimated. The result suggests that internet access is an enabling condition, but access alone may not be sufficient to explain differences in adoption once broader ecosystem conditions are considered.

Regulatory quality changes from an insignificant negative coefficient in the preferred static model (-0.1320) to a statistically significant negative coefficient in the preferred dynamic model (-0.3845 , $p < 0.01$). This difference is central to interpreting the two approaches. The dynamic result suggests that, conditional on previous FinTech adoption and the other explanatory variables, higher values of the regulatory-quality measure are associated with lower current adoption in the sample. One possible explanation is that regulatory systems can impose compliance and market-entry costs when they are not sufficiently adapted to rapidly changing FinTech business models. This interpretation should be treated cautiously because the coefficient measures the statistical relationship with the regulatory-quality indicator used in the study. The finding also differs from arguments that well-designed regulation can support FinTech by strengthening trust and reducing uncertainty, indicating that the effect of regulation may depend on institutional design and implementation (Frost et al., 2019).

Interest rates also change across specifications. The preferred static coefficient is small and statistically insignificant, whereas the preferred dynamic coefficient is -0.0016 and statistically significant at the 1% level. The dynamic result indicates that higher interest rates are associated with lower FinTech adoption after accounting for persistence. Higher financing costs may reduce demand for credit-related FinTech services and constrain investment by FinTech firms. This interpretation is consistent with evidence that financial and monetary conditions influence the development of FinTech credit markets (Claessens et al., 2018).

Taken together, the static and dynamic results should therefore be interpreted jointly rather than as competing models. GDP per capita is the most consistent determinant because it is positive and statistically significant in both preferred

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“Navigating Global Transformation in an Uncertain World: Interdisciplinary Perspective on Economics, Business, Education, Law, Agriculture, Food Technology, Politics and Society” July 30th, 2026

specifications. Internet penetration is positive in both models but loses statistical significance in the dynamic framework. Regulatory quality and interest rates are insignificant in the preferred static model but become statistically significant and negative in the preferred dynamic model. The difference is attributable to the inclusion of lagged adoption and the dynamic estimator's treatment of persistence and potential endogeneity. Accordingly, the static model is the primary specification for contemporaneous country-level relationships, while the Two-Step System GMM model provides the primary dynamic evidence.

CONCLUSION

This study examined the determinants of FinTech adoption in selected developing countries over 2010–2023 using static and dynamic panel-data methods. The analysis considered GDP per capita, internet penetration, regulatory quality, and interest rates and addressed methodological concerns through model-selection and diagnostic tests. The preferred static specification was a fixed-effects model with Driscoll–Kraay robust standard errors, while the preferred dynamic specification was the Two-Step System GMM model.

The results show that GDP per capita is positively and significantly associated with FinTech adoption in both preferred specifications, making economic capacity the most consistent determinant in the analysis. Internet penetration is positive and significant in the static model but positive and insignificant in the dynamic model. Regulatory quality and interest rates are not significant in the preferred static model but become negative and significant in the preferred dynamic model. In addition, the lagged FinTech adoption coefficient is positive and highly significant, demonstrating strong persistence in adoption over time.

These differences reinforce the importance of distinguishing contemporaneous relationships from dynamic relationships. The findings do not support a single-factor explanation of FinTech adoption. Instead, adoption reflects the interaction of economic capacity, digital access, institutional conditions, and macroeconomic conditions. For policymakers, the results indicate the relevance of expanding digital infrastructure and economic opportunities while ensuring that regulatory frameworks remain compatible with innovation and that macroeconomic conditions do not unnecessarily constrain digital financial activity.

The study is subject to several limitations. The analysis uses country-level indicators and therefore does not directly capture individual behavioral factors such as trust, perceived usefulness, financial literacy, or perceived risk. In addition, the developing-country sample is heterogeneous, so the estimated average relationships may differ across individual countries. Future research could incorporate additional country-

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level variables, investigate heterogeneous effects across income groups or regions, and combine macro-level panel data with micro-level adoption measures.

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