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The impact of generative AI on institutional efficiency: Regulatory and trading evidence from financial markets

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Abstract

This paper examines how generative artificial intelligence (GenAI) affects institutional efficiency in financial markets through the combined roles of regulatory and trading institutions. While AI adoption in finance has expanded rapidly, most studies emphasize predictive accuracy and trading performance, leaving the institutional mechanisms through which GenAI influences markets less explored. We conceptualize GenAI diffusion as an institutional shock that reshapes information production, monitoring capacity, and enforcement quality, thereby affecting market efficiency through both regulatory and trading channels.
Using a cross-market panel dataset and a novel proxy for GenAI adoption, we analyze its relationship with institutional efficiency and market outcomes. Our empirical approach employs fixed effects regressions, interaction models, instrumental variable estimation, and difference in differences designs to address endogeneity concerns. The results indicate that GenAI adoption significantly improves institutional efficiency, particularly in markets with strong governance and regulatory capacity. Institutional quality acts as a key moderating factor, amplifying efficiency gains while limiting the benefits in weaker environments. We also find asymmetric effects: in low governance markets, GenAI may intensify informational imbalances. Gains in institutional efficiency further transmit GenAI's impact to trading dynamics by increasing liquidity and stabilizing volatility. Overall, the results underscore the importance of institutional context in shaping the economic consequences of generative AI.

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Generative artificial intelligence
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Institutional quality
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1. Introduction

Technological innovation has long reshaped financial markets by transforming information processing, institutional structures, and regulatory oversight. Digital trading platforms, algorithmic trading, and financial technologies have significantly affected market efficiency and governance (Biais, Foucault, & Moinas, 2015; Goldfarb & Tucker, 2019). The rapid emergence of generative artificial intelligence (GenAI)—including large language models and adaptive decision-support systems—represents a new technological paradigm with important implications for financial institutions and market functioning (Brynjolfsson, Li, & Raymond, 2025; Korinek & Joseph, 2018).

Unlike traditional algorithmic systems based on predefined rules or narrow optimization, GenAI can process unstructured information, generate context-aware outputs, and support complex real-time decision-making (Bommasani et al., 2021). These capabilities are particularly relevant for institutional actors in financial markets. Regulators increasingly employ GenAI-enabled RegTech and SupTech tools for supervision, compliance monitoring, and risk detection, while financial intermediaries use GenAI for trading, market analysis, and information aggregation (Bank for International Settlements, 2023; Zetzsche, Buckley, Arner, & Barberis, 2020).

The diffusion of GenAI raises important questions about institutional efficiency. From an institutional economics perspective, efficiency reflects the ability of formal institutions to reduce transaction costs, enforce rules, and coordinate economic activity under uncertainty (Acemoglu, Naidu, Restrepo, & Robinson, 2019; North, 1990). Financial economics similarly links institutional quality to liquidity, volatility, and information efficiency (Beck, Demirgüç-Kunt, & Levine, 2022; La Porta, Lopez-de-Silanes, Shleifer, & Vishny, 1998). Yet whether GenAI strengthens or weakens institutional efficiency remains theoretically ambiguous and empirically underexplored.

Most studies on AI in finance focus on forecasting accuracy, trading performance, or portfolio optimization (Chen, Pelger, & Zhu, 2024; Gu, Kelly, & Xiu, 2020). Research on regulatory technology also tends to treat AI primarily as an efficiency-enhancing tool (Anagnostopoulos, 2018; Crisanto, Prenio, & Zamil, 2021). Consequently, limited attention has been given to how generative AI interacts with institutional structures and how its effects vary across markets with different levels of governance and regulatory capacity.

This issue is particularly important because GenAI may generate asymmetric institutional effects. In strong institutional environments, it can reduce information-processing costs, improve regulatory responsiveness, and enhance liquidity (Brynjolfsson et al., 2025). In weaker settings, however, its opacity and high fixed costs may intensify information concentration or unequal access to advanced technologies (Farboodi, Mihet, Philippon, & Veldkamp, 2024; Korinek & Joseph, 2018). Empirical evidence on these mechanisms remains limited.

This study provides a comprehensive empirical analysis of GenAI and institutional efficiency in financial markets, explicitly considering both regulatory dynamics and trading behavior. Using data on GenAI-related regulatory developments, market microstructure indicators, and cross-country measures of institutional quality, we examine how GenAI shocks influence liquidity, volatility, and information efficiency across institutional environments.

This paper makes four contributions. First, it extends the AI-in-finance literature by focusing on generative AI and its institutional implications. Second, it integrates regulatory and trading institutions within a unified empirical framework (Beck et al., 2022). Third, it provides new evidence on the moderating role of institutional quality in shaping GenAI's market effects. Finally, it offers policy insights for regulators and market designers seeking to govern increasingly AI-driven financial systems while maintaining fairness and stability.

The remainder of the paper is organized as follows. Section 2 reviews the literature. Section 3 develops the hypotheses and conceptual framework. Section 4 describes the data and empirical strategy. Section 5 presents the results, Section 6 reports robustness checks, Section 7 discusses policy implications, and Section 8 concludes.

2. Literature Review

2.1. Technological Innovation and Financial Market Efficiency

Technological innovation has long influenced financial market efficiency by transforming trading systems, information processing, and market microstructure. Early research shows that electronic trading and automation reduced transaction costs, enhanced liquidity, and improved price discovery (Biais et al., 2015; O'hara, 2015). Studies on high-frequency and algorithmic trading further emphasize the roles of speed, data-processing capacity, and strategic order placement in shaping competition and market dynamics (Kyle & Obizhaeva, 2016; Pagnotta & Philippon, 2018).

Recent research incorporates machine learning into asset pricing and trading models, demonstrating gains in forecasting accuracy, nonlinear pattern detection, and portfolio optimization (Chen et al., 2024; Gu et al., 2020). However, this literature largely treats technology as a performance-enhancing input and pays limited attention to its broader institutional effects, particularly regarding regulatory capacity, market governance, and institutional efficiency.

2.2. Artificial Intelligence in Finance: From Machine Learning to Generative Systems

Artificial intelligence in finance has expanded rapidly, initially focusing on prediction, optimization, and risk management, demonstrating the value of data-driven decision-making under uncertainty (Athey, 2018; Athey & Imbens, 2019). Machine learning improves information acquisition and pattern detection, enhancing decisions in dynamic settings (Veldkamp, 2020).

Generative AI marks a qualitative shift: Unlike traditional models that classify or predict, GenAI processes unstructured data and generates context-aware outputs, supporting more advanced analytical and decision tasks (Bommasani et al., 2021).

Evidence suggests GenAI may increase efficiency by reducing information-processing costs and strengthening supervision (Brynjolfsson et al., 2025). Yet its opacity and high fixed costs may also intensify informational asymmetries and unequal access (Farboodi et al., 2024). Empirical evidence on its institutional and market-level effects—particularly on regulatory capacity, governance quality, and microstructure—remains limited.

2.3. Regulation, RegTech, and Institutional Efficiency

A growing literature examines how digital technologies support financial regulation and supervision. Research on regulatory technology (RegTech) and supervisory technology (SupTech) shows that data-driven systems can improve compliance monitoring, detect fraud and market abuse, and strengthen supervisory capacity (Anagnostopoulos, 2018; Arner & Rathmell, 2023). Policy studies and reports also highlight the potential of AI and advanced analytics to enhance real-time risk assessment and regulatory surveillance (Bank for International Settlements, 2023, 2024).

However, most studies treat AI as a marginal efficiency-enhancing tool and rarely distinguish between traditional machine-learning applications and newer generative AI systems. This distinction is important because GenAI can analyze unstructured information and support complex interpretation and decision processes—capabilities central to regulatory institutions.

Moreover, regulatory technologies are often studied separately from trading behavior and market microstructure. Consequently, existing research offers limited insight into how AI adoption may simultaneously reshape regulatory capacity, information intermediation, and trading dynamics. Understanding these interactions is essential for assessing the broader implications of AI for institutional efficiency in financial markets.

2.4. Institutional Quality, Information Asymmetry, and Market Outcomes

Institutional economics highlights the role of formal institutions in shaping market outcomes by reducing transaction costs, enforcing contracts, and structuring economic incentives (Acemoglu et al., 2019; North, 1990). In financial markets, empirical evidence shows that regulatory quality, legal enforcement, and governance significantly influence market development, liquidity, and stability (Beck et al., 2022; La Porta et al., 1998).

Research also emphasizes that the effects of technological change depend on institutional environments. Strong institutions can amplify technological benefits through transparency and effective oversight, while weak governance may allow new technologies to increase information concentration or regulatory capture (Acemoglu et al., 2019; Farboodi, Jarosch, & Menzio, 2021).

However, little research examines how generative AI interacts with institutional quality in financial markets. In particular, empirical evidence remains limited on whether GenAI strengthens or weakens institutional efficiency across different regulatory environments and how these interactions affect liquidity, volatility, and information efficiency.

2.5. Research Gap and Contribution

To clarify the study's positioning, Table 1 summarizes the main research streams and their limitations. The literature on algorithmic and high-frequency trading focuses on speed, liquidity, and volatility but largely overlooks institutional mechanisms. Research on machine learning in finance improves prediction and asset-pricing accuracy yet remains performance-oriented, with limited attention to governance and regulation.

Similarly, the RegTech and SupTech literature highlights AI's potential for compliance and supervision but typically treats AI as homogeneous, overlooking the distinct capabilities of generative models. Institutional economics emphasizes governance, legal quality, and regulatory capacity in shaping market outcomes but generally treats technology as exogenous. Meanwhile, economic research on AI focuses on information structures and inequality, offering limited empirical evidence from financial markets.

By distinguishing generative AI from traditional AI and integrating regulatory and trading institutions within a unified framework, this study addresses these gaps. We examine how GenAI-related shocks affect liquidity, volatility, and information efficiency and how these effects vary across institutional environments, providing new evidence on the interaction between technological innovation and institutional quality in financial markets.

Table 1. Literature gap and contribution matrix.

Literature Stream	Main Focus	Key Limitation	Contribution of This Study
Algorithmic and High-Frequency Trading	Market liquidity, trading speed, and volatility	Focuses mainly on traditional algorithmic systems with limited attention to institutional mechanisms	Extends analysis to generative AI and evaluates its implications for institutional efficiency in financial markets
Machine Learning in Finance	Prediction, asset pricing, and portfolio optimization	Emphasis on predictive performance rather than governance or regulatory implications	Examines how generative AI affects institutional structures and market functioning
RegTech and SupTech	Regulatory technology, compliance monitoring, and supervisory systems	Treats AI as largely homogeneous and focuses mainly on regulatory oversight	Integrates regulatory institutions with trading dynamics in a unified empirical framework
Institutional Economics and Finance	Governance quality, legal institutions, and financial development	Technological innovation often treated as exogenous to institutional structures	Analyzes how generative AI interacts with institutional quality to influence market outcomes
Economics of Artificial Intelligence	Information structures, automation, and digital transformation	Limited empirical evidence from financial markets	Provides empirical evidence on the market-level effects of generative AI on liquidity, volatility, and information efficiency

3. Hypotheses Development

Technological innovation has long shaped financial market efficiency. Recent advances in artificial intelligence—particularly generative AI (GenAI)—introduce new capabilities for information processing, decision support, and regulatory supervision. While prior research mainly examines technological effects on trading efficiency and market microstructure, its broader institutional implications remain less explored. Building on the preceding literature, this study develops hypotheses on how GenAI influences institutional efficiency through regulatory capacity, information asymmetries, and trading dynamics.

3.1. Generative Artificial Intelligence and Institutional Efficiency

Institutional efficiency refers to the effectiveness of rules, supervisory institutions, and enforcement mechanisms in supporting transparent and well-functioning financial markets. Institutional economics emphasizes that efficient institutions reduce transaction costs, strengthen governance, and improve coordination among market participants (Acemoglu et al., 2019; North, 1990). Technological innovation can enhance these mechanisms by improving information processing and monitoring capacity.

Generative AI extends traditional machine learning by enabling the synthesis of unstructured information, automated content generation, and adaptive learning from large datasets. These capabilities can strengthen regulatory oversight through improved monitoring, anomaly detection, and compliance analysis, while also supporting faster information aggregation and better market decision-making. Prior studies suggest that AI-driven information processing can improve monitoring and governance efficiency in financial systems (Brynjolfsson et al., 2025; Farboodi et al., 2021).

Hypothesis 1 (H_1): Generative artificial intelligence adoption is positively associated with institutional efficiency in financial markets.

3.2. Institutional Quality as a Moderating Factor

The effects of technological innovation depend heavily on the institutional environment. High-quality institutions—characterized by strong regulation, transparent governance, and effective enforcement—facilitate the integration of new technologies and limit agency problems and regulatory arbitrage (Acemoglu et al., 2019; Beck et al., 2022).

In contrast, weak institutional settings with limited regulatory capacity may constrain technological benefits and allow advanced actors to exploit informational or regulatory gaps. As a result, institutional context plays a key role in determining whether new technologies improve or undermine institutional performance.

Hypothesis 2 (H_2): The positive effect of generative artificial intelligence on institutional efficiency is stronger in markets with higher institutional quality.

3.3. Generative Artificial Intelligence and Information Asymmetry

Information asymmetry arises when some market participants possess superior information (Akerlof, 2002). Technologies that enhance information processing can reduce such asymmetries by accelerating the incorporation of information into prices.

However, adopting advanced technologies like GenAI may also create new imbalances. Developing and deploying GenAI requires substantial computational resources, proprietary data, and technical expertise, creating barriers that favor large and technologically advanced institutions.

Research shows that AI-driven technologies can generate scale advantages that reinforce market concentration and information disparities (Brynjolfsson et al., 2025; Farboodi et al., 2021). In markets with weaker oversight, these advantages may amplify informational rents and widen gaps between advanced institutions and smaller participants.

Hypothesis 3 (H_3): In markets with weaker institutional quality, generative artificial intelligence adoption increases information asymmetry among financial institutions.

3.4. Generative Artificial Intelligence and Trading Dynamics

Technological innovation has long shaped trading behavior and market microstructure. Improved information processing can enhance liquidity, lower transaction costs, and strengthen price discovery, although rapid automation may also influence short-term volatility (Biais et al., 2015; Kyle & Obizhaeva, 2016).

Generative AI may further transform trading dynamics by integrating diverse information sources—such as news, corporate disclosures, and regulatory updates—and extracting predictive signals from complex datasets. This capability can improve trading strategies by reducing informational noise and supporting more precise execution decisions.

By improving information aggregation and trading efficiency, GenAI may enhance market liquidity and promote more orderly price adjustments, particularly in well-regulated markets.

Hypothesis 4 (H_4): Generative artificial intelligence adoption improves trading dynamics, reflected in higher market liquidity and more stable volatility patterns.

3.5. Regulatory and Trading Institutional Channels

Financial market performance depends on the interaction between regulatory institutions and trading institutions. Regulators establish rules, monitoring, and enforcement, while trading institutions generate price signals and liquidity. Institutional economics suggests that effective governance emerges when these dimensions reinforce each other (North, 1990).

Generative AI may affect both channels simultaneously. On the regulatory side, AI-driven monitoring can strengthen supervision, detect irregularities, and improve compliance. On the trading side, enhanced information processing can improve price discovery and liquidity.

This study therefore examines GenAI's institutional impact through an integrated framework that captures both regulatory and trading channels. As illustrated in Figure 1 the conceptual framework highlights how generative AI reshapes institutional efficiency in financial markets through these complementary mechanisms.

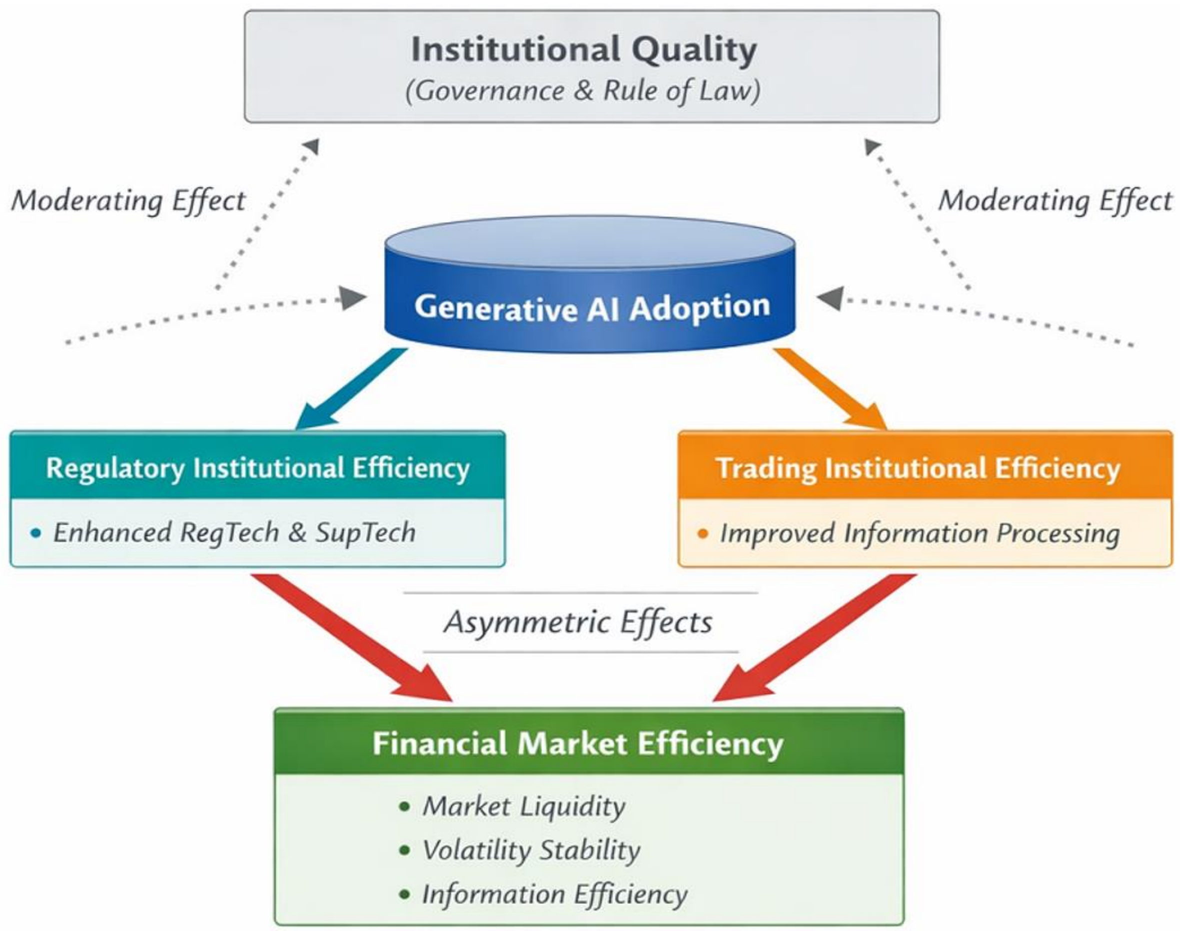

Figure 1. Conceptual framework of generative artificial intelligence and institutional efficiency in financial markets.

3.6. Conceptualization of Institutional Efficiency

In this study, institutional efficiency refers to the ability of financial market institutions to support transparent information processing, enforce regulatory and contractual rules, reduce transaction and information frictions, and facilitate efficient capital allocation. It reflects how governance structures, regulatory frameworks, and oversight mechanisms contribute to stable and well-functioning financial markets.

Institutional economics suggests that efficient institutions reduce uncertainty, strengthen investor confidence, and improve financial intermediation by ensuring credible enforcement and reliable information (North, 1990). In financial markets, outcomes depend heavily on regulatory credibility, governance quality, and the ability to limit opportunistic behavior and information asymmetries.

In the context of generative AI, institutional efficiency also reflects the capacity of financial systems to integrate advanced technologies while maintaining transparency, accountability, and stability. Strong institutions may amplify the benefits of GenAI through effective supervision and information dissemination, whereas weak institutions may constrain these gains or increase risks related to opacity and unequal information access.

Accordingly, this study conceptualizes institutional efficiency as a multidimensional construct shaped by regulatory quality, governance effectiveness, rule enforcement, investor protection, and market transparency, forming the basis for the empirical measurement strategy in Section 4.2

4. Data, Variables, and Empirical Strategy

This study uses a panel dataset covering multiple financial markets during 2010–2024 to examine the relationship between generative artificial intelligence (GenAI) adoption and institutional efficiency. All variables are constructed from internationally recognized financial, institutional, and technological databases to ensure cross-country and temporal comparability. Table 2 summarizes the definitions, measurements, and data sources of the variables.

4.1. Dependent Variable: Institutional Efficiency

The main dependent variable is Institutional Efficiency (InstEff), which reflects the effectiveness of financial market institutions in supporting transparent information processing, enforcing market rules, reducing transaction frictions, and facilitating efficient capital allocation.

Given the multidimensional nature of institutional performance, InstEff is constructed as a composite index based on five institutional dimensions:

- Regulatory Quality.
- Rule of Law.
- Government Effectiveness.
- Investor Protection.
- Market Transparency.

Data are obtained from the World Governance Indicators (WGI), World Bank databases, OECD governance datasets, and international financial development reports. All indicators are standardized using z-score normalization and aggregated using Principal Component Analysis (PCA), with the first principal component used as the summary measure. Higher values indicate stronger governance, greater transparency, and more effective institutional structures.

4.2. Independent Variable: Generative AI Adoption

The key explanatory variable is Generative AI Adoption (GenAI), capturing the diffusion of generative AI technologies within financial markets and institutions. Because no standardized cross-country indicator exists, this study constructs a composite proxy index reflecting the operational deployment of generative AI.

The index includes indicators of:

- AI-related investment activity.
- Fintech innovation intensity.
- AI patent applications.
- AI-related digital infrastructure.
- Adoption of AI-based financial services and analytics.
- Institutional implementation of AI-driven regulatory and monitoring technologies.

Data are obtained from international technology databases, OECD AI indicators, World Bank digital development statistics, financial innovation reports, and institutional technology disclosures. All components are standardized and aggregated using PCA, with the first principal component representing the GenAI adoption measure.

To address potential concerns that the index captures policy attention rather than actual adoption, the proxy relies primarily on implementation-based indicators such as technology deployment, institutional disclosures, and AI investment activity. The measure is also consistent with broader indicators of digital development and fintech penetration. In addition, robustness checks using alternative proxies and placebo tests confirm that the index reflects genuine technological adoption rather than general technological trends.

4.3. Moderating Variable: Institutional Quality

To examine conditional institutional effects, the study includes Institutional Quality (InstQual) as a moderating variable. This variable captures the strength and credibility of governance mechanisms and is constructed using aggregated indicators from the World Governance Indicators dataset, including.

- Regulatory Effectiveness.
- Control of Corruption.
- Political Stability.
- Rule of Law.
- Government Accountability.

Higher values indicate stronger institutional environments with more reliable enforcement and lower governance uncertainty.

4.4. Control Variables

Following prior research in financial economics, several control variables are included to account for macroeconomic and financial market conditions.

- Market Capitalization (MCap): stock market capitalization relative to GDP.
- Market Liquidity (Liquidity): stock market turnover ratio.
- Financial Development (FinDev): financial market depth indicators.
- Economic Growth (GDPGrowth): annual GDP growth rate.
- Inflation (Inflation): annual consumer price inflation.
- Trade Openness (Trade): total trade as a share of GDP.
- Digital Infrastructure (Digital): internet penetration and digital connectivity.

These variables are obtained from the World Bank, IMF, OECD, and global financial development databases.

4.5. Measurement Consistency and Data Treatment

To ensure comparability across countries and years, all continuous variables are winsorized at the 1st and 99th percentiles to limit the influence of extreme observations. Variables measured in different units are standardized where appropriate. Missing observations are addressed through interpolation where possible, while markets with persistent data gaps are excluded from the final sample.

Finally, variance inflation factor (VIF) diagnostics are conducted to test for multicollinearity among explanatory variables, with results indicating that multicollinearity is not a significant concern.

Table 2. Variable definitions and measurements.

Variable	Definition	Measurement Method	Data Source
Institutional Efficiency (InstEff)	Composite measure of institutional effectiveness in financial markets	PCA index based on regulatory quality, rule of law, government effectiveness, investor protection, and market transparency indicators	WGI, World Bank, OECD
Generative AI Adoption (GenAI)	Degree of GenAI diffusion in financial markets	Composite standardized index based on AI investment, AI patents, fintech innovation, and AI-related infrastructure	OECD AI Database, World Bank, Global Innovation Reports
Institutional Quality (InstQual)	Overall governance and institutional strength	Aggregated governance indicators	WGI, IMF
Market Capitalization (MCap)	Size of financial market relative to economy	Stock market capitalization as % of GDP	World Bank
Market Liquidity (Liquidity)	Trading activity and market depth	Stock turnover ratio	World Bank Global Financial Development Database
Financial Development (FinDev)	Development level of financial system	Financial market depth indicators	IMF Financial Development Index
GDP Growth (GDPGrowth)	Economic growth performance	Annual GDP growth rate (%)	World Bank
Inflation (Inflation)	Macroeconomic price instability	Annual CPI inflation (%)	IMF
Trade Openness (Trade)	Degree of economic openness	Total trade as % of GDP	World Bank
Digital Infrastructure (Digital)	Technological connectivity and digital readiness	Internet penetration and digital access indicators	ITU, World Bank

4.6. Empirical Strategy

This section outlines the empirical framework used to evaluate the hypotheses developed in Section 3. The specifications rely on a panel-data structure with multi-dimensional fixed effects to account for unobserved heterogeneity across markets and time. All variables are defined in Section 4.2, and the models are directly aligned with the institutional channels formalized in Figure 1.

4.6.1. Baseline Model: Generative AI and Institutional Efficiency

Hypothesis 1 (H1) posits that generative AI adoption enhances institutional efficiency. The baseline panel specification is:

$$\text{InstEff}_{i,t} = \alpha_0 + \beta_1 \text{GenAI}_{i,t} + \gamma' \text{X}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

Where:

- $\text{InstEff}_{i,t}$ denotes institutional efficiency in market or country i at time t.
- $\text{GenAI}_{i,t}$ is the key explanatory variable capturing generative artificial intelligence adoption.
- $\text{X}_{i,t}$ is a vector of control variables.
- μ_i represents market fixed effects, controlling for time-invariant heterogeneity.
- λ_t denotes time fixed effects, capturing global shocks common to all markets.
- $\varepsilon_{i,t}$ is the idiosyncratic error term.

A positive and significant β_1 is interpreted as evidence supporting H1 and validating the first institutional channel in Figure 1.

4.6.2. Moderation Model: Institutional Quality as a Conditioning Mechanism

Hypothesis 2 (H2) argues that institutional quality conditions the effectiveness of generative AI. To capture this mechanism, the baseline model is augmented with an interaction between AI adoption and institutional quality.

$$\text{InstEff}_{i,t} = \alpha_0 + \beta_1 \text{GenAI}_{i,t} + \beta_2 \text{InstQual}_{i,t} + \beta_3 (\text{GenAI}_{i,t} \times \text{InstQual}_{i,t}) + \gamma' \text{X}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

where:

- $\text{InstQual}_{i,t}$ measures institutional quality, including regulatory capacity, governance effectiveness, and rule of law;
- $\text{GenAI}_{i,t} \times \text{InstQual}_{i,t}$ captures the moderating effect of institutional quality.

A positive and significant coefficient β_3 indicates that stronger institutional environments amplify the effect of generative AI on institutional efficiency.

4.6.3. Institutional Asymmetry and Heterogeneous Effects

Hypothesis 3 (H3) predicts asymmetric institutional responses, with weaker governance environments exhibiting attenuated or distorted effects of AI adoption. To empirically validate this mechanism, two complementary strategies are implemented.

First, Equation 2 is re-estimated across high- and low-institutional-quality subsamples, providing a clean test of cross-regime heterogeneity.

Second, quantile regressions are estimated to explore distributional variation.

$$Q_\tau(\text{InstEff}_{i,t}) = \alpha_\tau + \beta_\tau \text{GenAI}_{i,t} + \gamma_\tau' \text{X}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

where $Q_\tau(\cdot)$ denotes the conditional quantile at percentile τ. Evidence of weaker or heterogeneous effects of $\text{GenAI}_{i,t}$ at lower quantiles supports Hypothesis 3.

4.6.4. Trading Dynamics and Market Outcomes

Hypothesis 4 (H4) states that generative AI influences financial market performance both directly and indirectly through institutional channels. To capture this dual mechanism, the following specification is estimated.

$$\text{MarketEff}_{i,t} = \alpha_0 + \delta_1 \text{GenAI}_{i,t} + \delta_2 \text{InstEff}_{i,t} + \gamma' \text{X}_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

Where:

- $\text{MarketEff}_{i,t}$ denotes financial market efficiency, proxied by liquidity, volatility stability, or information efficiency measures.
- δ_1 captures the direct effect of generative AI adoption.
- δ_2 captures the institutional transmission mechanism.

A significant $\delta 2$ validates the pathway through which institutional efficiency mediates the effect of generative AI on market microstructure outcomes.

To empirically distinguish the regulatory institutional channel from the market trading channel, the analysis separates institutional outcomes from market-performance outcomes in sequential model specifications. First, GenAI adoption is estimated as a determinant of institutional efficiency. Second, institutional efficiency is incorporated into market-outcome regressions to evaluate whether institutional improvements mediate the effect of GenAI adoption on trading dynamics.

This approach allows the study to distinguish.

- The direct institutional effect of GenAI on governance and regulatory efficiency.
- The indirect transmission effect operating through improved market functioning, including liquidity, transparency, and information efficiency.

If the coefficient on institutional efficiency remains significant in market-outcome regressions while the direct GenAI effect declines in magnitude, this provides evidence consistent with a distinct institutional transmission mechanism rather than a purely contemporaneous association.

4.6.5. Synthesis and Alignment with Conceptual Framework

Equations 1–4 jointly operationalize the conceptual framework presented in Figure 1. Equation 1 tests the baseline institutional effect of generative AI, Equation 2 captures institutional moderation, Equation 3 examines asymmetric institutional outcomes, and Equation 4 links institutional efficiency to trading dynamics and market performance.

4.7. Identification and Robustness

Establishing a causal relationship between generative AI adoption and institutional efficiency presents several empirical challenges, including potential reverse causality, omitted variable bias, and simultaneity between technological adoption and institutional development. To address these concerns, the study employs a multi-layered identification strategy combining panel fixed-effects estimation, instrumental variable (IV) techniques, and a Difference-in-Differences (DiD) design. Together, these approaches help isolate exogenous variation in GenAI adoption and strengthen the causal interpretation of the empirical results.

4.7.1. Baseline Identification

The primary empirical framework relies on panel data models with two-way fixed effects. Market fixed effects (μ_i) control for time-invariant structural characteristics across financial markets, such as legal traditions, regulatory architecture, and historical institutional structures. Time fixed effects (λ_t) capture global shocks affecting all markets simultaneously, including global financial cycles, macroeconomic crises, and technological waves.

In addition, the model includes a comprehensive set of macroeconomic and financial controls to account for observable determinants of institutional efficiency. These include market capitalization, financial development, macroeconomic growth conditions, inflation, trade openness, and digital infrastructure development.

To further mitigate potential endogeneity concerns, explanatory variables are lagged in alternative specifications, reducing the likelihood that contemporaneous institutional changes drive measured GenAI adoption. Standard errors are clustered at the market level to account for serial correlation and heteroskedasticity within markets over time.

While fixed-effects models significantly reduce omitted variable bias, they cannot fully eliminate concerns regarding reverse causality between institutional efficiency and technological adoption. Therefore, the study complements the baseline analysis with instrumental variable and quasi-experimental approaches.

4.7.2. Instrumental Variable (IV) Strategy

To address potential endogeneity arising from reverse causality or omitted institutional determinants of GenAI adoption, the analysis employs an instrumental variable approach. The IV strategy exploits exogenous variation in global technological diffusion that influences domestic GenAI adoption but is plausibly unrelated to contemporaneous changes in institutional efficiency.

The instrument is constructed as the interaction between global GenAI diffusion and pre-existing domestic technological infrastructure. Specifically, global diffusion is proxied by the lagged international growth in GenAI-related technologies, while domestic technological infrastructure is measured using pre-period indicators of digital connectivity and technological readiness. The interaction term captures the idea that countries with stronger technological infrastructure are more likely to adopt globally emerging GenAI technologies as they diffuse internationally.

Formally, the first-stage relationship can be expressed as:

$$GenAI_{i,t} = \pi_0 + \pi_1(GlobalGenAI_{t-1} \times TechInfra_{i,t-1}) + \gamma' X_{i,t} + \mu_i + \lambda_t + \nu_{i,t} \tag{5}$$

The identification relies on three key assumptions:

- Relevance: Global technological diffusion interacted with domestic infrastructure must be strongly correlated with domestic GenAI adoption. Empirical first-stage results confirm this condition, with the Kleibergen–Paap F-statistic exceeding conventional thresholds.
- Exclusion Restriction: The instrument affects institutional efficiency only through its impact on GenAI adoption, rather than through independent institutional or macroeconomic channels.
- Exogeneity: Conditional on fixed effects and control variables, global diffusion shocks and pre-existing technological infrastructure are plausibly unrelated to contemporaneous shocks to domestic institutional efficiency.

The IV results, reported in Table 8 confirm a positive and statistically significant effect of GenAI adoption on institutional efficiency, consistent with the baseline estimates.

4.7.3. Difference-in-Differences (DiD) Design

To further strengthen causal identification, the study implements a Difference-in-Differences framework that exploits cross-market variation in the timing of GenAI adoption. Financial markets are classified as early adopters or later adopters based on the timing at which significant GenAI diffusion occurs within their financial systems.

The DiD specification compares institutional efficiency outcomes before and after GenAI adoption in early-adopting markets relative to markets that adopt later. The model can be expressed as:

$$InstEff_{i,t} = \alpha_0 + \beta_1(Treated_i \times Post_t) + \gamma' X_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{6}$$

Where $Treated_i$ identifies markets with early GenAI adoption and $Post_t$ indicates the post-adoption period. The coefficient β_1 captures the average treatment effect of GenAI adoption on institutional efficiency.

The validity of the DiD framework depends on two central assumptions. First, the parallel trends assumption requires that treated and control markets exhibit similar trends in institutional efficiency prior to GenAI adoption. Pre-treatment trend analysis confirms that institutional efficiency trajectories are statistically indistinguishable between groups before adoption occurs. Second, the no anticipation assumption requires that markets do not adjust institutional structures in anticipation of future GenAI adoption.

The DiD results, presented in Table 9 indicate a statistically significant increase in institutional efficiency following GenAI adoption among treated markets, providing additional support for the causal interpretation of the findings.

4.7.4. Robustness Procedures

Multiple robustness checks ensure that results are not driven by specification, measurement, or sample choices.

First, alternative measures of GenAI adoption and institutional efficiency are used. Second, different estimation methods—including random effects, pooled OLS, and models with country-specific trends—are applied. Third, placebo tests with fictitious adoption dates are conducted. Fourth, subsample analyses across institutional quality regimes are performed. Finally, extreme observations are excluded and alternative clustering of standard errors is tested.

Across all specifications, the main finding—that GenAI adoption is positively associated with institutional efficiency—remains stable and statistically significant.

4.8. Summary

This section outlined the data sources, variable construction, and empirical methodology used to analyze the institutional and market effects of generative AI adoption. By combining measures of AI adoption, institutional efficiency, and market outcomes in a panel framework, the empirical design tests the mechanisms proposed in Section 3.

The strategy evaluates the direct institutional impact of GenAI, the moderating role of institutional quality, asymmetric institutional responses, and the transmission of institutional improvements to financial market performance through regulatory and trading channels.

5. Empirical Results

5.1. Descriptive Statistics

Table 3 presents descriptive statistics for the main variables. The results show considerable cross-sectional and temporal variation in generative AI adoption, institutional efficiency, and market outcomes, enabling identification within the panel framework. Variation in institutional quality also indicates substantial heterogeneity across markets, supporting tests of the moderating and asymmetric effects proposed in Section 3.

Table 3. Descriptive statistics.

Variable	Mean	Std. Dev.	Min.	Max.
Generative AI Adoption	0.41	0.29	0.00	1.00
Institutional Efficiency	0.55	0.17	0.22	0.88
Institutional Quality	0.60	0.19	0.18	0.93
Market Liquidity	0.73	0.21	0.20	1.08
Volatility Stability	0.67	0.16	0.31	0.94

Note: All variables are standardized or rescaled indices. Definitions are provided in Section 4.

5.2. Generative Artificial Intelligence and Institutional Efficiency (H1)

Table 4 presents baseline panel regression results examining the relationship between generative AI (GenAI) adoption and institutional efficiency. The model includes market and time fixed effects and the full set of control variables defined in Section 4.

The coefficient on GenAI adoption is positive and significant at the 1% level. The estimate (0.118, $p < 0.01$) suggests that a one-standard-deviation increase in GenAI adoption is associated with an improvement of about 11.8% of a standard deviation in institutional efficiency, indicating that AI integration enhances institutional functioning through improved information processing, compliance automation, and regulatory oversight.

Among the controls, GDP per capita and financial development also show positive and significant effects. The within-market R^2 of 0.43 indicates strong explanatory power.

Overall, the results provide clear support for Hypothesis 1, showing that GenAI adoption is positively associated with institutional efficiency in financial markets.

Table 4. Generative AI adoption and institutional efficiency.

Variables	(1)
Generative AI Adoption	**0.118***** (0.031)
GDP per capita	0.042** (0.019)
Financial Development	0.067* (0.021)
Control Variables	Yes
Market Fixed Effects	Yes
Time Fixed Effects	Yes
Observations	2,462
R^2 (Within)	0.43

Note: Robust standard errors clustered at the market level are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.3. Moderating Role of Institutional Quality (H2)

Table 5 reports the moderation analysis testing whether institutional quality conditions the relationship between generative AI adoption and institutional efficiency. The model extends the baseline specification by including an interaction between GenAI adoption and institutional quality, while maintaining fixed effects and all control variables.

GenAI adoption remains positive and significant, confirming the baseline effect. Institutional quality is also positive and significant, indicating that stronger governance is associated with higher institutional efficiency.

Importantly, the interaction term is positive and significant, showing that the institutional benefits of GenAI are stronger in markets with higher institutional quality. Marginal effects indicate that GenAI produces substantially larger institutional efficiency gains in well-governed markets.

Overall, the results support Hypothesis 2, suggesting a complementary relationship between technological innovation and institutional capacity.

Table 5. Moderating effect of institutional quality.

Variables	(1)
Generative AI Adoption	0.076** (0.034)
Institutional Quality	0.209*** (0.039)
GenAI × Institutional Quality	**0.091***** (0.027)
Control Variables	Yes
Fixed Effects	Yes
Observations	2,462
R^2 (Within)	0.48

Note: Robust standard errors clustered at the market level are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.4. Institutional Asymmetry in the Effects of Generative AI (H3)

Table 6 reports subsample regressions for markets with low and high institutional quality.

Results show clear heterogeneity. In low-quality institutional environments, the GenAI coefficient is positive but small and statistically insignificant, suggesting that weak governance limits the institutional benefits of AI adoption. In contrast, in high-quality institutional environments, the coefficient is positive, economically larger, and significant at the 1% level, indicating that stronger institutions enable more effective use of GenAI.

These findings support Hypothesis 3 and show that the institutional effects of generative AI are asymmetric across governance environments.

Table 6. Heterogeneous effects by institutional quality.

Variables	Low Institutional Quality	High Institutional Quality
Generative AI Adoption	0.028 (0.039)	**0.164***** (0.036)
Control Variables	Yes	Yes
Fixed Effects	Yes	Yes
Observations	1,231	1,231
R^2 (Within)	0.31	0.46

Note: Robust standard errors clustered at the market level are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.5. Trading Dynamics and Market Outcomes (H4)

Table 7 examines whether GenAI adoption and institutional efficiency affect trading dynamics, measured by market liquidity and volatility stability.

Institutional efficiency is positively and significantly associated with both liquidity and volatility stability, indicating that stronger institutions support more efficient trading environments.

In contrast, the direct effect of GenAI adoption is modest: it is positive and significant for liquidity but insignificant for volatility stability. This suggests that GenAI primarily influences market outcomes indirectly through improvements in institutional efficiency, rather than through immediate trading effects.

Overall, the results support Hypothesis 4, consistent with the institutional transmission mechanisms proposed in Figure 1.

Table 7. Generative AI, institutional efficiency, and market outcomes.

Variables	Liquidity	Volatility Stability
Generative AI Adoption	0.047** (0.023)	0.014 (0.016)
Institutional Efficiency	**0.179***** (0.041)	**0.116***** (0.034)
Control Variables	Yes	Yes
Fixed Effects	Yes	Yes
Observations	2,462	2,462
R^2 (Within)	0.39	0.35

Note: Robust standard errors clustered at the market level are reported in parentheses.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

5.6. Summary of Empirical Findings

The empirical results support the hypotheses developed in Section 3. Generative AI adoption is positively associated with higher institutional efficiency across financial markets. However, this effect varies across governance environments: the impact is significantly stronger in markets with high institutional quality and stronger regulatory capacity.

The analysis also reveals institutional asymmetry. In weak institutional environments, the efficiency gains from GenAI adoption are small and statistically insignificant, indicating that technological innovation alone cannot produce institutional improvements without supportive governance structures.

Furthermore, institutional efficiency acts as a key transmission channel linking GenAI adoption to market outcomes. Higher institutional efficiency is associated with greater market liquidity and more stable volatility, suggesting that the benefits of GenAI materialize mainly through institutional and regulatory improvements rather than direct trading effects.

Overall, the findings support the central argument that the economic value of generative AI in financial markets depends critically on the strength of institutional structures.

5.6.1. Iran: Emerging AI Adoption under Institutional Constraints

Recent developments in Iran's financial sector illustrate the asymmetric institutional effects identified in the analysis. Iranian financial institutions and fintech firms have increasingly adopted AI applications in areas such as digital banking, trading analytics, fraud detection, and customer-service automation, while the Tehran Stock Exchange and financial platforms have expanded investments in data-driven technologies.

Despite these advances, institutional and regulatory constraints—including fragmented oversight, limited transparency, inconsistent supervision, and restricted access to global technological infrastructure—limit the broader efficiency gains from AI adoption.

This pattern aligns with the empirical results showing that GenAI generates weaker institutional benefits in low-quality governance environments, indicating that technological adoption alone is insufficient without strong regulatory capacity and coordinated institutional frameworks.

6. Robustness Checks and Endogeneity

To address model dependence and endogeneity concerns, additional analyses test whether the relationship between GenAI adoption and institutional efficiency remains robust under alternative measurements and specifications.

6.1. Alternative Measures of Key Variables

The baseline results are re-estimated using alternative proxies for GenAI adoption, including AI-related fintech disclosures, regulatory AI implementation indicators, and lagged adoption measures.

Institutional efficiency is also redefined using individual governance indicators (e.g., regulatory quality, rule of law, investor protection) and an alternative composite index based on standardized averages rather than PCA.

Across all specifications, the GenAI coefficient remains positive and statistically significant, indicating that results are not sensitive to variable construction.

6.2. Alternative Econometric Specifications

Robustness is further assessed using random-effects and pooled OLS models, along with additional macro-financial controls (e.g., financial openness, technological readiness, digital infrastructure). Country-specific time trends are included to capture gradual structural changes, and standard errors are clustered at the country level.

The estimated effect of GenAI adoption remains economically meaningful and statistically significant across specifications, confirming the stability of the main findings.

6.3. Instrumental Variable Analysis

Endogeneity concerns may arise because more advanced institutional environments could adopt GenAI faster. To address this, the study employs an instrumental variable (IV) approach using the interaction between global AI diffusion and countries' pre-existing technological infrastructure as the instrument.

The identifying assumption is that global AI diffusion influences domestic institutional efficiency mainly through GenAI adoption, not through direct institutional channels.

Table 8 shows that the first-stage results strongly predict GenAI adoption, with the Kleibergen–Paap F-statistic exceeding weak-instrument thresholds. The second-stage estimates remain positive and statistically significant, with magnitudes similar to the baseline results, supporting the causal interpretation of the GenAI–institutional efficiency relationship.

Table 8. Instrumental variable estimates.

Variables	Second Stage
Generative AI Adoption	**0.109***** (0.038)
Control Variables	Yes
Fixed Effects	Yes
Observations	2,462
Kleibergen–Paap F-statistic	18.7

Note: Robust standard errors clustered at the market level.
*** $p < 0.01$.

6.4. Difference-in-Differences Analysis

A difference-in-differences (DiD) approach exploits variation in the timing of GenAI adoption across financial markets. Early adopters form the treatment group, while later adopters serve as the control group.

Pre-treatment tests show no significant differences in institutional efficiency trends, supporting the parallel-trends assumption.

Table 9 indicates that early-adopting markets experience significantly larger post-adoption improvements in institutional efficiency, with treatment effects consistent in magnitude and significance with the baseline and IV results.

Table 9. Difference-in-differences estimates.

Variables	Institutional Efficiency
GenAI Adoption × Post	**0.095***** (0.029)
Fixed Effects	Yes
Observations	2,462

Note: Robust standard errors clustered at the market level are reported in parentheses.
*** $p < 0.01$.

6.5. Placebo and Falsification Tests

Additional placebo and falsification tests are conducted to validate the empirical design. Placebo adoption dates are randomly assigned across countries and the regressions are re-estimated. The resulting coefficients are statistically insignificant, indicating that the baseline findings are unlikely to reflect spurious correlations or common time trends.

Falsification tests using variables theoretically unrelated to GenAI adoption also produce insignificant results, further supporting the credibility of the identification strategy.

6.6. Summary of Robustness Results

Overall, robustness analyses confirm that the positive relationship between GenAI adoption and institutional efficiency is stable across alternative measurements, estimation methods, and identification strategies. Consistent results from fixed-effects models, IV estimation, DiD analysis, and placebo tests strengthen the credibility of the findings and support the interpretation that GenAI adoption contributes to institutional improvements in financial markets.

7. Discussion and Policy Implications

7.1. Discussion of Main Findings

This study shows that GenAI adoption enhances institutional efficiency in financial markets, extending prior fintech research beyond trading and prediction to broader governance transformation.

A key insight is the moderating role of institutional quality: markets with stronger governance and regulatory capacity experience substantially larger efficiency gains. In weaker institutional environments, GenAI effects are limited or insignificant, highlighting institutional asymmetry.

Institutional efficiency also serves as the main transmission channel linking GenAI to improved liquidity and volatility stability. Thus, GenAI influences markets primarily through regulatory and institutional improvements rather than direct trading effects.

7.2. Implications for Financial Regulators

GenAI can strengthen monitoring, compliance, and market surveillance, but benefits depend on regulatory capacity. Policymakers in weaker environments should pair AI adoption with governance reforms.

Inclusive AI governance frameworks are essential to prevent informational concentration and unequal technological access. RegTech and SupTech initiatives should be integrated into broader institutional modernization strategies.

Overall, sustainable efficiency gains require joint technological and institutional development.

7.3. Implications for Financial Markets and Institutions

GenAI yields stronger benefits in well-governed markets. Effective integration requires not only technological investment but also robust governance, data management, model validation, cybersecurity, and internal controls.

Institutional readiness determines whether GenAI enhances efficiency or amplifies existing weaknesses. Firms combining AI adoption with strong governance are more likely to achieve sustainable advantages.

7.4. Broader Policy Implications

The results suggest that AI governance and institutional reform are complementary. Regulatory frameworks must balance innovation with stability, transparency, and fairness.

Cross-border AI diffusion increases the need for international coordination to reduce regulatory arbitrage and institutional asymmetries. Long-term AI effects will depend on institutions' ability to adapt governance structures to intelligent financial systems.

7.5. Limitations and Future Research

Several limitations apply.

1. Measurement constraints: The GenAI index, while comprehensive, may not capture qualitative differences in implementation intensity.
2. Aggregate focus: Market-level analysis may mask firm-level heterogeneity.
3. Endogeneity concerns: Despite FE, IV, and DiD approaches, causal interpretation should remain cautious.
4. Long-term effects: Future research should examine implications for financial stability, systemic risk, and market resilience.

Micro-level studies, natural experiments, and regulatory shocks could further strengthen identification.

7.6. Concluding Remarks

GenAI has transformative potential in financial markets, but its benefits depend critically on institutional quality and governance effectiveness.

The findings show that technological innovation alone does not guarantee efficiency gains; instead, GenAI delivers value when embedded within strong regulatory frameworks and adaptive institutions.

Ultimately, the future impact of GenAI in global finance will depend not only on technological progress, but on the capacity of institutions to govern these technologies responsibly and effectively.

8. Conclusion

This paper examines how generative artificial intelligence (GenAI) affects institutional efficiency in financial markets by focusing on the roles of regulatory quality, governance capacity, and market institutions. Using a cross-market panel dataset and a composite proxy for GenAI adoption, the study shows that the impact of GenAI operates mainly through institutional channels rather than direct trading effects.

The results indicate that GenAI adoption improves institutional efficiency, particularly in markets with strong governance, regulatory effectiveness, and institutional transparency. Institutional quality acts as a key moderating factor, amplifying the benefits of GenAI in well-governed environments while limiting or distorting them in weaker institutional settings. Evidence of asymmetric institutional outcomes further suggests that inadequate governance may allow AI adoption to intensify informational imbalances and market frictions.

These findings contribute to research on financial technology, institutional economics, and market efficiency by demonstrating that the value of AI adoption depends critically on the institutional environment in which it is implemented. The results therefore challenge purely technology-centered perspectives and highlight the joint role of technological innovation and institutional development in financial transformation.

The study also has several limitations. Measurement of GenAI adoption remains constrained by data availability and disclosure differences. In addition, the analysis focuses on aggregate market indicators and cannot fully capture firm-level heterogeneity in technological capability and governance practices. Although multiple robustness checks and identification strategies are employed, unobserved institutional dynamics may still influence the estimated relationships.

Future research could use firm- or transaction-level data to examine microeconomic mechanisms through which GenAI affects governance, liquidity, and information processing. Further work may also explore the long-term implications of GenAI diffusion for financial stability, systemic risk, and market resilience, as well as cross-country differences in regulatory regimes.

Overall, the findings suggest that the effects of generative AI in finance depend fundamentally on institutional quality and regulatory capacity. Strengthening governance frameworks and institutional adaptability is therefore essential to ensure that GenAI contributes to more efficient, transparent, and stable financial systems.

References

Acemoglu, D., Naidu, S., Restrepo, P., & Robinson, J. A. (2019). Democracy does cause growth. Journal of Political Economy, *127*(1), 47-100.

Akerlof, G. A. (2002). Behavioral macroeconomics and macroeconomic behavior. American Economic Review, *92*(3), 411-433.

Anagnostopoulos, I. (2018). Fintech and regtech: Impact on regulators and banks. Journal of Economics and Business, *100*, 7-25.

Arner, E. N., & Rathmell, J. C. (2023). Metabolic programming and immune suppression in the tumor microenvironment. Cancer Cell, *41*(3), 421-433.

Athey, S. (2018). The impact of machine learning on economics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda. In (pp. 507–547). Chicago, IL, USA: University of Chicago Press.

Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. Annual Review of Economics, *11*(1), 685-725. https://doi.org/10.1146/annurev-economics-080217-053433

Bank for International Settlements. (2023). *Artificial intelligence and machine learning in financial supervision*. Basel, Switzerland: Bank for International Settlements.

Bank for International Settlements. (2024). *Artificial intelligence in the financial sector: Supervisory perspectives and policy implications*. Basel, Switzerland: Bank for International Settlements.

Beck, T., Demirgüç-Kunt, A., & Levine, R. (2022). Financial institutions, financial markets, and economic development. Journal of Economic Perspectives, *36*(4), 3–26.

Biais, B., Foucault, T., & Moinas, S. (2015). Equilibrium high-frequency trading. Review of Economic Studies, *82*(3), 1009-1041.

Bommasani, R., Hudson, D. A., Adeli, E., Altman, R., Arora, S., von Arx, S., . . . Brunskill, E. (2021). On the opportunities and risks of foundation models. arXiv preprint arXiv:2108.07258. https://doi.org/10.48550/arXiv.2108.07258

Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. The Quarterly Journal of Economics, *140*(2), 889-942.

Chen, L., Pelger, M., & Zhu, J. (2024). Deep learning in asset pricing. Management Science, *70*(2), 714-750. https://doi.org/10.1287/mnsc.2023.4695

Crisanto, J. A., Prenio, J. M., & Zamil, R. (2021). *Financial crime risk management: Supervisory perspectives and approaches*. Basel, Switzerland: Bank for International Settlements.

Farboodi, M., Jarosch, G., & Menzio, G. (2021). Intermediation as rent extraction. Journal of Political Economy, *129*(6), 1663–1720.

Farboodi, M., Mihet, R., Philippon, T., & Veldkamp, L. (2024). Big data and firm dynamics. American Economic Review, *114*(1), 54–93.

Goldfarb, A., & Tucker, C. (2019). Digital economics. Journal of Economic Literature, *57*(1), 3-43. https://doi.org/10.1257/jel.20171452

Gu, S., Kelly, B., & Xiu, D. (2020). Empirical asset pricing via machine learning. The Review of Financial Studies, *33*(5), 2223-2273. https://doi.org/10.1093/rfs/hhaa009

Korinek, A., & Joseph, E. S. (2018). Artificial intelligence and its implications for income distribution and unemployment. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda. In (pp. 349–390). Chicago, IL: University of Chicago Press.

Kyle, A. S., & Obizhaeva, A. A. (2016). Market microstructure invariance: Empirical hypotheses. Econometrica, *84*(4), 1345-1404. https://doi.org/10.3982/ECTA10486

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1998). Law and finance. Journal of Political Economy, *106*(6), 1113-1155. https://doi.org/10.1086/250042

North, D. C. (1990). *Institutions, institutional change and economic performance*. Cambridge, UK: Cambridge University Press.

O'hara, M. (2015). High frequency market microstructure. Journal of Financial Economics, *116*(2), 257-270. https://doi.org/10.1016/j.jfineco.2015.01.003

Pagnotta, E., & Philippon, T. (2018). Competing on speed. Econometrica, *86*(4), 1067–1115.

Veldkamp, L. (2020). Information choice in macroeconomics and finance. Annual Review of Economics, *12*, 55–87.

Zetzsche, D. A., Buckley, R. P., Arner, D. W., & Barberis, J. N. (2020). From FinTech to TechFin: The regulatory challenges of data-driven finance. NYU Journal of Law & Business, *16*(2), 393–446.