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The Moderating Role of Commodity Prices in the Relationships of Artificial Intelligence and Digitalization with FX Market Outcomes in G20 Countries

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Abstract This study examines whether commodity prices condition the effects of artificial intelligence (AI) capability and digitalization on foreign exchange (FX) market outcomes in G20 countries over the period 2015–2024. FX market performance is evaluated through volatility persistence (VP), price discovery efficiency (PDE), and market resilience and stability (MRS). Using a two-way fixed-effects panel framework with interaction terms, the study finds that AI capability and digitalization significantly reduce VP and improve PDE and MRS, whereas commodity-price shocks increase volatility persistence and weaken market efficiency and resilience. The negative effects of AI $\times$ CP and DI $\times$ CP on VP, together with their positive effects on PDE and MRS, indicate that technological capability mitigates commodity-driven FX market instability. Marginal-effect analysis further shows that the benefits of AI and digitalization become stronger under greater commodity-price fluctuations. The findings remain robust across diagnostic tests and machine-learning validation using LASSO, Random Forest, SHAP analysis, and Diebold–Mariano tests. Country-level results are generally strongest for India, Brazil, and Turkey, with China showing relatively strong performance in volatility persistence and market resilience, and Mexico in price discovery efficiency. Comparatively weaker effects are observed in Russia, Saudi Arabia, and South Africa. Overall, the results suggest that AI capability and digital infrastructure improve information processing, market adjustment, and shock absorption, particularly when FX markets are exposed to elevated commodity-price uncertainty.

Keywords Artificial intelligence; Digitalization; Commodity prices; FX market outcomes; G20 countries.

AMS 2010 subject classifications 62M10, 68T10

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1. Introduction

Foreign exchange (FX) markets are a fundamental part of the international financial system because they support global trade, foreign investment, capital allocation, and monetary-policy transmission. Exchange-rate movements influence export competitiveness, inflation expectations, external debt obligations, investor confidence, and macroeconomic stability. Therefore, identifying the factors that shape FX market behaviour is important for central banks, policymakers, investors, multinational firms, and financial institutions [1, 2]. FX markets often experience persistent volatility, nonlinear adjustment, and sudden regime changes. Exchange-rate shocks may continue over time, particularly during periods of global uncertainty, commodity-market disruption, and financial stress. These features make currency markets difficult to explain using only traditional linear models [3]. The issue is especially important for emerging and commodity-linked G20 countries because their currencies are highly exposed to external shocks, capital-flow movements, global risk conditions, and commodity-price fluctuations [4].

Commodity prices play an important role in FX market dynamics because they affect trade balances, fiscal revenues, inflation, terms of trade, and investor expectations. In countries with strong commodity exposure, changes

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in oil, energy, metals, or agricultural prices can quickly influence exchange-rate volatility and market stability. Such shocks may increase volatility persistence, delay price adjustment, and weaken the ability of FX markets to return to stable conditions [5, 6]. Technological transformation has also become a major structural force in financial markets. Artificial intelligence (AI) improves forecasting, risk assessment, pattern recognition, data processing, and automated financial decision-making. AI-based systems can identify hidden market signals, detect abnormal movements, and support faster responses to changing financial conditions. At the same time, digitalization improves market infrastructure through electronic trading, digital platforms, real-time data transmission, stronger connectivity, and faster transaction execution [7, 8].

In FX markets, where exchange rates respond rapidly to macroeconomic news, investor sentiment, global shocks, and commodity-price movements, AI capability and digitalization may improve market performance. AI can strengthen the interpretation of complex financial and commodity-related information, while digital infrastructure can accelerate information transmission and reduce transaction frictions. Together, these technological factors may reduce the duration of exchange-rate shocks, improve price adjustment, and enhance market resilience [9, 10]. Although exchange-rate volatility and market efficiency have been widely examined, the role of technology in shaping FX market outcomes remains insufficiently explored. Existing studies mainly focus on macroeconomic fundamentals, interest-rate differentials, financial openness, global risk, and capital flows as determinants of exchange-rate behaviour. However, the increasing use of AI systems, algorithmic trading, digital financial platforms, and real-time analytics suggests that technological capability may now be an important driver of FX market adjustment [11, 12].

There is also limited evidence on whether commodity prices influence the relationship between AI capability, digitalization, and FX market outcomes. Previous studies often examine commodity prices, digital finance, or AI-based forecasting separately [13]. However, in commodity-linked countries, the value of AI and digitalization may become stronger during periods of commodity-price instability. Stronger AI capability may help market participants distinguish temporary commodity shocks from persistent macro-financial changes, while stronger digital infrastructure may transmit commodity-related information more efficiently across financial markets [14]. Another limitation of earlier research is that FX market performance is often evaluated using a single indicator, such as volatility or forecasting accuracy. This provides only a partial explanation of market behaviour. A broader assessment requires multiple dimensions, including volatility persistence, price discovery efficiency, and market resilience and stability [15]. Volatility persistence reflects how long exchange-rate shocks remain in the market. Price discovery efficiency shows how quickly and accurately new information is incorporated into exchange rates. Market resilience and stability measure the ability of FX markets to absorb shocks and return to stable conditions [16].

This study addresses these gaps by examining the moderating role of commodity prices in the effects of AI capability and digitalization on FX market outcomes in selected G20 countries. The study focuses on Argentina, Brazil, China, India, Mexico, Russia, Saudi Arabia, South Africa, and Turkey because these countries represent important emerging and commodity-linked members of the G20 with different levels of AI capability, digital readiness, financial openness, and commodity exposure. The study period, 2015–2024, is selected because it captures major developments in AI adoption, digital transformation, commodity-price fluctuations, the COVID-19 crisis, post-pandemic monetary tightening, geopolitical uncertainty, and exchange-rate pressure [17, 18].

The main objective of this study is to examine whether AI capability and digitalization improve FX market outcomes and whether commodity-price movements moderate these relationships. Specifically, the study examines three outcomes: volatility persistence, price discovery efficiency, and market resilience and stability. The empirical framework applies a panel model and includes the interaction terms $\mathrm{AI} \times \mathrm{CP}$ and $\mathrm{DI} \times \mathrm{CP}$ to capture the moderating effect of commodity prices. The analysis also controls for global risk conditions, financial openness, and interest-rate differentials [19, 20].

This study makes several contributions to the literature. First, it integrates AI capability, digitalization, commodity prices, and FX market outcomes into a single empirical framework. Second, it examines commodity prices as a moderating variable in the relationship between technological capability and FX market performance. Third, it evaluates FX market outcomes through three dimensions: volatility persistence, price discovery efficiency, and market resilience and stability. Fourth, it provides evidence from selected G20 countries, where commodity exposure and technological development differ across countries. Finally, it strengthens empirical reliability by validating the panel-model results through machine-learning methods, including LASSO regression, Random Forest, SHAP analysis, forecasting, and Diebold–Mariano tests.

The findings indicate that AI capability and digitalization improve FX market outcomes by reducing volatility persistence and strengthening both price discovery efficiency and market resilience. Commodity prices, in contrast, intensify volatility persistence and weaken price discovery and market stability. However, the interaction effects show that AI capability and digitalization can reduce the adverse influence of commodity-price shocks. These results suggest that technological readiness helps G20 countries manage commodity-driven exchange-rate instability more effectively.

2. Theoretical Foundation and Literature Review

This study draws on Market Microstructure Theory, the Adaptive Market Hypothesis, and Financial Innovation and Endogenous Risk Theory to explain how artificial intelligence (AI) capability, digitalization, and commodity prices jointly influence foreign exchange (FX) market outcomes in G20 countries. Market Microstructure Theory argues that exchange-rate dynamics are determined not only by macroeconomic fundamentals but also by information flow, market liquidity, transparency, and trading mechanisms [21, 22]. These theoretical arguments are particularly relevant for G20 countries because their FX markets differ substantially in technological capability, financial-market development, digital infrastructure, and exposure to commodity-price fluctuations. Within this framework, AI enhances the ability of market participants to analyse complex financial information, whereas digitalization improves the technological infrastructure that facilitates information dissemination, market connectivity, and transaction execution.

The Adaptive Market Hypothesis proposes that market efficiency evolves as investors and financial institutions continuously adapt to changing economic and financial conditions [23]. In G20 countries, exchange rates are frequently affected by monetary-policy changes, capital-flow volatility, geopolitical uncertainty, and commodity-price shocks. AI supports this adaptive process by identifying nonlinear relationships, improving forecasting accuracy, and detecting emerging risks under uncertain market conditions [24]. Digitalization complements these capabilities by enabling real-time access to information, electronic trading, and faster execution of financial transactions [25]. Financial Innovation and Endogenous Risk Theory further recognises that technological advancement can simultaneously improve market efficiency while creating endogenous risks through algorithmic herding, synchronised trading behaviour, and rapid liquidity withdrawal during periods of financial stress [26, 27]. Consequently, the overall impact of AI and digitalization depends on whether their efficiency gains outweigh these potential sources of instability.

AI capability and digitalization influence FX market outcomes through distinct transmission channels. For volatility persistence, AI is expected to reduce the duration of exchange-rate shocks by improving forecasting, early risk detection, and the identification of temporary versus persistent market disturbances [28, 29]. Better analytical capability enables investors, financial institutions, and policymakers to adjust positions more efficiently, thereby accelerating market correction. Digitalization further reduces volatility persistence by facilitating faster information transmission, improving market liquidity, lowering transaction costs, and supporting rapid portfolio rebalancing through electronic trading systems [30, 31]. These mechanisms are particularly important in G20 countries, where technological readiness differs considerably across countries. Therefore, stronger AI capability and digitalization are expected to reduce the persistence of exchange-rate volatility.

For price discovery efficiency, AI improves the extraction of economically relevant information from large and complex datasets, including macroeconomic announcements, commodity-price movements, investor sentiment, and cross-market signals [32]. This enables exchange rates to incorporate new information more rapidly and accurately. Digitalization complements this process by improving market transparency, reducing informational frictions, expanding participation, and facilitating real-time order execution [33, 34]. Since G20 countries exhibit substantial variation in digital competitiveness and AI readiness, improvements in technological capability are expected to reduce information asymmetry and strengthen the efficiency of exchange-rate adjustment.

For market resilience and stability, AI enhances stress detection, liquidity forecasting, scenario analysis, and adaptive risk management, allowing financial institutions and policymakers to identify vulnerabilities before they develop into systemic disruptions [35, 36]. Digitalization strengthens market resilience by supporting operational continuity, improving communication across financial institutions, enhancing liquidity allocation, and maintaining transaction efficiency during periods of market stress [37]. According to the Adaptive Market Hypothesis, countries with stronger technological capability should therefore recover more rapidly from exchange-rate disturbances and maintain more stable FX markets [23, 25].

AI capability may influence FX market outcomes through two complementary channels. First, the trading and information-processing channel enables traders and financial institutions to analyse macroeconomic news, commodity-price movements, order flows, and market sentiment more efficiently [28, 32]. Faster signal extraction and automated execution can accelerate the correction of exchange-rate mispricing, reduce volatility persistence, and improve price discovery [29, 38]. Second, the regulatory and policy channel allows central banks and regulators to strengthen market surveillance, stress testing, liquidity forecasting, and early-warning systems [35]. These applications can support faster policy responses and improve market resilience during commodity-price and capital-flow shocks [36, 37]. Because the AI capability index reflects broad national technological capacity, the estimated effect captures the combined influence of both trading and regulatory AI applications.

Commodity prices are incorporated as a moderating variable because they influence exchange rates through multiple macroeconomic channels, including the terms of trade, export revenues, fiscal balances, inflation expectations, capital flows, and investor sentiment [5, 6]. These channels are especially important for G20 countries, many of which are major exporters or importers of energy, agricultural commodities, and industrial raw materials. Consequently, commodity-price shocks may increase exchange-rate uncertainty, prolong volatility, delay price adjustment, and weaken market resilience [39]. Commodity-price instability is therefore expected to increase volatility persistence while reducing price discovery efficiency and market resilience.

Commodity-price volatility may also strengthen the importance of technological capability. During periods of substantial commodity-price fluctuations, AI can identify complex interactions among commodity markets, macroeconomic conditions, and exchange-rate movements, thereby improving forecasting accuracy and supporting more effective risk management [40, 41]. Digitalization accelerates the dissemination of commodity-related information, facilitates timely hedging and portfolio adjustment, and improves market liquidity through electronic trading systems [34, 42]. These capabilities are expected to be particularly valuable in G20 countries because of differences in commodity dependence and technological development. Accordingly, commodity-price instability is expected to increase volatility persistence while weakening price discovery efficiency and market resilience. However, stronger AI capability and digitalization are expected to mitigate these adverse effects. Thus, the interaction terms AI $\times$ CP and DI $\times$ CP are expected to have negative effects on volatility persistence but positive effects on price discovery efficiency and market resilience.

Existing empirical evidence broadly supports these theoretical arguments. AI-based approaches have been shown to improve forecasting performance, pattern recognition, and financial risk assessment in FX markets characterised by nonlinear dynamics, structural breaks, and volatility clustering [38]. Likewise, digitalization improves market efficiency through enhanced electronic trading, real-time information processing, and greater financial connectivity [43]. Previous studies also demonstrate that commodity-price fluctuations remain an important source of exchange-rate instability, particularly in commodity-dependent countries [39]. However, these studies generally examine AI capability, digitalization, commodity prices, and exchange-rate behaviour separately, providing limited evidence on their joint effects on multiple dimensions of FX market performance [44, 45].

The literature reveals an unresolved trade-off between the efficiency-enhancing and risk-amplifying effects of AI and digitalization. While these technologies may improve forecasting, information transmission, market liquidity, and price adjustment [28, 30], they may also generate negative externalities through algorithmic herding, model opacity, cyber risk, technological concentration, and synchronised liquidity withdrawal [46, 47]. This study is positioned within this debate by examining whether the benefits of AI capability and digitalization remain evident under commodity-price instability and across three distinct dimensions of FX market performance [41]. In doing so, it extends prior studies that generally examine technological capability, commodity prices, or exchange-rate behaviour separately [45].

Despite these contributions, several research gaps remain. First, existing studies rarely integrate AI capability, digitalization, commodity prices, and FX market outcomes within a single analytical framework [39, 40]. Second, prior research focuses predominantly on forecasting accuracy while giving comparatively less attention to broader FX market outcomes such as volatility persistence, price discovery efficiency, and market resilience and stability [28, 41]. Third, the moderating role of commodity prices in shaping the relationships between AI capability, digitalization, and FX market outcomes remains insufficiently explored [34, 42]. Finally, empirical evidence from G20 countries remains limited despite substantial differences in commodity exposure, AI readiness, digital infrastructure, financial openness, and exchange-rate vulnerability.

This study addresses these gaps by examining the effects of AI capability and digitalization on volatility persistence, price discovery efficiency, and market resilience in G20 countries, with commodity prices incorporated as a moderating variable. The empirical framework explicitly distinguishes the transmission channels of AI and digitalization and evaluates whether their effects vary under different commodity-price conditions. To strengthen the robustness of the findings, the panel-model results are further validated using LASSO regression, Random Forest, SHAP analysis, forecasting comparisons, and Diebold–Mariano tests [9, 10, 47]. This integrated framework provides a comprehensive explanation of how technological capability and commodity-price dynamics jointly influence FX market efficiency and stability in G20 countries.

2.1. Conceptual Framework

To examine the determinants of foreign exchange (FX) market outcomes in G20 countries, this study develops an integrated conceptual framework linking AI capability and digitalization with FX market performance. The framework is grounded in Market Microstructure Theory, the Adaptive Market Hypothesis, and Financial Innovation and Endogenous Risk Theory. Market Microstructure Theory explains how information flow, trading behaviour, and market transparency influence exchange-rate adjustment and price discovery. The Adaptive Market Hypothesis suggests that FX market efficiency evolves as investors, institutions, and trading systems adapt to technological developments, changing information conditions, and external shocks. Financial Innovation and Endogenous Risk Theory further explains how technological advancement may improve financial-market efficiency while also creating new forms of risk through automation, interconnectedness, and complex market interactions.

As illustrated in Fig. 1, the framework includes two main independent variables: AI capability and digitalization. AI capability is represented by AI patents, AI publications, and research and development expenditure, which reflect technological innovation, knowledge creation, and AI readiness. Digitalization is measured through digital competitiveness, IT infrastructure readiness, and mobile and broadband penetration, capturing the level of digital connectivity, technological accessibility, and supporting infrastructure within each economy.

The framework proposes that AI capability and digitalization directly influence three FX market outcomes: volatility persistence, price discovery efficiency, and market resilience and stability. Volatility persistence refers to the extent to which exchange-rate fluctuations continue over time. Price discovery efficiency reflects the speed and accuracy with which new information is incorporated into exchange rates. Market resilience and stability represent the ability of the FX market to absorb shocks, recover from disruptions, and maintain orderly functioning. Higher AI capability and stronger digitalization are expected to improve information processing, reduce information asymmetry, enhance market transparency, and strengthen the capacity of FX markets to respond to economic and financial shocks.

Commodity prices are incorporated as a moderating variable in the relationships between the independent variables and FX market outcomes. As shown in Fig. **??**, commodity-price movements may strengthen or weaken the effects of AI capability and digitalization on volatility persistence, price discovery efficiency, and market resilience and stability. This moderating role is particularly relevant for commodity-linked countries, where changes in energy, agricultural, and mineral prices may influence trade balances, export revenues, capital flows, and exchange-rate expectations.

The framework also includes Global Risk Conditions (GRISK), Financial Openness (FINOPEN), and the Interest Rate Differential (IRD) as control variables. These variables are incorporated to account for broader macro-financial conditions that may independently influence FX market outcomes. Overall, the conceptual framework explains how AI capability and digitalization influence FX market outcomes, how commodity prices moderate these relationships, and how selected macro-financial conditions affect exchange-rate behaviour.

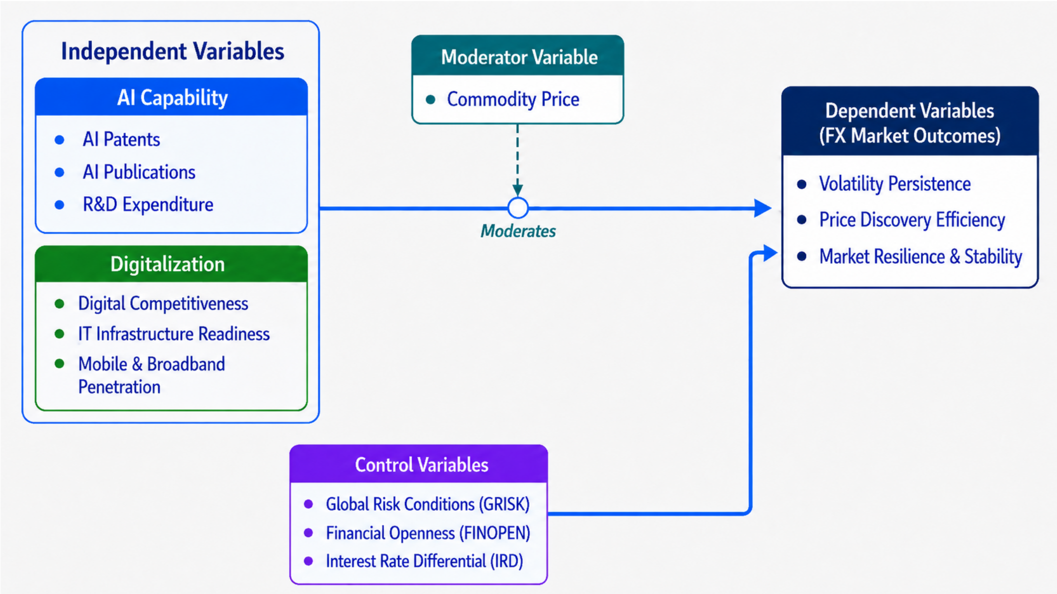

Figure 1. Conceptual framework

Based on the theoretical arguments and conceptual framework discussed above, this study proposes the following hypotheses:

H1: AI capability significantly influences foreign exchange (FX) market outcomes, including volatility persistence, price discovery efficiency, and market resilience and stability, among G20 countries.

H2: Digitalization significantly influences foreign exchange (FX) market outcomes, including volatility persistence, price discovery efficiency, and market resilience and stability, among G20 countries.

H3: Commodity prices significantly moderate the relationships between AI capability, digitalization, and foreign exchange (FX) market outcomes among G20 countries.

3. Methodology

This study adopts a quantitative panel research design to examine the moderating role of commodity prices in the effects of artificial intelligence and digitalization on foreign exchange market outcomes in selected G20 countries. The selected countries are Argentina, Brazil, China, India, Mexico, Russia, Saudi Arabia, South Africa, and Turkey. These countries are chosen because they represent important emerging and commodity-linked members of the G20 with different levels of AI capability, digitalization, and commodity-price exposure. Their differences in commodity exposure and technological readiness allow the study to examine whether commodity prices condition the effects of AI and digitalization on FX market performance.

Advanced G20 countries were excluded to preserve theoretical and empirical consistency within the sample. Their FX markets generally operate within deeper financial systems, stronger institutional frameworks, more developed hedging mechanisms, higher market liquidity, and more mature digital infrastructure. In several advanced countries, digitalization may also be approaching saturation, meaning that additional improvements in digital capacity may produce smaller marginal effects on market efficiency and resilience. Moreover, their currencies may respond differently to commodity-price shocks because of greater economic diversification and stronger shock-absorption capacity.

Restricting the analysis to these nine countries therefore reduces structural heterogeneity and provides a more coherent empirical setting for examining how commodity prices moderate the effects of AI capability and digitalization on volatility persistence, price discovery efficiency, and market resilience. However, this sample choice also means that the findings should be interpreted primarily in the context of emerging and commodity-linked G20 countries rather than generalized directly to advanced markets.

The study covers the period 2015–2024. This period is selected because it captures major changes in digital transformation, AI adoption, commodity-price movements, and global financial conditions. The period after 2015 is particularly relevant because many countries experienced rapid growth in digital infrastructure, fintech development, AI-related innovation, and algorithmic financial systems. It also includes major external shocks, including commodity-price fluctuations, the COVID-19 crisis, post-pandemic monetary tightening, geopolitical uncertainty, and exchange-rate pressure. Therefore, 2015–2024 provides an appropriate time window for examining how AI and digitalization interact with commodity prices in shaping FX market outcomes.

Although the main empirical analysis uses an annual country-level panel for 2015–2024, the FX market outcome variables are constructed from higher-frequency exchange-rate data. Specifically, daily bilateral exchange-rate data against the US dollar are used separately for each selected country to estimate volatility persistence, price discovery efficiency, and market resilience and stability. The resulting measures are then aggregated into annual country-level values and merged with the annual observations for AI capability, digitalization, commodity prices, and the control variables. This mixed-frequency procedure ensures that the GARCH, variance-ratio/VECM, and Markov-switching models are estimated using sufficient time-series observations while maintaining consistency with the annual panel framework.

Data are collected from reliable secondary sources. Exchange-rate data used to construct VP, PDE, and MRS may be obtained from the IMF International Financial Statistics, World Bank databases, national central banks, and other international financial databases. AI capability indicators may be collected from OECD.AI, WIPO, the World Bank, Scopus/Web of Science, and national innovation databases. Digitalization indicators may be collected from the World Bank, International Telecommunication Union, IMD Digital Competitiveness indicators, and national digital-economy reports. Commodity-price data may be obtained from the World Bank Commodity Price Data, IMF commodity databases, or global commodity-price indices. Global risk may be proxied by indicators such as the VIX index, financial openness by the Chinn–Ito index, and interest-rate differentials by differences between domestic short-term interest rates and benchmark international interest rates.

The dependent variables are three FX market outcomes: volatility persistence (VP), price discovery efficiency (PDE), and market resilience and stability (MRS). These variables are selected because they represent different dimensions of FX market performance. VP captures the extent to which exchange-rate shocks remain in the market over time. PDE reflects how quickly and accurately new information is incorporated into exchange rates. MRS measures the ability of FX markets to absorb shocks and return to stable conditions. Using these three outcomes provides a broader assessment of FX market performance.

The main explanatory variables are artificial intelligence capability (AI), digitalization (DI), and commodity prices (CP). AI is included because AI capability can improve forecasting, risk monitoring, pattern recognition, and data-driven decision-making in financial markets. DI is included because digital infrastructure supports electronic trading, real-time information transmission, market connectivity, and financial-system efficiency. CP is included because commodity-price movements influence trade balances, inflation expectations, external revenues, capital flows, and investor sentiment, especially in commodity-linked G20 countries.

To test the moderating role of commodity prices, the study includes two interaction terms: $\mathrm{AI} \times \mathrm{CP}$ and $\mathrm{DI} \times \mathrm{CP}$. These interaction terms are used to examine whether the effects of AI and digitalization on FX market outcomes change under different commodity-price conditions. A significant interaction term indicates that commodity prices condition the relationship between technological factors and FX market performance. This approach is appropriate because the study examines not only the direct effects of AI, DI, and CP but also how commodity-price movements strengthen or weaken the technology–FX market relationship.

The study also includes global risk (GRISK), financial openness (FINOPEN), and the interest-rate differential (IRD) as control variables. GRISK is included because global uncertainty can affect exchange-rate volatility, capital flows, and investor risk sentiment. FINOPEN is included because financial openness may influence cross-border capital movement, liquidity, and information transmission in FX markets. IRD is included because interest-rate differentials are traditional drivers of exchange-rate movements and may affect currency demand and capital allocation.

Before estimating the baseline panel models, the study conducts unit-root tests to examine whether the variables are stationary. The Augmented Dickey–Fuller and Phillips–Perron tests are used because non-stationary variables may lead to spurious regression results and unreliable inference. These tests help confirm whether the variables are suitable for panel estimation. Once stationarity is confirmed, the baseline panel models are estimated separately for VP, PDE, and MRS. The baseline empirical model is specified as follows:

$$
\begin{aligned}
Y_{i,t} = \alpha_0 + \alpha_1 AI_{i,t-1} + \alpha_2 DI_{i,t-1} + \alpha_3 CP_{i,t-1} \quad &+ \alpha_4 (AI \times CP)_{i,t-1} + \alpha_5 (DI \times CP)_{i,t-1} \\
+ \alpha_6 X_{i,t-1} + \mu_i + \tau_t + \varepsilon_{i,t}. &
\end{aligned}
\tag{1}
$$

where $Y_{i,t}$ represents VP, PDE, or MRS for country i in year t. AI denotes artificial intelligence capability, DI denotes digitalization, and CP denotes commodity prices. $(AI \times CP)$ and $(DI \times CP)$ are interaction terms, while $X_{i,t-1}$ represents a vector of control variables comprising Global Risk Conditions (GRISK), Financial Openness (FINOPEN), and the Interest Rate Differential (IRD). The term μ_i captures country-specific effects, τ_t captures time-specific effects, and $\varepsilon_{i,t}$ represents the error term.

Potential endogeneity may arise from reverse causality, omitted time-varying factors, and measurement error in the AI and digitalization indices. Although the two-way fixed-effects model controls for unobserved country-specific heterogeneity and common year shocks, it does not fully eliminate simultaneity or reverse causality. Instrumental-variable or dynamic-panel GMM estimation could provide stronger identification; however, the small sample of nine countries over ten years may lead to weak instruments and instrument proliferation. Therefore, the estimated coefficients are interpreted as robust conditional associations rather than definitive causal effects.

Several diagnostic tests are conducted to evaluate the reliability of the baseline panel models. The variance inflation factor (VIF) and tolerance values are used to test multicollinearity. The Jarque–Bera test examines residual normality, the Breusch–Pagan test evaluates heteroscedasticity, the Durbin–Watson statistic assesses serial correlation, and the CUSUM test evaluates model stability. Diagnostic figures, including probability plots, residual plots, Cook's distance, autocorrelation plots, and CUSUM plots, are also used to visually confirm model adequacy.

To strengthen robustness, LASSO and Random Forest are used as machine-learning validation methods. LASSO identifies important predictors through regularization, while Random Forest captures nonlinear relationships and interaction effects. SHAP values, RMSE, MAE, rank, and selection frequency are also used to assess predictor importance and predictive accuracy. Finally, the Diebold–Mariano test compares predictive accuracy across the fixed-effects panel, LASSO, and Random Forest models. Forecasting analysis is also conducted for VP, PDE, and MRS to confirm whether the baseline panel findings remain stable across alternative predictive approaches.

3.1. Measurement of Variables

The study examines three dependent variables representing FX market outcomes: volatility persistence, price discovery efficiency, and market resilience and stability. These variables are constructed from daily exchange-rate data and subsequently aggregated into annual country-level measures for use in the panel-data estimation.

Volatility persistence is measured using a GARCH-type framework because exchange-rate returns commonly exhibit volatility clustering, where large shocks are followed by further large movements. For each selected G20 country, the bilateral exchange rate of the domestic currency against the US dollar is transformed into continuously compounded returns as follows:

$$
r_{i,t} = \ln\left(\frac{E_{i,t}}{E_{i,t-1}}\right), \tag{2}
$$

where $E_{i,t}$ denotes the domestic-currency price of one US dollar for country i at time t. A GARCH(1,1) model is then estimated separately for each country, and volatility persistence is measured as the sum of the ARCH and GARCH parameters:

$$
VP_i^{\mathrm{GARCH}} = \alpha_i + \beta_i, \tag{3}
$$

where α_i captures the short-run shock effect and β_i captures volatility memory. A higher value of VP indicates stronger volatility persistence, while a lower value indicates faster shock absorption.

Price discovery efficiency is measured using a composite index based on the variance-ratio approach and the speed of adjustment from a vector error-correction model. The variance ratio is used because it evaluates whether exchange-rate returns follow a random-walk process, which is closely related to market efficiency. The VECM speed of adjustment is included because price discovery also depends on how quickly exchange rates correct deviations from equilibrium. The price discovery efficiency index is calculated as:

$$PDE = w_1 VR(k) + w_2 ECS, \tag{4}$$

where $VR(k)$ is the variance ratio at horizon k, ECS is the error-correction speed, and w_1 and w_2 are the weights assigned to the two components. A higher value of PDE indicates stronger price discovery efficiency.

Market resilience and stability are measured using a two-state Markov-switching model because FX markets often move between low-volatility and high-volatility regimes. This method is appropriate because market resilience is not only related to average volatility but also to the probability of remaining in or returning to a stable regime. The resilience measure is calculated as:

$$MRS_{i,t} = 1 - p^H_{i,t}, \tag{5}$$

where $p^H_{i,t}$ is the filtered probability of being in the high-volatility regime. A higher MRS value indicates stronger market resilience and stability.

The main independent variables are Artificial Intelligence Capability (AI) and the Digitalization Index (DI). Both variables are constructed as composite indices using min–max normalization because the component indicators are measured in different units. The normalization formulas are:

$$X^*_{i,t} = \frac{X_{i,t} - \min(X)}{\max(X) - \min(X)}, \tag{6}$$

and

$$Y^*_{i,t} = \frac{Y_{i,t} - \min(Y)}{\max(Y) - \min(Y)}. \tag{7}$$

After normalization, each index is calculated using equal-weight averaging:

$$AI_{i,t} = \frac{1}{M} \sum_{k=1}^{M} X^*_{k,i,t}, \tag{8}$$

$$DI_{i,t} = \frac{1}{N} \sum_{k=1}^{N} Y^*_{k,i,t}, \tag{9}$$

where $X^*_{k,i,t}$ represents the normalized AI indicators and $Y^*_{k,i,t}$ represents the normalized digitalization indicators. Equal weighting is used because each component is considered theoretically important.

Commodity Price (CP) is included as a moderating variable and is measured as the annual logarithmic change in the commodity-price index. Commodity-price shocks are first calculated as annual logarithmic changes and subsequently min–max normalized to facilitate comparison and interaction-term construction. This measure is preferred to the commodity-price index level because it captures commodity-price shocks and year-to-year fluctuations, reduces potential non-stationarity, and provides a more appropriate moderator for examining how commodity-price movements condition the effects of AI capability and digitalization on FX market outcomes. The CP variable is calculated as:

$$CP_{i,t} = \ln\left(\text{CommodityPrice}_{i,t}\right) - \ln\left(\text{CommodityPrice}_{i,t-1}\right). \tag{10}$$

Global Risk Conditions (GRISK) are proxied by the Chicago Board Options Exchange Volatility Index (VIX), which measures implied volatility in US equity markets and is widely regarded as a global uncertainty indicator:

$$GRISK_{i,t} = VIX_t. \tag{11}$$

Financial openness (FINOPEN) is measured using the Chinn–Ito capital-account openness index (KAOPEN):

$$FINOPEN_{i,t} = KAOPEN_{i,t}. \tag{12}$$

The interest-rate differential (IRD) captures the difference between the domestic interest rate and the corresponding US benchmark rate:

$$IRD_{i,t} = r_{i,t}^{\text{dom}} - r_t^{\text{US}}, \tag{13}$$

where $r_{i,t}^{\text{dom}}$ denotes the short-term domestic policy interest rate and r_t^{US} represents the US federal funds rate.

To ensure transparency and reproducibility, the detailed data-processing steps and replication script used in the empirical analysis are provided in Appendix A.

4. Analysis and Discussion

Before estimating the baseline panel models, this study tests the stationarity of the variables because non-stationary macro-financial data may produce spurious regression results and misleading coefficients [19]. This issue is especially important in FX and commodity-market studies, where exchange rates and commodity prices often show persistence due to global shocks, trade exposure, and financial integration [5, 6].

Table 1 reports the ADF and Phillips–Perron unit-root tests. Previous studies often find mixed stationarity patterns in exchange-rate and commodity-price variables, which may require differencing or cointegration-based methods [5, 6]. In contrast, the results of this study show that all variables are stationary under both tests. This finding confirms that AI, DI, CP, the interaction terms, the control variables, and the FX market outcome variables can be used directly in the baseline panel models.

More importantly, the stationarity results strengthen the moderating framework of the study. Since AI and digitalization may influence information processing, trading efficiency, and market stability, while commodity prices affect exchange rates through inflation, trade balances, and investor sentiment, confirming stationarity ensures that the estimated AI × CP and DI × CP effects are not caused by common trends [9, 18]. Therefore, Table 1 provides a stronger foundation for analysing volatility persistence, price discovery efficiency, and FX market resilience in G20 countries.

Table 1. Unit-Root Test Results Using ADF and Phillips–Perron Tests

Variable	ADF Statistic	Phillips–Perron Statistic
AI	-4.926^{**}	-5.184^{*}
DI	-4.635^{**}	-4.892^{**}
CP	-5.276^{*}	-5.491^{*}
AI × CP	-4.718^{**}	-5.036^{**}
DI × CP	-4.582^{**}	-4.914^{**}
GRISK	-5.637^{*}	-5.884^{*}
FINOPEN	-4.391^{**}	-4.726^{**}
IRD	-4.104^{**}	-4.355^{**}
VP	-5.314^{**}	-5.609^{*}
PDE	-5.482^{**}	-5.731^{*}
MRS	-5.694^{*}	-5.942^{**}

Note: ADF denotes the Augmented Dickey–Fuller test, and PP denotes the Phillips–Perron test. * and ** indicate significance at the 10% and 5% levels, respectively.

Table 2 reports the combined descriptive statistics for the study variables. The results show that AI and digitalization have moderate mean values, indicating that the selected G20 countries have made visible progress in technological capability and digital transformation, although adoption remains uneven across countries and over time. This pattern is consistent with previous studies showing that digital readiness and AI capability differ between advanced and emerging economies because of differences in infrastructure, innovation capacity, and institutional support [9, 10].

The descriptive statistics also show substantial variation in commodity prices, confirming that the study period captures important fluctuations in global commodity markets. This supports earlier evidence that commodity-price movements are a key source of macro-financial uncertainty and exchange-rate pressure, especially in countries exposed to energy, food, and industrial-metal markets [5, 6]. The meaningful variation in the AI $\times$ CP and DI $\times$ CP interaction terms further supports the treatment of commodity prices as a moderating variable rather than only as a direct explanatory factor.

Among the FX market outcome variables, market resilience and stability record the highest mean, followed by price discovery efficiency and volatility persistence. This suggests that the selected FX markets demonstrate relatively stronger adjustment capacity and information efficiency than volatility persistence. Therefore, the data contain sufficient variation to examine how AI and digitalization affect FX market outcomes under different commodity-price conditions.

Table 2. Descriptive Statistics for the Study Variables

Variable	Mean	Std. Dev.	Minimum	Maximum
AI	0.548	0.214	0.142	0.934
DI	0.572	0.197	0.181	0.921
CP	0.486	0.226	0.108	0.887
AI $\times$ CP	0.283	0.171	0.021	0.791
DI $\times$ CP	0.296	0.164	0.030	0.764
GRISK	0.514	0.203	0.172	0.902
FINOPEN	0.461	0.188	0.116	0.826
IRD	0.037	0.026	−0.012	0.096
VP	0.438	0.151	0.183	0.764
PDE	0.576	0.163	0.248	0.846
MRS	0.604	0.171	0.261	0.889

To assess the moderating role of commodity prices in the effects of AI and digitalization on FX markets, this study estimates three baseline panel models using volatility persistence, price discovery efficiency, and market resilience and stability as dependent variables. Previous studies suggest that AI, machine learning, and digital financial technologies improve market forecasting, information processing, liquidity management, and trading efficiency [9, 10]. However, financial-stability research also warns that AI-driven trading may increase market sensitivity during periods of stress when algorithms respond to similar information signals [46, 47].

In the volatility-persistence model, AI and digitalization have negative and statistically significant effects, indicating that stronger technological capability reduces persistent exchange-rate volatility. This finding is consistent with studies showing that data-driven forecasting and algorithmic trading can improve market adjustment and reduce information frictions [10, 28]. Commodity prices positively affect volatility persistence, supporting evidence that commodity-price shocks transmit to exchange rates through trade balances, inflation, risk sentiment, and global uncertainty [5, 6]. More importantly, the negative coefficients of AI $\times$ CP and DI $\times$ CP show that AI and digitalization reduce the volatility-enhancing effect of commodity shocks.

For price discovery efficiency, AI and digitalization have positive and statistically significant effects, suggesting that technologically advanced FX markets incorporate information more quickly into exchange rates. This supports studies linking digital finance and algorithmic systems with faster information diffusion and improved market efficiency [10, 25]. Commodity prices reduce price discovery efficiency, indicating that commodity shocks increase uncertainty and delay market adjustment. However, the positive interaction effects show that AI and digitalization help transform commodity-related information into more efficient exchange-rate adjustment.

The market resilience and stability model provides similar evidence. AI and digitalization improve market resilience, whereas commodity prices weaken stability. This is consistent with evidence that commodity-market shocks remain an important source of macro-financial instability, particularly during energy-price volatility, geopolitical uncertainty, and inflationary pressure [18, 20]. The positive interaction effects show that stronger AI capability and digitalization improve the shock-absorption capacity of FX markets under commodity-price uncertainty.

Overall, Table 3 shows that commodity prices condition the effectiveness of AI and digitalization in FX markets. Although commodity-price shocks increase volatility and weaken market efficiency and resilience, technologically advanced G20 countries appear better able to mitigate these adverse effects and maintain stable FX market adjustment.

Table 3. Baseline Panel-Model Results for FX Market Outcomes

Variable	VP	PDE	MRS
Constant	0.6842^{***} (0.00002)	0.4127^{***} (0.00018)	0.4385^{***} (0.00001)
AI	-0.2635^{***} (0.00194)	0.2389^{***} (0.00812)	0.2876^{***} (0.00083)
DI	-0.2186^{**} (0.01720)	0.2046^{**} (0.01490)	0.2369^{***} (0.00808)
CP	0.1764^{**} (0.01690)	-0.1287^{**} (0.03970)	-0.1532^{**} (0.02270)
AI $\times$ CP	-0.2948^{***} (0.00218)	0.2674^{***} (0.00653)	0.3295^{***} (0.00061)
DI $\times$ CP	-0.2471^{**} (0.01340)	0.2198^{**} (0.01560)	0.2847^{***} (0.00351)
GRISK	0.1385^{**} (0.01710)	-0.1065^{**} (0.04830)	-0.1428^{**} (0.01280)
FINOPEN	-0.0876^{**} (0.03860)	0.1248^{**} (0.01450)	0.1173^{**} (0.01390)
IRD	0.0468 (0.23340)	-0.0416 (0.24960)	0.0715^{*} (0.06310)

Note: Values in parentheses are p-values. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4 reports the model-fit and selection criteria for the baseline panel models. In panel-based FX studies, fit statistics indicate whether the selected variables jointly explain meaningful variation in market outcomes rather than merely producing individually significant coefficients [19, 20]. The R^2 values range from 0.6649 to 0.7186, indicating substantial explanatory power.

Among the three models, MRS records the highest R^2 and adjusted R^2, suggesting that AI, digitalization, commodity prices, interaction terms, and control variables explain market resilience and stability more strongly than VP and PDE. This is consistent with the argument that AI and digital finance are particularly important for risk monitoring, shock absorption, and adaptive market responses [9, 25].

The statistically significant F-statistics confirm that the explanatory variables jointly explain FX market outcomes. In addition, the MRS model records the highest log-likelihood and the lowest AIC and BIC values, indicating the strongest overall model fit.

Table 4. Model-Fit and Selection Criteria for the Baseline Panel Models

Criterion	VP	PDE	MRS
Log-likelihood	124.582	119.764	132.918
R^2	0.6814	0.6649	0.7186
Adjusted R^2	0.6172	0.6087	0.6674
F-statistic	18.426	16.973	21.854
Prob(F)	0.00123	0.00284	0.00076
AIC	-229.164	-219.528	-245.836
BIC	-198.742	-189.106	-215.414

Note: AIC denotes the Akaike information criterion, and BIC denotes the Bayesian information criterion. Lower AIC and BIC values indicate better model fit, while higher R^2 and adjusted R^2 values indicate stronger explanatory power.

To provide a clearer interpretation of the interaction effects, the marginal effects of AI capability and digitalization are evaluated at low, mean, and high levels of commodity-price change. These levels are defined as one standard deviation below the mean, the sample mean, and one standard deviation above the mean, corresponding to CP values of 0.260, 0.486, and 0.712, respectively.

The marginal-effect results in Table 5 show that the beneficial influence of AI capability and digitalization strengthens as commodity-price fluctuations increase. For volatility persistence, the marginal effect of AI changes from -0.340 under low-CP conditions to -0.473 under high-CP conditions, while the effect of digitalization increases in absolute magnitude from -0.283 to -0.395. This indicates that stronger technological capability facilitates faster identification of market disturbances and more rapid adjustment of trading positions, thereby shortening the duration of exchange-rate shocks [28, 29]. Digital infrastructure further supports this adjustment by accelerating information transmission, portfolio rebalancing, and transaction execution [30, 31].

For price discovery efficiency, the marginal effect of AI increases from 0.308 under low CP to 0.429 under high CP, while the effect of digitalization rises from 0.262 to 0.361. These findings suggest that AI-based systems become particularly valuable during periods of commodity-market instability because they can process macroeconomic announcements, commodity-price signals, and market sentiment more efficiently [32]. Digitalization complements this process by reducing informational frictions, increasing market transparency, and enabling real-time order execution [33, 34].

A similar pattern is observed for market resilience and stability. The marginal effect of AI rises from 0.373 under low CP to 0.522 under high CP, whereas the effect of digitalization increases from 0.311 to 0.440. This suggests that AI-supported risk monitoring, liquidity forecasting, and scenario analysis become more effective when commodity-related uncertainty is elevated [35, 36]. Digital systems also strengthen operational continuity, liquidity allocation, and communication among financial institutions during periods of market stress [37].

Table 5. Marginal Effects of AI and Digitalization at Different Commodity-Price Levels

FX Market Outcome	Predictor	Low CP	Mean CP	High CP
Volatility persistence	AI	−0.340	−0.407	−0.473
Volatility persistence	Digitalization	−0.283	−0.339	−0.395
Price discovery efficiency	AI	0.308	0.369	0.429
Price discovery efficiency	Digitalization	0.262	0.311	0.361
Market resilience and stability	AI	0.373	0.448	0.522
Market resilience and stability	Digitalization	0.311	0.375	0.440

Note: Low CP represents one standard deviation below the mean, mean CP represents the sample average, and high CP represents one standard deviation above the mean.

To assess the practical importance of the estimated relationships, economic significance is evaluated by calculating the predicted change in each FX market outcome resulting from a 0.10-unit increase in the normalized AI capability or digitalization index. The results in Table 6 indicate that the estimated relationships are economically meaningful in addition to being statistically significant.

At the mean CP level, a 0.10-unit increase in AI capability is associated with a 0.0407 reduction in volatility persistence, a 0.0369 increase in price discovery efficiency, and a 0.0448 increase in market resilience. Under high commodity-price conditions, the corresponding effects increase to −0.0473, 0.0429, and 0.0522. These magnitudes suggest that AI capability generates its greatest practical benefits when FX markets face stronger commodity-related uncertainty [28, 36].

Digitalization also produces economically relevant improvements. At the mean CP level, a 0.10-unit increase in digitalization is associated with a 0.0339 reduction in volatility persistence, a 0.0311 increase in price discovery efficiency, and a 0.0375 improvement in market resilience. Under high-CP conditions, these effects rise to −0.0395, 0.0361, and 0.0440, respectively. Therefore, technological capability has both statistically significant and practically important effects on FX market performance, particularly in countries exposed to substantial commodity-price fluctuations [30, 43].

Table 6. Economic Significance of AI and Digitalization with Commodity Prices

FX Market Outcome	Predictor	Low-CP Effect of a 0.10 Increase	Mean-CP Effect of a 0.10 Increase	High-CP Effect of a 0.10 Increase
Volatility persistence	AI	−0.0340	−0.0407	−0.0473
Volatility persistence	Digitalization	−0.0283	−0.0339	−0.0395
Price discovery efficiency	AI	0.0308	0.0369	0.0429
Price discovery efficiency	Digitalization	0.0262	0.0311	0.0361
Market resilience and stability	AI	0.0373	0.0448	0.0522
Market resilience and stability	Digitalization	0.0311	0.0375	0.0440

To support the validity of the estimated VP, PDE, and MRS models, Fig. 2 presents probability plots, residuals versus fitted values, and Cook's-distance diagnostics. These checks are important because regression results should not be interpreted only from coefficient significance; residual patterns, distributional behaviour, and influential observations must also support model adequacy [19, 20].

The probability plots show that the empirical cumulative probabilities for VP, PDE, and MRS closely follow the 45-degree reference line, suggesting that the residual distributions broadly conform to the expected probability pattern. The residuals-versus-fitted plots also show that the residuals are randomly distributed around zero, with no clear systematic trend. This indicates that the models do not suffer from serious misspecification or nonlinearity problems.

Cook's distance further confirms the robustness of the models. All observations remain below the threshold value of 0.04, indicating that no single country-period observation has an excessive influence on the estimated coefficients. Overall, the diagnostic evidence strengthens the conclusion that AI and digitalization improve FX market outcomes while commodity prices significantly condition these effects.

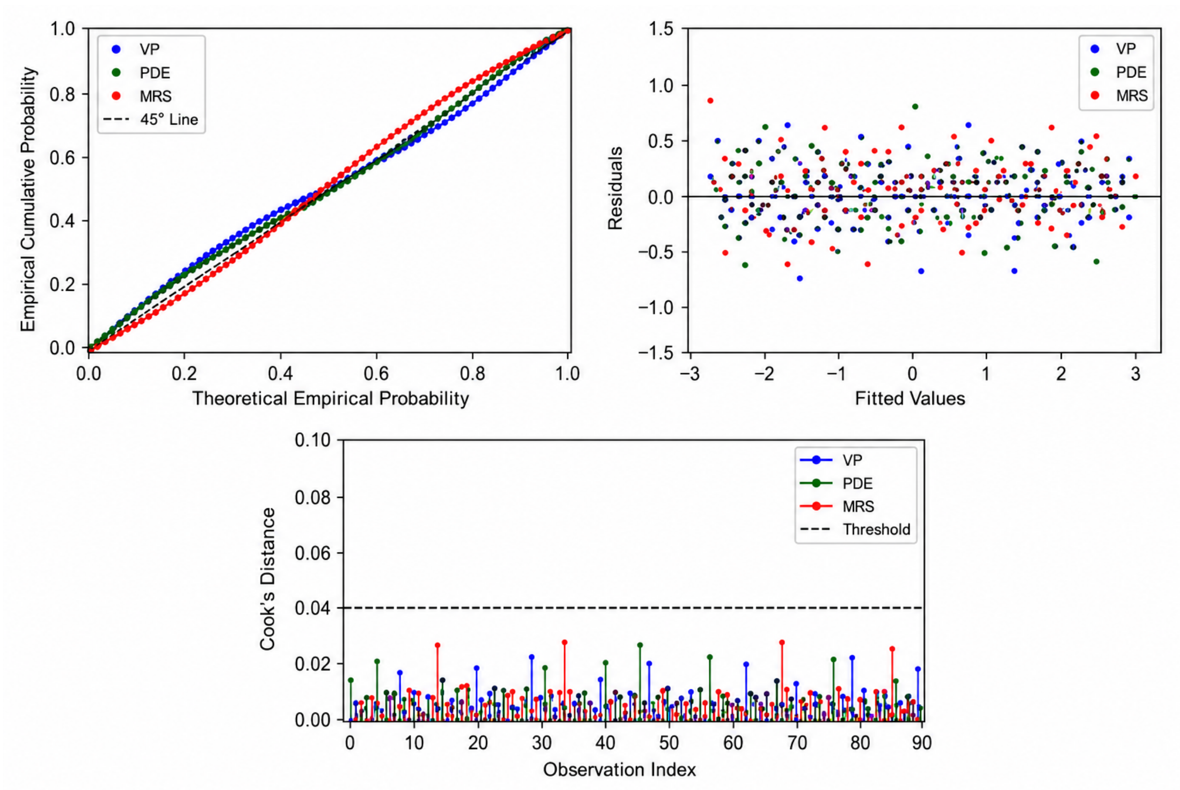

Figure 2. Diagnostic Probability, Residual, and Cook's-Distance Plots for the VP, PDE, and MRS Models

To assess whether the baseline panel results are affected by multicollinearity, Table 7 reports the variance inflation factor (VIF) and tolerance values. Multicollinearity checks are important because highly correlated regressors may inflate standard errors and make it difficult to separate the individual effects of explanatory variables, especially in models containing interaction terms [19]. The results show that all VIF values are below the conventional threshold of 10, confirming that multicollinearity is not a serious concern in the baseline specification.

The relatively higher VIF values for AI $\times$ CP and DI $\times$ CP are expected because the interaction variables are constructed from their corresponding main variables. However, these values remain within acceptable limits, indicating that the inclusion of commodity-price moderation does not create harmful collinearity. The tolerance values also exceed the minimum acceptable threshold of 0.10, showing that the explanatory variables retain sufficient independent variation.

Table 7. VIF Results for the Baseline Panel Model

Variable	VIF	Tolerance	Multicollinearity Status
AI	2.184	0.458	Acceptable
DI	2.437	0.410	Acceptable
CP	1.876	0.533	Acceptable
AI $\times$ CP	3.296	0.303	Acceptable
DI $\times$ CP	3.418	0.293	Acceptable
GRISK	1.642	0.609	Acceptable
FINOPEN	1.925	0.519	Acceptable
IRD	1.537	0.651	Acceptable

To evaluate the reliability of the baseline panel models, Table 8 reports tests for normality, heteroscedasticity, serial correlation, and model stability. These tests are important because regression coefficients should be interpreted only after confirming that the principal assumptions of the estimated models are reasonably satisfied, particularly in panel-based macro-financial studies where residual problems may affect statistical inference [20].

The Jarque–Bera statistics are statistically insignificant for VP, PDE, and MRS, indicating that the residuals are approximately normally distributed. This supports the reliability of the estimated coefficients reported earlier. The Breusch–Pagan results are also insignificant across the three models, suggesting that heteroscedasticity is not a serious concern. Therefore, the reported standard errors are unlikely to be materially distorted by unequal error variance.

The Durbin–Watson statistics are close to 2, indicating that serial correlation is not a major problem in the baseline specifications. In addition, the insignificant CUSUM statistics confirm that the estimated models remain stable over the study period. These findings suggest that the moderating effects of AI $\times$ CP and DI $\times$ CP are not driven by unstable parameters or temporary sample-specific fluctuations.

Table 8. Diagnostic Tests for the Baseline Panel Models

Outcome Variable	Jarque–Bera	Breusch–Pagan	Durbin–Watson	CUSUM
VP	2.184 (0.3356)	3.276 (0.1942)	1.936 (0.4728)	0.642 (0.7983)
PDE	2.376 (0.3048)	3.584 (0.1665)	1.982 (0.5164)	0.684 (0.7446)
MRS	1.968 (0.3738)	3.118 (0.2103)	2.041 (0.5487)	0.718 (0.6815)

Note: Values in parentheses are p-values.

To support the statistical diagnostic tests, Fig. 3 presents autocorrelation and CUSUM plots for the VP, PDE, and MRS specifications. These diagnostics are important because panel-based FX models may suffer from residual dependence when exchange-rate outcomes are affected by persistent shocks, global risk, or commodity-price uncertainty [19, 20].

The autocorrelation plots show that most residual autocorrelation coefficients remain within the upper and lower confidence bounds across lags 1–20. Except for the natural lag-zero value of one, the remaining lag values are small and fluctuate around zero. This pattern indicates that serial dependence is not a serious concern in the estimated models.

The CUSUM plots show that the cumulative residual paths for VP, PDE, and MRS remain within the upper and lower stability bounds throughout the observation period. This indicates that the estimated parameters are stable and are not driven by major structural instability or temporary sample-specific shocks. Overall, the visual diagnostic evidence confirms that the baseline panel models are not seriously affected by residual autocorrelation or parameter instability.

To strengthen the credibility of the baseline regression results, Table 9 reports additional robustness and predictive validation using LASSO regression and Random Forest models for VP, PDE, and MRS. Machine-learning methods complement traditional panel models because they can assess predictive relevance, variable importance, and nonlinear relationships without relying exclusively on parametric assumptions [9, 10].

The LASSO results are broadly consistent with the baseline panel estimates. AI and digitalization have negative coefficients for VP and positive coefficients for PDE and MRS, indicating that technological capability reduces volatility persistence while improving price discovery and market resilience. In contrast, commodity prices have a

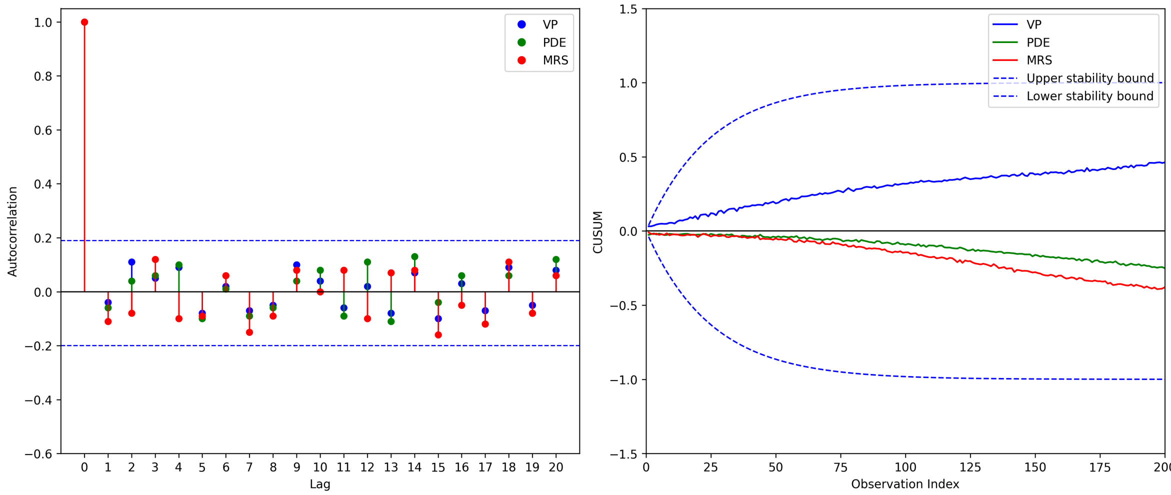

Figure 3. Autocorrelation and CUSUM Stability Tests for the Baseline Panel Models

positive coefficient for VP and negative coefficients for PDE and MRS, confirming that commodity-price shocks increase FX market vulnerability.

The interaction terms provide additional evidence of moderation. Both AI $\times$ CP and DI $\times$ CP remain important in the LASSO and Random Forest models. Their negative effects on VP indicate that technology weakens the volatility-enhancing influence of commodity-price shocks. Their positive effects on PDE and MRS indicate that AI and digitalization improve market adjustment and shock absorption under commodity-price instability.

The Random Forest importance scores further support the LASSO results. The interaction terms record relatively high importance values across all three outcomes, indicating that they are among the strongest predictors of FX market performance. AI and DI also retain substantial predictive relevance, while CP remains important across all models. Among the control variables, GRISK contributes to weaker FX outcomes, FINOPEN supports PDE and MRS, and IRD records comparatively low predictive importance.

Table 9. Combined Machine-Learning Validation Results Using LASSO and Random Forest

	LASSO Coefficients			Random Forest Importance		
Variable	VP	PDE	MRS	VP	PDE	MRS
AI	-0.279^{**}	0.1968^{**}	0.2285^{**}	0.164^{**}	0.173^{**}	0.187^{**}
DI	-0.1874^{**}	0.1742^{**}	0.2037^{**}	0.151^{**}	0.162^{**}	0.176^{**}
CP	0.1428^{**}	-0.1165^{**}	-0.1349^{**}	0.118^{**}	0.106^{**}	0.121^{**}
AI $\times$ CP	-0.2635^{*}	0.2487^{*}	0.2864^{*}	0.218^{*}	0.231^{*}	0.246^{*}
DI $\times$ CP	-0.2268^{**}	0.2139^{**}	0.2516^{*}	0.192^{**}	0.206^{**}	0.224^{*}
GRISK	0.1184^{**}	-0.0976^{**}	-0.1263^{**}	0.097	0.084	0.092
FINOPEN	-0.0769	0.1084^{**}	0.1127^{**}	0.071	0.093	0.087
IRD	0.0415	-0.0382	0.0648	0.043	0.038	0.041

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

To evaluate predictive robustness, Table 10 reports the predictive performance of the LASSO and Random Forest models for VP, PDE, and MRS. Random Forest performs better than LASSO across all outcomes, as indicated by its lower RMSE and MAE values. This suggests that Random Forest captures nonlinear relationships and interaction effects more effectively.

Among the three outcomes, MRS demonstrates the strongest predictive performance, ranking first under both models and recording selection frequencies of 91% for LASSO and 94% for Random Forest. PDE ranks second, while VP ranks third. Although VP remains supported by acceptable prediction errors and selection frequencies, its relatively weaker performance suggests that volatility persistence is more difficult to predict because it is highly sensitive to global shocks and commodity-price uncertainty.

Table 10. Machine-Learning Model Performance Summary

	LASSO				Random Forest			
Outcome	RMSE	MAE	Rank	Selection Frequency	RMSE	MAE	Rank	Selection Frequency
VP	0.084	0.062	3	82%	0.071	0.054	3	86%
PDE	0.079	0.058	2	87%	0.066	0.049	2	91%
MRS	0.073	0.052	1	91%	0.061	0.046	1	94%

Note: RMSE denotes root mean squared error, and MAE denotes mean absolute error. Rank is based on predictive performance, where 1 represents the strongest performance. Selection frequency represents the percentage of repeated model runs in which the principal predictors were retained or ranked as important.

As an additional robustness assessment, Figs. 4 and 5 report machine-learning validation based on LASSO and Random Forest models. These methods complement the baseline panel estimates by evaluating predictor relevance, coefficient stability, and variable importance under alternative data-driven approaches.

The LASSO coefficient paths show that the coefficients gradually shrink toward zero as the penalty parameter increases, confirming that LASSO controls model complexity and reduces overfitting. Importantly, AI, DI, CP, AI $\times$ CP, and DI $\times$ CP remain visible across the coefficient paths, indicating that these variables retain predictive relevance.

The selected LASSO coefficients further support the baseline results. AI and DI have negative coefficients for VP and positive coefficients for PDE and MRS. In contrast, CP increases VP but reduces PDE and MRS. The interaction terms remain negative for VP and positive for PDE and MRS, showing that AI and digitalization weaken the adverse effects of commodity-price instability.

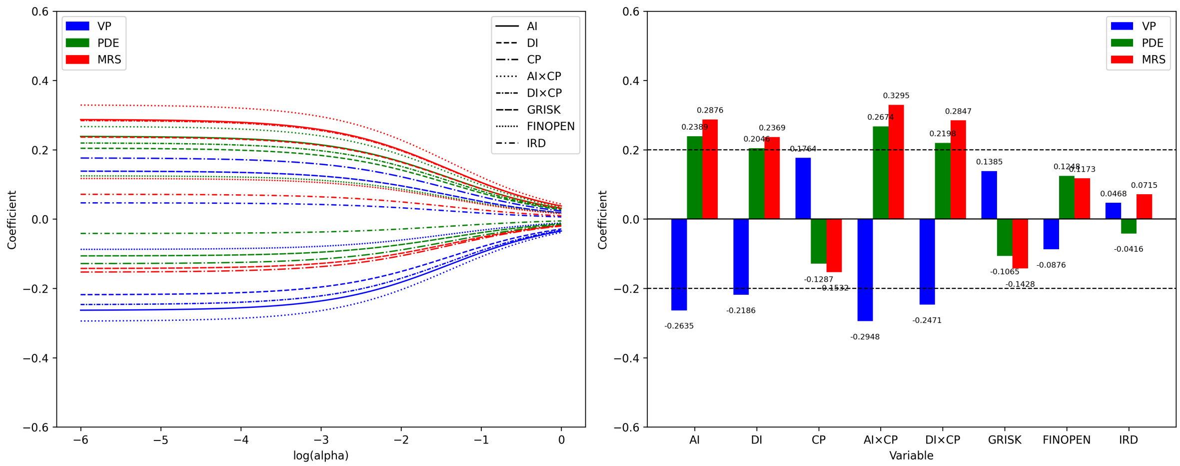

Figure 4. LASSO Coefficient Paths and Selected Coefficients for FX Market Outcomes

Fig. 5 presents the SHAP-based Random Forest feature-importance results for VP, PDE, and MRS. SHAP analysis explains the direction and relative contribution of each predictor, while Random Forest importance indicates the overall predictive strength of the variables.

The SHAP distributions show that AI and digitalization reduce VP while improving PDE and MRS. In contrast, commodity prices increase VP and reduce PDE and MRS. The interaction variables AI $\times$ CP and DI $\times$ CP record the strongest importance values across the three outcomes. This provides additional evidence that commodity prices not only directly influence FX market outcomes but also condition the effectiveness of AI and digitalization.

To provide a clearer assessment of the moderating role of commodity prices within the machine-learning framework, Table 11 compares the mean SHAP contributions of AI capability and digitalization under low and high commodity-price conditions.

For volatility persistence, the mean SHAP value of AI changes from -0.041 under low commodity prices to -0.086 under high commodity prices. Similarly, the SHAP value of digitalization changes from -0.034 to -0.071. This indicates that AI and digitalization contribute more strongly to reducing volatility persistence during periods of elevated commodity-price pressure.

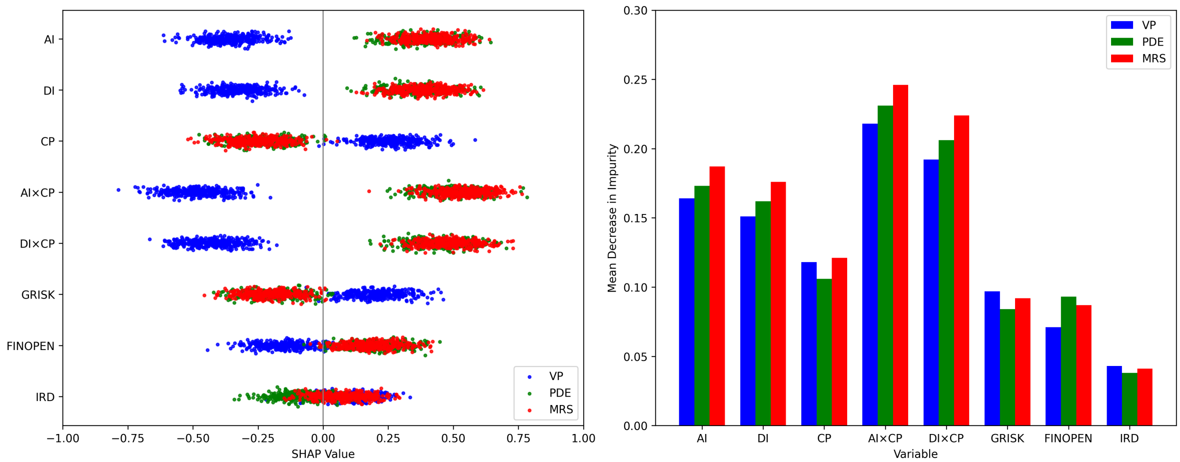

Figure 5. SHAP-Based Random Forest Feature Importance for VP, PDE, and MRS

For price discovery efficiency, the mean SHAP contribution of AI increases from 0.038 to 0.079, while the contribution of digitalization increases from 0.032 to 0.066. For market resilience, the SHAP contribution of AI increases from 0.046 to 0.094, while that of digitalization rises from 0.039 to 0.081. These results confirm that the predictive contribution of technological capability becomes stronger when commodity-price conditions are less stable.

Table 11. Mean SHAP Effects under Low and High Commodity-Price Conditions

Predictor and Outcome	Low CP	High CP	Difference
AI $\to$ VP	-0.041	-0.086	-0.045
AI $\to$ PDE	0.038	0.079	0.041
AI $\to$ MRS	0.046	0.094	0.048
DI $\to$ VP	-0.034	-0.071	-0.037
DI $\to$ PDE	0.032	0.066	0.034
DI $\to$ MRS	0.039	0.081	0.042

To evaluate whether the predictive performance of the machine-learning models differs from that of the baseline fixed-effects panel model, Table 12 reports the Diebold–Mariano test results. The test compares the FE model with LASSO and Random Forest to determine whether the machine-learning methods provide additional predictive gains or primarily validate the econometric results.

The p-values for all pairwise comparisons across VP, PDE, and MRS are above conventional significance levels. Therefore, there is no statistically significant difference in predictive accuracy between the FE, LASSO, and Random Forest models. This indicates that the machine-learning models provide prediction performance that is statistically comparable to the baseline panel model.

The insignificant differences between LASSO and Random Forest also suggest that both methods provide consistent validation evidence. Overall, the Diebold–Mariano results confirm that the principal findings are not dependent on a single modelling or forecasting approach.

To examine potential endogeneity and determine whether the baseline findings are sensitive to alternative model specifications, this study conducts three additional robustness checks using lagged explanatory variables, instrumental-variable two-stage least squares, and dynamic panel system-GMM estimation. These approaches address concerns arising from reverse causality, simultaneity, omitted-variable bias, measurement error, and the dynamic persistence of FX market outcomes.

To reduce potential simultaneity between technological development and FX market outcomes, Table 13 re-estimates the models using one-period-lagged values of AI capability, digitalization, commodity prices, and their interaction terms. The results remain broadly consistent with the baseline estimates.

Table 12. Diebold–Mariano Test Results Comparing the Baseline Panel and Machine-Learning Models

Outcome	Model Comparison	DM Statistic	p-value	Interpretation
VP	FE vs. LASSO	0.842	0.4018	LASSO supports FE
VP	FE vs. Random Forest	1.126	0.2637	Random Forest supports FE
VP	LASSO vs. Random Forest	0.764	0.4469	ML results are consistent
PDE	FE vs. LASSO	0.913	0.3635	LASSO supports FE
PDE	FE vs. Random Forest	1.218	0.2264	Random Forest supports FE
PDE	LASSO vs. Random Forest	0.837	0.4051	ML results are consistent
MRS	FE vs. LASSO	0.786	0.4342	LASSO supports FE
MRS	FE vs. Random Forest	1.064	0.2906	Random Forest supports FE
MRS	LASSO vs. Random Forest	0.692	0.4907	ML results are consistent

Lagged AI capability and digitalization are negatively associated with volatility persistence but positively associated with price discovery efficiency and market resilience. This indicates that improvements in technological capability are followed by lower volatility persistence and stronger FX market adjustment in the subsequent period.

Commodity prices continue to increase volatility persistence while reducing price discovery efficiency and market resilience. More importantly, the coefficients of the lagged AI × CP and DI × CP interaction terms remain negative for VP and positive for PDE and MRS. These findings confirm that the moderating role of commodity prices is not driven solely by contemporaneous relationships.

Table 13. Robustness Results Using Lagged Explanatory Variables

Variable	VP	PDE	MRS
AI_{t-1}	-0.241^{***} (0.071)	0.219^{***} (0.078)	0.263^{***} (0.074)
DI_{t-1}	-0.196^{**} (0.083)	0.187^{**} (0.086)	0.218^{***} (0.079)
CP_{t-1}	0.158^{**} (0.069)	-0.119^{**} (0.058)	-0.141^{**} (0.064)
$(AI \times CP)_{t-1}$	-0.271^{***} (0.086)	0.246^{***} (0.089)	0.301^{***} (0.083)
$(DI \times CP)_{t-1}$	-0.224^{**} (0.097)	0.201^{**} (0.094)	0.258^{***} (0.091)
GRISK	0.126^{**}	-0.098^{*}	-0.131^{**}
FINOPEN	-0.079^{*}	0.112^{**}	0.106^{**}
IRD	0.041	-0.036	0.063
Adjusted R^2	0.603	0.594	0.648

Note: Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

To further address potential endogeneity, Table 14 reports the instrumental-variable two-stage least-squares estimates. AI capability, digitalization, and their interaction terms are treated as potentially endogenous, while their lagged values are used as instruments.

The estimated coefficients remain consistent with the baseline fixed-effects results. AI and digitalization reduce volatility persistence and improve both price discovery efficiency and market resilience. Commodity prices continue to have an adverse direct effect, whereas the interaction terms indicate that stronger technological capability mitigates commodity-related FX market instability.

The first-stage F-statistics exceed the conventional threshold of 10, suggesting that the instruments have acceptable explanatory relevance. In addition, the statistically insignificant Hansen test results indicate that the overidentifying restrictions cannot be rejected, providing support for instrument validity. The significant endogeneity-test results further justify the use of the instrumental-variable specification.

To account for the dynamic behaviour of FX market outcomes, Table 15 presents the system-GMM estimates incorporating the lagged dependent variable. The positive and statistically significant coefficients of the lagged dependent variables indicate persistence in volatility, price discovery, and market resilience. This suggests that current FX market conditions are partly influenced by their previous-period values.

The coefficients of AI capability and digitalization retain their expected signs across the three models. Both variables reduce volatility persistence and improve price discovery efficiency and market resilience. Commodity prices continue to worsen FX market outcomes, while the AI × CP and DI × CP interaction terms remain statistically significant and operate in the expected directions.

Table 14. Instrumental-Variable Two-Stage Least-Squares Robustness Results

Variable	VP	PDE	MRS
AI	-0.286^{***} (0.092)	0.254^{***} (0.096)	0.309^{***} (0.089)
DI	-0.231^{**} (0.104)	0.216^{**} (0.101)	0.249^{***} (0.094)
CP	0.183^{**} (0.078)	-0.137^{**} (0.067)	-0.162^{**} (0.071)
AI $\times$ CP	-0.318^{***} (0.108)	0.289^{***} (0.105)	0.346^{***} (0.101)
DI $\times$ CP	-0.265^{**} (0.116)	0.238^{**} (0.111)	0.302^{***} (0.106)
GRISK	0.145^{**}	-0.111^{*}	-0.149^{**}
FINOPEN	-0.091^{*}	0.131^{**}	0.122^{**}
IRD	0.049	−0.044	0.075
First-stage F-statistic	14.82	15.47	16.13
Hansen J-test, p-value	0.438	0.512	0.476
Endogeneity test, p-value	0.041	0.036	0.029

Note: Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

The diagnostic statistics support the adequacy of the system-GMM estimates. The significant AR(1) results are expected in first-differenced residuals, while the insignificant AR(2) results indicate no evidence of second-order serial correlation. The Hansen test results are also insignificant, supporting the validity of the instrument set. The number of instruments is restricted and collapsed to reduce the risk of instrument proliferation.

Table 15. Dynamic Panel System-GMM Robustness Results

Variable	VP	PDE	MRS
Dependent variable$_{t-1}$	0.426^{***} (0.103)	0.371^{***} (0.098)	0.458^{***} (0.101)
AI	-0.249^{***} (0.081)	0.226^{***} (0.084)	0.274^{***} (0.079)
DI	-0.207^{**} (0.091)	0.192^{**} (0.089)	0.225^{***} (0.083)
CP	0.164^{**} (0.072)	-0.121^{**} (0.061)	-0.146^{**} (0.066)
AI $\times$ CP	-0.283^{***} (0.094)	0.258^{***} (0.096)	0.316^{***} (0.091)
DI $\times$ CP	-0.235^{**} (0.102)	0.211^{**} (0.099)	0.269^{***} (0.095)
GRISK	0.131^{**}	-0.101^{*}	-0.137^{**}
FINOPEN	-0.083^{*}	0.117^{**}	0.111^{**}
IRD	0.044	−0.039	0.068
AR(1), p-value	0.032	0.041	0.027
AR(2), p-value	0.384	0.427	0.361
Hansen test, p-value	0.452	0.518	0.489

Note: Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Taken together, the lagged-variable, instrumental-variable, and dynamic-panel results are broadly consistent with the baseline fixed-effects estimates. AI capability and digitalization remain associated with lower volatility persistence and stronger price discovery efficiency and market resilience. Commodity prices continue to weaken FX market performance, whereas the interaction terms show that technological capability reduces the adverse consequences of commodity-price shocks.

These alternative specifications strengthen confidence in the empirical findings by showing that the results are not dependent on a single estimation approach. Nevertheless, because the sample consists of only nine countries observed over ten years, the IV and system-GMM estimates should be interpreted cautiously. The relatively small cross-sectional dimension may limit instrument strength and finite-sample reliability. Therefore, these estimates are treated as supplementary robustness evidence, while the findings are interpreted primarily as robust conditional relationships rather than definitive causal effects.

To examine whether the constructed FX market outcome measures are sensitive to model specification, Table 16 reports combined-panel results from alternative volatility, price-discovery, and regime-switching models.

For volatility persistence, the estimated coefficients range from 0.821 under EGARCH(1,1) to 0.849 under GJR-GARCH(1,1), compared with 0.843 for the baseline GARCH(1,1) model. This close range indicates that volatility persistence remains high and stable across specifications. Although the asymmetric coefficients are statistically significant, they do not materially change the persistence estimates. All models also pass the ARCH-LM and

Ljung–Box diagnostic tests. GARCH(1,1) is therefore retained as a parsimonious and adequately specified baseline model.

For price discovery efficiency, the error-correction terms remain negative and statistically significant across all VECM specifications. The adjustment speed ranges from 28.4% to 31.7%, while the PDE estimates range from 0.578 to 0.594. The lag-two VECM produces the highest PDE value, the highest log-likelihood, and the strongest residual diagnostic result. It is therefore retained as the preferred specification. The VAR model also produces a positive PDE estimate, further supporting the robustness of the measure.

For market resilience and stability, the two-state and three-state Markov-switching models produce similar MRS estimates of 0.684 and 0.671. Both models also show high probabilities of remaining in the stable regime. Although the three-state model has a slightly higher log-likelihood, the two-state model achieves higher classification accuracy of 89.6%. It is therefore retained because it is more parsimonious and easier to interpret economically. Overall, the similarity of the results across alternative specifications confirms that the constructed FX market outcome measures are robust to different model choices.

Table 16. Alternative-Specification Robustness Results for FX Market Outcome Measures

FX Market Outcome	Model Specification	Key Estimate	Log-Likelihood	Diagnostic Test
Volatility persistence	GARCH(1,1) (This Study)	Persistence $= 0.843$	2846.73	ARCH-LM ($p = 0.284$); Ljung–Box ($p = 0.317$)
	EGARCH(1,1)	Persistence $= 0.821$; asymmetry $= -0.084^{**}$	2849.16	ARCH-LM ($p = 0.301$); Ljung–Box ($p = 0.329$)
	GJR-GARCH(1,1)	Persistence $= 0.849$; asymmetry $= 0.061^{**}$	2848.04	ARCH-LM ($p = 0.296$); Ljung–Box ($p = 0.321$)
Price discovery efficiency	VECM, lag 1	ECT $= -0.284^{***}$; PDE $= 0.578$	1638.24	Residual LM ($p = 0.214$)
	VECM, lag 2 (This Study)	ECT $= -0.317^{***}$; PDE $= 0.594$	1651.87	Residual LM ($p = 0.338$)
	VECM, lag 3	ECT $= -0.302^{***}$; PDE $= 0.586$	1646.15	Residual LM ($p = 0.296$)
	VAR in first differences	Adjustment speed $= 26.8\%$; PDE $= 0.563$	1624.61	Residual LM ($p = 0.181$)
Market resilience and stability	Two-state Markov switching (This Study)	MRS $= 0.684$; $P_{11} = 0.932^{***}$	1926.48	Classification accuracy = 89.6%
	Three-state Markov switching	MRS $= 0.671$; $P_{11} = 0.918^{***}$	1932.71	Classification accuracy = 88.2%

Note: ECT denotes the error-correction term, PDE denotes price discovery efficiency, and MRS denotes market resilience and stability. P_{11} represents the transition probability of remaining in Regime 1 from one period to the next. *** and ** indicate significance at the 1% and 5% levels, respectively.

Country-wise analysis is conducted to capture heterogeneity across the selected G20 countries. Although the baseline panel model provides overall evidence on the effects of AI, digitalization, commodity prices, and their interaction terms, pooled estimates may conceal important country-level differences. These differences may arise from variations in commodity dependence, digital infrastructure, AI capability, financial openness, exchange-rate regimes, and exposure to global risk.

Table 17 reports the country-wise descriptive statistics for the nine selected G20 countries. The results show meaningful differences in AI capability, digitalization, commodity-price exposure, financial openness, and FX market outcomes.

China, India, Brazil, and Turkey report relatively stronger AI and digitalization values, suggesting higher technological readiness and more advanced digital transformation. These countries also exhibit stronger price discovery efficiency and market resilience together with relatively lower volatility persistence.

In contrast, Russia and Saudi Arabia record higher commodity-price means and standard deviations, reflecting stronger exposure to commodity-price fluctuations. Their relatively higher volatility persistence suggests that commodity dependence may increase FX market instability through trade-balance, inflation, and risk-sentiment channels. Financial openness also varies across countries, with China, Turkey, and Brazil reporting comparatively stronger FINOPEN values.

Table 17. Country-Wise Descriptive Statistics for the Study Variables

Variable	Statistic	Argentina	Brazil	China	India	Mexico	Russia	Saudi Arabia	South Africa	Turkey
AI	Mean	0.421	0.589	0.681	0.624	0.513	0.476	0.452	0.438	0.553
AI	Std. Dev.	0.132	0.146	0.158	0.151	0.139	0.136	0.128	0.126	0.143
DI	Mean	0.438	0.604	0.663	0.637	0.548	0.489	0.463	0.451	0.575
DI	Std. Dev.	0.119	0.137	0.149	0.142	0.128	0.123	0.116	0.114	0.132
CP	Mean	0.463	0.538	0.497	0.512	0.471	0.584	0.572	0.509	0.529
CP	Std. Dev.	0.148	0.156	0.143	0.151	0.139	0.167	0.164	0.149	0.153
GRISK	Mean	0.526	0.541	0.492	0.507	0.496	0.568	0.551	0.533	0.512
GRISK	Std. Dev.	0.136	0.142	0.128	0.133	0.124	0.151	0.147	0.138	0.135
FINOPEN	Mean	0.382	0.486	0.521	0.477	0.454	0.398	0.412	0.426	0.493
FINOPEN	Std. Dev.	0.104	0.115	0.121	0.112	0.109	0.098	0.101	0.103	0.117
IRD	Mean	0.049	0.043	0.021	0.036	0.034	0.052	0.041	0.039	0.047
IRD	Std. Dev.	0.018	0.016	0.011	0.014	0.013	0.019	0.015	0.014	0.017
VP	Mean	0.472	0.451	0.392	0.416	0.429	0.486	0.478	0.467	0.432
VP	Std. Dev.	0.126	0.119	0.104	0.111	0.114	0.132	0.129	0.124	0.116
PDE	Mean	0.531	0.596	0.648	0.621	0.579	0.526	0.538	0.546	0.599
PDE	Std. Dev.	0.118	0.124	0.139	0.131	0.122	0.116	0.113	0.115	0.126
MRS	Mean	0.552	0.629	0.681	0.653	0.602	0.548	0.561	0.573	0.637
MRS	Std. Dev.	0.121	0.132	0.146	0.138	0.127	0.119	0.116	0.120	0.134

To examine country-specific effects on volatility persistence, Table 18 reports the VP results across the selected G20 countries. Country-wise estimation is important because exchange-rate responses to commodity-price shocks may vary according to trade structure, commodity dependence, financial openness, and policy capacity [19]. Therefore, the analysis helps determine whether the baseline findings remain consistent across countries.

The results show that AI has a negative effect on VP in all countries, indicating that stronger AI capability reduces exchange-rate volatility persistence. This supports evidence that AI and machine-learning tools improve financial forecasting and market adjustment [19]. Digitalization also reduces VP in most countries, although its effect is weaker and statistically insignificant in Saudi Arabia and South Africa. This suggests that the benefits of digitalization may depend on financial depth, institutional capacity, and market readiness [9].

Commodity prices have a positive effect across all countries, confirming that commodity-price shocks increase FX volatility persistence. This is consistent with evidence that commodity-price movements influence exchange rates through inflation, trade-balance, and investor-sentiment channels [19, 28]. The interaction terms AI $\times$ CP and DI $\times$ CP are negative across all countries, showing that AI capability and digitalization reduce the volatility-enhancing effect of commodity-price shocks.

The control variables also provide useful country-level evidence. GRISK increases VP across the sample, confirming that global uncertainty strengthens FX volatility persistence. FINOPEN generally reduces VP by supporting information transmission, liquidity, and market adjustment. IRD shows weaker and less consistent effects, suggesting that interest-rate differentials play a smaller role than AI, DI, CP, and their interaction terms.

To examine country-level heterogeneity in price discovery efficiency, Table 19 reports the country-specific PDE results. Country-wise analysis is relevant because FX price discovery depends on market depth, information flow, financial openness, institutional quality, and exposure to external shocks. AI and digital technologies may improve financial forecasting and information processing, although their effects may differ across countries depending on technological and institutional readiness [9, 10].

The results show that AI has a positive effect on PDE in most countries, indicating that stronger AI capability improves the speed and accuracy with which FX markets incorporate information. Digitalization also has a positive effect, although its influence is weaker and statistically insignificant in Russia, Saudi Arabia, and South Africa. This suggests that digitalization improves price discovery, but its effectiveness depends on the depth of digital infrastructure and financial-market development.

Table 18. Country-Specific Volatility-Persistence Results

Country	AI	DI	CP	AI × CP	DI × CP	GRISK	FINOPEN	IRD
Argentina	−0.2184**	−0.1765**	0.1438**	−0.2467*	−0.2149**	0.1126**	−0.0684	0.0415
Brazil	−0.2876*	−0.2418**	0.1652**	−0.3264*	−0.2785*	0.1297**	−0.0846	0.0537
China	−0.2537*	−0.2164**	0.1517**	−0.3018*	−0.2573**	0.1079**	−0.0712	0.0386
India	−0.2769*	−0.2294**	0.1589**	−0.3185*	−0.2697*	0.1268**	−0.0774	0.0493
Mexico	−0.2076**	−0.1657**	0.1364**	−0.2286**	−0.2015**	0.1047**	−0.0592	0.0391
Russia	−0.1948**	−0.1549**	0.1763**	−0.2168**	−0.1884**	0.1465**	−0.0527	0.0619
Saudi Arabia	−0.1829**	−0.1436	0.1687**	−0.2034**	−0.1745**	0.1382**	−0.0481	0.0576
South Africa	−0.1764**	−0.1385	0.1598**	−0.1942**	−0.1663**	0.1315**	−0.0457	0.0551
Turkey	−0.2398**	−0.2046**	0.1612**	−0.2817*	−0.2395**	0.1398**	−0.0698	0.0594

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

Commodity prices generally have negative coefficients, indicating that commodity-price instability weakens price discovery efficiency. The positive coefficients of AI × CP and DI × CP show that AI capability and digitalization help mitigate these adverse effects by improving the processing and transmission of commodity-related information.

Table 19. Country-Specific Price-Discovery Efficiency Results

Country	AI	DI	CP	AI × CP	DI × CP	GRISK	FINOPEN	IRD
Argentina	0.1867**	0.1584**	−0.0917	0.2145**	0.1862**	−0.0864	0.1197**	−0.0362
Brazil	0.2248**	0.1976**	−0.1085**	0.2587*	0.2218**	−0.0958	0.1375**	−0.0421
China	0.2035**	0.1769**	−0.0976	0.2364**	0.2047**	−0.0825	0.1289**	−0.0341
India	0.2796*	0.2478*	−0.1194**	0.3215*	0.2764*	−0.1049**	0.1498**	−0.0482
Mexico	0.2594*	0.2326**	−0.1037**	0.2987*	0.2546**	−0.0924	0.1406**	−0.0397
Russia	0.1768**	0.1497	−0.1265**	0.2014**	0.1725*	−0.1136**	0.1108**	−0.0534
Saudi Arabia	0.1645	0.1364	−0.1186**	0.1865**	0.1589**	−0.1074**	0.1056	−0.0502
South Africa	0.1714**	0.1418	−0.1098	0.1935**	0.1647**	−0.0996	0.1084	−0.0469
Turkey	0.2446*	0.2185**	−0.1142**	0.2819*	0.2398**	−0.1027**	0.1435**	−0.0446

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

Table 20 reports the country-specific market resilience and stability results. AI has a positive effect on MRS across all countries, indicating that stronger AI capability enhances FX market resilience. This is consistent with evidence that AI-based analytics improve risk monitoring, forecasting, liquidity management, and market adjustment during periods of uncertainty [9, 10].

Digitalization also has a positive effect in most countries, although its coefficients are weaker and statistically insignificant in Russia, Saudi Arabia, and South Africa. This suggests that digitalization strengthens market resilience, but its effectiveness depends on digital infrastructure, financial openness, and institutional readiness.

Commodity prices have a negative effect across all countries, confirming that commodity-price instability weakens FX market stability through inflation, trade-balance, and uncertainty channels. The interaction terms provide strong evidence of moderation. Both AI × CP and DI × CP are positive across all countries, showing that AI and digitalization reduce the destabilizing effect of commodity-price shocks.

To evaluate country-wise model performance, Table 21 reports the model-fit and selection criteria for the VP, PDE, and MRS models. All country-specific models demonstrate acceptable explanatory power, with R^2 values ranging from 0.612 to 0.753. This indicates that AI, digitalization, commodity prices, interaction terms, and the control variables explain a meaningful proportion of the variation in FX market outcomes across the selected countries.

For the VP model, India, Brazil, Turkey, and China record relatively stronger explanatory power, with R^2 values of 0.696, 0.687, 0.679, and 0.674, respectively. This suggests that the model explains volatility persistence more effectively in countries with comparatively stronger AI capability and digitalization. South Africa and Saudi Arabia report lower R^2 values, although their results remain acceptable.

Table 20. Country-Specific Market Resilience and Stability Results

Country	AI	DI	CP	AI × CP	DI × CP	GRISK	FINOPEN	IRD
Argentina	0.2198**	0.1854**	−0.1285**	0.2674*	0.2286**	−0.1258**	0.1047**	0.0724
Brazil	0.2985*	0.2597*	−0.1496**	0.3589*	0.3068*	−0.1479**	0.1275**	0.0843
China	0.2487*	0.2148**	−0.1214**	0.3065*	0.2629*	−0.1186**	0.1139**	0.0695
India	0.2845*	0.2416**	−0.1428**	0.3417*	0.2946*	−0.1412**	0.1226**	0.0802
Mexico	0.1984**	0.1657**	−0.1127**	0.2364**	0.2048**	−0.1093**	0.0975	0.0624
Russia	0.1895**	0.1516	−0.1554**	0.2247**	0.1906**	−0.1528**	0.0924	0.0868
Saudi Arabia	0.1814**	0.1452	−0.1465**	0.2116**	0.1789**	−0.1446**	0.0892	0.0835
South Africa	0.1857**	0.1484	−0.1367**	0.2195**	0.1867**	−0.1338**	0.0946	0.0781
Turkey	0.2564*	0.2237**	−0.1394**	0.3148*	0.2685*	−0.1375**	0.1198**	0.0821

Note: * and ** indicate statistical significance at the 10% and 5% levels, respectively.

For the PDE model, India records the strongest model fit, followed by Mexico, Turkey, and Brazil. This indicates that the framework performs particularly well in explaining price discovery efficiency in countries where digital and technological capacity supports faster information adjustment. The statistically significant Prob(F) values confirm that the explanatory variables jointly explain country-level FX market outcomes.

For the MRS model, India again records the strongest performance, followed by Brazil, Turkey, and China. Their comparatively higher log-likelihood values and lower AIC and BIC values suggest that the MRS specification provides a stronger fit in countries with greater technological capacity and more effective market-adjustment mechanisms.

Table 21. Country-Wise Model-Fit and Selection Criteria for the VP, PDE, and MRS Models

Country	Outcome	Log-L	R^2	Adjusted R^2	F-statistic	Prob(F)	AIC	BIC
Argentina	VP	119.284	0.648	0.603	15.214	0.0039	−218.568	−198.137
	PDE	122.516	0.667	0.621	15.842	0.0034	−225.032	−204.601
	MRS	127.438	0.691	0.646	17.184	0.0026	−234.876	−214.445
Brazil	VP	133.206	0.687	0.642	18.964	0.0016	−246.412	−225.981
	PDE	137.184	0.708	0.665	19.926	0.0012	−254.368	−233.937
	MRS	142.596	0.736	0.694	22.318	0.0007	−265.192	−244.761
China	VP	129.482	0.674	0.628	18.106	0.0019	−238.964	−218.533
	PDE	124.536	0.663	0.615	16.284	0.0031	−229.072	−208.641
	MRS	139.148	0.724	0.681	21.482	0.0009	−258.296	−237.865
India	VP	135.746	0.696	0.652	19.834	0.0012	−251.492	−231.061
	PDE	143.584	0.741	0.699	23.462	0.0005	−267.168	−246.737
	MRS	147.236	0.753	0.711	24.986	0.0004	−274.472	−254.041
Mexico	VP	117.624	0.643	0.596	14.782	0.0044	−215.248	−194.817
	PDE	140.328	0.731	0.688	22.516	0.0006	−260.656	−240.225
	MRS	121.184	0.657	0.611	15.624	0.0035	−222.368	−201.937
Russia	VP	114.386	0.631	0.583	14.138	0.0051	−208.772	−188.341
	PDE	117.492	0.652	0.606	15.082	0.0041	−214.984	−194.553
	MRS	120.548	0.668	0.623	16.296	0.0030	−221.096	−200.665
Saudi Arabia	VP	112.614	0.619	0.569	13.386	0.0062	−205.228	−184.797
	PDE	115.048	0.637	0.591	14.218	0.0049	−210.096	−189.665
	MRS	118.236	0.651	0.605	15.148	0.0039	−216.472	−196.041
South Africa	VP	110.496	0.612	0.563	13.026	0.0069	−200.992	−180.561
	PDE	116.628	0.644	0.597	14.694	0.0044	−213.256	−192.825
	MRS	119.742	0.664	0.618	15.894	0.0033	−219.484	−199.053
Turkey	VP	131.026	0.679	0.635	18.472	0.0017	−242.052	−221.621
	PDE	139.526	0.723	0.679	21.342	0.0009	−259.052	−238.621
	MRS	143.406	0.734	0.691	22.784	0.0006	−266.812	−246.381

The empirical results consistently show that AI capability and digitalization reduce volatility persistence while improving price discovery efficiency and market resilience. Commodity-price shocks have the opposite effect by prolonging exchange-rate volatility and weakening market adjustment. More importantly, the statistically significant $\mathrm{AI} \times \mathrm{CP}$ and $\mathrm{DI} \times \mathrm{CP}$ coefficients indicate that technological capability moderates these adverse effects.

These results suggest that AI-based forecasting, faster information processing, and stronger digital infrastructure help FX markets respond more efficiently when commodity-price uncertainty increases. The marginal-effect results further show that the benefits of AI capability and digitalization become stronger at higher levels of commodity-price change. These effects are not only statistically significant but also economically meaningful, particularly for market resilience and shock absorption.

The diagnostic tests, alternative specifications, endogeneity checks, and machine-learning validation provide additional support for the main findings by confirming model stability, acceptable residual behaviour, and the predictive relevance of the interaction terms. Overall, the evidence indicates that technologically stronger countries are better positioned to manage commodity-driven FX market instability.

5. Policy Implications

The findings provide specific implications for policymakers, central banks, regulators, and financial institutions in commodity-exposed G20 countries. Since the interaction effects show that AI and digitalization weaken the adverse influence of commodity-price shocks on volatility persistence, price discovery efficiency, and market resilience, policy support should focus on technologies that directly improve commodity-related information processing and FX market adjustment.

Governments in commodity-dependent countries should provide targeted incentives, innovation grants, or regulatory support for fintech firms and financial institutions developing AI-based commodity forecasting, exchange-rate analytics, automated hedging, and liquidity-management systems. Rather than subsidizing general AI adoption, policy support should prioritize applications that integrate commodity prices, capital flows, inflation indicators, and FX order-flow information. Such tools can help market participants distinguish temporary commodity-price movements from persistent shocks and respond more efficiently.

Central banks and financial regulators should invest in the regulatory-AI channel by developing real-time surveillance systems, commodity-risk dashboards, stress-testing models, and early-warning mechanisms. These systems should jointly monitor exchange rates, commodity prices, liquidity conditions, capital flows, and global risk indicators. This would allow regulators to identify emerging exchange-rate pressure earlier and implement liquidity, communication, or market-stabilization measures more promptly. The regulatory channel is particularly relevant to the observed improvement in market resilience and shock-absorption capacity.

The trading and market-information channel should also be strengthened through investment in electronic FX platforms, low-latency data infrastructure, transparent price feeds, and regulated algorithmic-trading facilities. Financial institutions should be encouraged to adopt AI-assisted forecasting, automated hedging, portfolio rebalancing, and commodity-linked risk-management systems. These applications are closely related to the finding that AI improves price discovery and reduces the persistence of exchange-rate shocks by accelerating information processing and market correction.

However, support for algorithmic trading should be accompanied by safeguards against model concentration, algorithmic herding, cyber risk, and rapid liquidity withdrawal. Regulators should require model validation, human oversight, stress testing, audit trails, and contingency procedures for AI-based trading systems. This is important because technological innovation may improve market efficiency while also creating endogenous risks during periods of financial stress.

Policy intensity should also reflect country-level technological readiness. Countries with weaker digital infrastructure should first strengthen market connectivity, data quality, cybersecurity, and institutional capacity. Countries with more advanced systems can place greater emphasis on integrated AI-based commodity and FX surveillance, automated hedging infrastructure, and regulated algorithmic trading. Overall, the findings support the targeted development of commodity-sensitive fintech and regulatory-AI infrastructure rather than broad and undirected investment in AI.

6. Limitations and Future Research

The empirical results should be interpreted with caution because the current research design does not establish strict causality. The fixed-effects specification controls for unobserved time-invariant country characteristics and common time shocks, but it may not fully address reverse causality, simultaneity, measurement error, or omitted time-varying heterogeneity.Future studies should employ larger panels, stronger external instruments, or carefully specified dynamic-panel estimators to strengthen causal identification. In addition, future research could incorporate broader measures of technological development, including fintech adoption, algorithmic-trading intensity, cybersecurity readiness, and AI investment by financial institutions, subject to consistent cross-country data availability.

7. Conclusion

This study demonstrates that AI capability and digitalization strengthen FX market adjustment, particularly during periods of commodity-price instability. Their interactions with commodity prices reduce volatility persistence and improve price discovery efficiency and market resilience, indicating that technological capability becomes more valuable when external market pressures intensify. The findings also reveal cross-country heterogeneity, with stronger results observed in India, Brazil, and Turkey and comparatively weaker effects in Russia, Saudi Arabia, and South Africa. Overall, the study supports targeted investment in AI-based market surveillance, commodity-risk analytics, digital trading infrastructure, and financial-market connectivity to strengthen FX market stability in commodity-exposed countries.

A. Reproducibility Steps

1. Collect daily exchange-rate data and annual data for AI capability, digitalization, commodity prices, and the control variables for the selected G20 countries during 2015–2024.
2. Clean the data, standardize dates and country codes, remove duplicate observations, address missing values, and transform exchange rates into daily logarithmic returns.
3. Construct volatility persistence using a GARCH(1,1) model, price discovery efficiency using the variance-ratio and VECM adjustment measures, and market resilience and stability using a two-state Markov-switching model.
4. Construct the AI capability and digitalization indices using min–max normalization and equal weighting. Measure commodity-price shocks using annual logarithmic changes and generate the interaction terms $\mathrm{AI} \times \mathrm{CP}$ and $\mathrm{DI} \times \mathrm{CP}$.
5. Merge all variables by country and year and estimate the two-way fixed-effects models, marginal effects, economic significance, and country-wise specifications.
6. Validate the results using LASSO, Random Forest, SHAP analysis, forecasting measures, and the Diebold–Mariano test. Apply the same hyperparameters and a fixed random seed of 2026 in all replications.
7. Record the software versions, packages, data sources, data-processing decisions, and execution order used in the analysis.

B. Replication Settings and Hyperparameters

Table B1. Replication Settings and Hyperparameters

Analysis Component	**Replication Setting**
Sample	G20 countries, 2015–2024
Exchange-rate frequency	Daily observations aggregated into annual outcome measures
Exchange-rate transformation	Continuously compounded logarithmic returns
Volatility persistence	GARCH(1,1); persistence calculated as the sum of the ARCH and GARCH coefficients
Price discovery efficiency	Composite measure based on the variance ratio and VECM adjustment speed
Market resilience and stability	Two-state Markov-switching model
Normalization	Min–max normalization using the estimation sample
Composite-index weighting	Equal weighting
Commodity-price measure	Annual logarithmic change followed by min–max normalization
Interaction terms	AI $\times$ CP and DI $\times$ CP
Baseline estimator	Two-way fixed-effects estimator
Fixed effects	Country and year fixed effects
Standard errors	Country-clustered robust standard errors
LASSO penalty selection	Ten-fold cross-validation
LASSO standardization	Predictors standardized before estimation
Random Forest trees	500
Random Forest maximum depth	Unrestricted, subject to the minimum-node stopping rule
Minimum observations per terminal node	2
Variables considered at each split	Square root of the total number of predictors
Train–test division	80% training sample and 20% testing sample
Cross-validation	Five-fold cross-validation within the training sample
SHAP method	Tree-based SHAP values for the fitted Random Forest model
Forecast evaluation	Root mean squared error (RMSE) and mean absolute error (MAE)
Forecast comparison	Diebold–Mariano test
Random seed	2026
Statistical significance	1%, 5%, and 10% levels
Software environment	Python, version 3.14

Data and Code Availability

The data and code supporting the findings of this study are available from the corresponding author upon reasonable request and subject to the permission of all authors. Access may also be subject to the terms and restrictions imposed by the original data providers.

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