SBE
DOI 10.2478/sbe-2026-0011
Studies in Business and Economics: no. 21(1) 2026

THE IMPACT OF FINTECH INNOVATION ON MARKET PERFORMANCE: A COMPARATIVE ANALYSIS OF POST-PANDEMIC US FINTECH STOCKS

Nono HERYANA
Universitas Pendidikan Indonesia, Indonesia

Nugraha NUGRAHA
Universitas Pendidikan Indonesia, Indonesia

Disman DISMAN
Universitas Pendidikan Indonesia, Indonesia

Mayasari MAYASARI
Universitas Pendidikan Indonesia, Indonesia

Rini MAYASARI
Universitas Singaperbangsa Karawang, Indonesia

Solehudin SOLEHUDIN
Universitas Buana Perjuangan Karawang, Indonesia

Abstract:

This study examines whether fintech innovation is associated with superior market performance in the United States equity market during the July 2021 to December 2024 sample. Using daily data for eight publicly listed fintech firms representing heterogeneous models (digital lending, payments, crypto exchange exposure, trading platforms, and fintech-adjacent software) and a broad market benchmark, the analysis evaluates performance through risk-adjusted indicators, downside risk measures, and Capital Asset Pricing Model (CAPM) regressions. The results show substantial cross-sectional dispersion. A small subset of firms delivers positive and comparatively strong risk-adjusted outcomes, while several exhibit persistent underperformance and extreme drawdowns, indicating that fintech equities are not a homogeneous asset class in the study period. CAPM estimates yield economically small and statistically insignificant beta coefficients with near-zero explanatory power, implying that systematic market risk accounts for only a negligible share of fintech return variation. Instead, performance differences are consistent with firm-specific dynamics linked to business model structure and institutional integration. Robustness tests confirm that the main conclusions are stable across alternative specifications and validation settings. Overall, the findings indicate that innovation intensity alone is insufficient to guarantee sustained shareholder value without complementary institutional stability and risk discipline.

Key words: *Fintech innovation; market performance; post pandemic period; risk adjusted returns; CAPM; robustness analysis; United States equity market*

1. Introduction

The rapid global expansion of financial technology has fundamentally reshaped the financial ecosystem since 2020, with the United States emerging as a central hub for digital payments, blockchain applications, and artificial intelligence–driven financial services (S. Qiu, 2024; Tsanis & Stouraitis, 2022). Fintech adoption accelerated sharply during and after the COVID-19 pandemic, transforming traditional financial intermediation and redefining competitive dynamics across capital markets (Rahman et al., 2022; Toumi et al., 2023). This structural transformation reflects fintech's increasing role within modern financial systems.

Post-pandemic financial markets have experienced profound adjustments driven by digital acceleration, liquidity shocks, and heightened macroeconomic uncertainty. While technological adaptation has strengthened operational resilience among financial institutions, it has also intensified investor uncertainty regarding the valuation of innovation-driven firms (Kassamany et al., 2025; Reshma et al., 2024). Fintech firm valuations increasingly reflect expectations about regulatory stability, sustainability integration, and long-term profitability rather than short-term growth narratives (Anguelov & Stoyanova, 2025; Natarajan & Ramkumar, 2024).

Conceptually, fintech innovation is linked to market performance through its potential to improve efficiency, liquidity, and transparency, thereby fostering value creation (Imerman & Fabozzi, 2020; Varga, 2017). Theoretical perspectives suggest that digital financial transformation can enhance shareholder value by reducing transaction costs and information asymmetry (Goyal et al., 2025). However, fintech innovation also introduces new dimensions of financial risk, including cyber vulnerability, regulatory asymmetry, and revenue model fragility (W. Li & Ding, 2024; S. Qiu, 2024).

This duality creates inherent tension between innovation-driven growth and market stability. While some fintech firms achieve competitive advantage by aligning innovation with sustainable profitability, others face heightened volatility and speculative valuation dynamics (Kapoor et al., 2025; Sagala et al., 2023). From a theoretical standpoint, fintech operates simultaneously as a catalyst for value creation and a conduit for systemic fragility, reflecting broader debates on disruptive innovation within financial markets (Erdilek Karabay & Çağıl, 2017; Sánchez-Gutiérrez et al., 2019).

Empirical studies examining fintech performance report inconsistent findings, reflecting differences in methodology, market conditions, and firm heterogeneity (Chuang & Shrestha, 2025; Melati, 2024). While some research documents efficiency gains and enhanced investor confidence, other studies reveal volatility and misalignment between operational innovation and stock market performance (H. Chi, 2024; Rahman et al., 2022). These inconsistencies are particularly pronounced in the post-pandemic period, where rapid digital adoption coincides with monetary tightening and shifting investor risk preferences (Saha & Kansal, 2022; Tsanis & Stouraitis, 2022).

Against this backdrop, the post-pandemic period represents a critical empirical setting to reassess fintech market performance. Despite widespread digital adoption, gaps persist between operational resilience and market valuation, especially under conditions of elevated uncertainty and financial stress (Chellasamy & Debnath, 2022). These unresolved discrepancies underscore the need for a risk-adjusted evaluation of fintech firms that accounts for volatility, downside risk, and heterogeneity across business models (Aziz Abdul Rahman et al., 2023; H. Chi, 2024).

This study aims to evaluate the post-pandemic market performance of U.S. fintech firms through a risk-adjusted lens that integrates return dynamics, systematic risk, and firm-level heterogeneity (Chuang & Shrestha, 2025; Gil-Corbacho et al., 2023). It examines how fintech innovation influences market performance across different subsectors, including digital lending, payments, and blockchain-based services, while assessing the moderating role of regulatory maturity and business model structure (Jain et al., 2023; Qiang, 2024). By combining comparative performance analysis with risk-adjusted metrics, this study contributes empirically, theoretically, and methodologically to the fintech-performance literature, offering new insights into how innovation quality and institutional alignment shape sustainable market outcomes in post-pandemic financial environments (Ben Bouheni et al., 2025; Boscia et al., 2021; Nkatekho, 2024).

2. Literature review

Conceptual Foundations of Fintech Innovation

Fintech, or financial technology, refers to the integration of finance and digital innovation aimed at improving efficiency, inclusivity, and adaptability of financial services (Lu, 2024; Petruk et al., 2023). Beyond its technological dimension, fintech functions as an institutional and socio-economic mechanism that drives the modernization of financial systems by reducing intermediation costs and expanding access to financial services (Anifa et al., 2022; Bhatia, 2022; Varga, 2017). This transformation is underpinned by the convergence of algorithmic systems, data analytics, and automation that reshape decision-making processes and customer interaction in finance (Ghanem, 2022; Jarvis & Han, 2021).

The evolution of fintech reflects successive technological and regulatory shifts shaped by major economic disruptions and digital breakthroughs (Dodda, 2025; Moosa, 2022). Initially confined to back-office banking applications, fintech has expanded into a complex ecosystem encompassing peer-to-peer finance, crypto assets, and decentralized financial markets (Ruof, 2023). This expansion is widely associated with the fourth industrial revolution, where digitalization, artificial intelligence, and blockchain technologies redefine financial intermediation and business models (Erić, 2022; Sophia, 2021).

At its core, fintech innovation is characterized by deep technological embeddedness and a process of financial re-intermediation that replaces traditional hierarchical structures with platform-based systems (Lu, 2024; Panova et al., 2021). Through the use of blockchain, artificial intelligence, and big data, fintech firms create decentralized and trust-based networks that lower transaction frictions and improve capital allocation efficiency (Georgiev, 2024; Giglio, 2021). Conceptually, this shift represents a transition from static institutional intermediation toward dynamic technological orchestration of financial flows, marking a fundamental transformation in modern financial systems (Imerman & Fabozzi, 2020; Sanyaolu et al., 2024).

Fintech and Firm Performance: Empirical Evidence

Empirical evidence on fintech's effect on firm performance reveals mixed yet insightful outcomes across diverse contexts. Studies consistently show that fintech adoption enhances profitability, efficiency, and market access, primarily through reducing information asymmetry and transaction costs (Al-Matari et al., 2023; Cai, 2025). Fintech integration improves operational sustainability by optimizing capital allocation and promoting financial inclusion (Ferilli et al., 2024). Fintech-based credit access has also been found to reduce firm volatility and bankruptcy probability, particularly for small and medium-sized enterprises (Chen et al., 2022). Similarly, comparative stock performance analyses reveal that fintech firms outperform traditional financial institutions in risk-adjusted returns during post-crisis recovery phases (Gil-Corbacho et al., 2023; Moro-Visconti & Cesaretti, 2023).

However, other empirical evidence reveals that rapid fintech growth leads to increased volatility and non-convergence in valuation under global uncertainty (Matar, 2025; Son & Yoo, 2025). Differences in findings may be primarily attributed to methodological heterogeneity (e.g., event studies, VAR approaches and panel regression) and the length of observation period used (Tien & My, 2022; Xu et al., 2022). Research also suggests that the beneficial effect of fintech is contingent upon the quality of governance and external shocks (COVID-19, inflation, or geopolitical instability) (J. D. Chi & Su, 2017; Ferilli et al., 2024). In general, this argumentation supports a dual story in literature that fintech on the one hand increases efficiency and robustness but on the other it is increasing its exposure to market volatility and systemic risk (Thesmar & Thoenig, 2011; Tomar, 2015).

Asset Pricing Perspectives on Technology Driven Firms

Traditional asset pricing models such as the Capital Asset Pricing Model (CAPM) are increasingly viewed as inadequate in explaining the performance of technology-driven and fintech firms, particularly under high innovation intensity and market turbulence (Bin, 2024; Lyu, 2024). While CAPM assumes a linear risk-return relationship, empirical findings suggest persistent abnormal returns inconsistent with beta-based predictions, especially in digital-intensive sectors (H. Li, 2025; Xie, 2023). Fintech firms, characterized by high intangible asset ratios and rapid innovation cycles, tend to exhibit valuation discrepancies due to underpriced idiosyncratic risk and market sentiment effects (Reinganum, 1981). Consequently, multi-factor frameworks integrating behavioral and technological risk factors are better suited to capture fintech valuation dynamics.

Recent literature emphasizes that idiosyncratic volatility and uncertainty play a critical role in asset pricing for innovation-driven firms, challenging the classical notion of market equilibrium (Jacobs & Wang, 2004; Tompo, 2023). Technology adoption accelerates the pace of firm-specific shocks, causing dispersion in abnormal returns unaccounted for by systematic risk measures (Dar et al., 2024; Lin, 2014). For fintech and digital asset markets, this translates into lower beta coefficients but higher total volatility, reflecting investor overreaction, liquidity shifts, and technology diffusion uncertainty (Wan, 2025; Xiang, 2025). The relevance of asset pricing reformulations, including liquidity-adjusted CAPM and intertemporal CAPM, is increasingly recognized in explaining fintech's non-linear return structure (B. Qiu, 2025; Zhao, 2024).

Technology-oriented firms thus exhibit a structural divergence from traditional asset pricing paradigms, where innovation-induced uncertainty modifies both expected returns and risk premiums (Bin, 2024; G. Li, 2025). Empirical studies reveal that low-beta fintech portfolios can generate persistent excess returns, reflecting the market's misestimation of innovation-driven idiosyncratic components (Lyu, 2024; Sandhya et al., 2024). This anomaly aligns with the hypothesis that technological growth and uncertainty generate a premium unpriced by static equilibrium models, calling for asset pricing frameworks that integrate technological disruption and behavioral heterogeneity (Xie, 2023).

Post Pandemic Financial Markets and Fintech Stocks

The COVID-19 pandemic fundamentally reshaped global financial markets, inducing both valuation surges and structural volatility in fintech equities. Empirical evidence shows that fintech stocks experienced pronounced mispricing during the pandemic as investors overestimated digital adoption and innovation-driven earnings (Ali et al., 2025; Saha & Kansal, 2022). The transition to online finance, heightened liquidity, and accommodative fiscal measures inflated valuation multiples far beyond fundamentals (S. Qiu, 2024; Zhang et al., 2020). Yet, post-pandemic correction phases revealed that risk perceptions remained elevated, with fintech firms maintaining overvaluation driven by investor optimism and low-rate environments (Ali et al., 2025; Talbi et al., 2024). This indicates that the pandemic acted as both a catalyst and a distortion mechanism in fintech asset pricing.

The post-pandemic era also redefined the interaction between monetary policy, risk appetite, and fintech valuation. Research demonstrates that the effectiveness of monetary transmission weakened as fintech adoption altered credit, lending, and liquidity dynamics (Hasan et al., 2024; Wei & Han, 2021). Expansionary policies boosted speculative demand in high-growth digital sectors, while subsequent tightening cycles introduced valuation stress and idiosyncratic risk concentration (Budinský & Hütteroth, 2023; Thorbecke, 2023). Central bank policy adjustments indirectly influenced fintech market liquidity and investor sentiment, reinforcing a feedback loop between innovation enthusiasm and macroeconomic fragility (Bauer et al., 2023; Maghyereh & Cui, 2023). Consequently, studying post-pandemic fintech stocks provides a critical temporal lens to assess how technology, liquidity, and uncertainty collectively redefine modern financial valuation.

Research Gap and Hypothesis Development

Despite the growing body of fintech literature, several critical gaps remain unresolved. First, existing studies predominantly emphasize operational efficiency, innovation adoption, or firm valuation during crisis periods, while providing limited evidence on post-pandemic market performance from a risk-adjusted perspective. Second, empirical findings remain fragmented regarding whether fintech stock returns are driven by systematic market risk or firm-specific innovation dynamics, particularly across heterogeneous business models. These limitations constrain a comprehensive understanding of fintech valuation in the post-pandemic financial environment.

Building on these gaps, this study develops testable hypotheses that connect fintech innovation, market risk exposure, and performance heterogeneity. Specifically, it posits that fintech stocks exhibit heterogeneous post-pandemic market performance (H1), reflecting differences in business models and innovation intensity. It further hypothesizes that fintech stock returns are weakly explained by systematic market risk as captured by traditional asset pricing models (H2). Finally, it proposes that fintech firms with more integrated and regulated business models generate superior risk-adjusted returns relative to narrowly specialized platforms (H3).

3. Methodology

This study adopts a quantitative empirical design to examine the relationship between fintech innovation and market performance in the post-pandemic period. The population comprises publicly listed fintech firms operating in the United States equity market and representing diverse business models, including digital lending, payments, cryptocurrency platforms, and financial software services. The analytical framework focuses on return generation, risk exposure, and market integration to assess whether fintech innovation translates into superior investment performance relative to the broader market.

The selection of these eight firms follows a purposive sampling approach based on data continuity and market relevance during the July 30, 2021 to December 30, 2024 study window. All firms are publicly listed in the United States equity market and provide complete daily price observations over the 892 trading days analyzed. The sample is restricted to firms with uninterrupted daily price data over the full window and sufficient market visibility to represent distinct, commonly discussed fintech business models. Firms with discontinuous trading histories, missing observations, or corporate events that prevent a consistent return series within July 2021 to December 2024 are excluded to preserve comparability across models. The sample was constructed to reflect heterogeneity within the fintech sector, covering digital lending platforms (SOFI, UPST, AFRM, LC), payment and transaction services (PYPL), cryptocurrency exchange exposure (COIN), retail trading platform services (HOOD), and financial software with fintech exposure (INTU). The objective is comparative cross-model analysis rather than sector-wide enumeration. Therefore, conclusions are interpreted within the boundaries of this structured comparative sample.

Table 1. Business Model Classification of Sample Firms

Ticker	Business model category
SOFI	Digital lending and regulated fintech platform
UPST	AI-based consumer lending platform
AFRM	Buy-now-pay-later (consumer credit)
LC	Marketplace lending

Ticker	Business model category
PYPL	Digital payments
COIN	Cryptocurrency exchange exposure
HOOD	Retail trading platform
INTU	Fintech-adjacent financial software

Source: own elaboration.

To operationalize the business-model heterogeneity embedded in the purposive sample, the eight firms are explicitly classified into fintech-relevant categories that reflect their dominant revenue logic and exposure channels (Table 1). The taxonomy separates digital lending and consumer credit models (SOFI, UPST, AFRM, LC) from payments infrastructure (PYPL), crypto-exchange exposure (COIN), retail trading intermediation (HOOD), and fintech-adjacent financial software services (INTU). This classification is not intended as an exhaustive industry mapping, but as a structured basis for cross-model comparison, enabling the analysis to interpret performance dispersion and risk profiles in relation to business-model structure and institutional integration, consistent with the logic of Hypothesis 3.

Market performance is operationalized using a comprehensive set of risk–return indicators that capture both central tendency and downside exposure. The market benchmark is the S&P 500, denoted as MARKET in the tables, selected to represent the broad U.S. equity market over the same trading days. The S&P 500 is employed as a proxy for the aggregate market portfolio, consistent with conventional applications of the Capital Asset Pricing Model in U.S. equity research. As summarized in Table 2, the dependent variables include daily returns, annualized returns, volatility, Sharpe ratio, maximum drawdown, and win rate. Independent variables consist of market returns and benchmark-adjusted measures used to evaluate systematic risk and abnormal performance. Employing multiple performance metrics mitigates reliance on a single indicator and strengthens internal validity.

Table 2. Variables Description

Variable	Symbol	Measurement	Description
Daily Return	R	Percentage	Logarithmic daily return of stock i
Market Return	RM	Percentage	Logarithmic daily return of MARKET benchmark index
Mean Return	MeanR	Percentage	Average daily return over the sample
Volatility	Sigma	Percentage	Standard deviation of daily returns
Sharpe Ratio	SR	Ratio	Risk-adjusted return measure
Maximum Drawdown	MDD	Percentage	Largest peak-to-trough loss
Alpha	Alpha	Percentage	Abnormal return from CAPM
Beta	Beta	Coefficient	Market sensitivity from CAPM

Source: own elaboration.

Daily asset returns are computed using logarithmic transformation to stabilize variance and facilitate comparability across securities with different price levels. The return for asset *i* at time *t* is calculated as

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \quad (1)$$

This formulation allows aggregation into mean returns reported in Table 3, where SOFI records an average daily return of 0.5073 percent, substantially exceeding the market benchmark mean of 0.0700 percent.

Risk adjusted performance is assessed using the Sharpe ratio, which evaluates excess return per unit of total risk. The Sharpe ratio is defined as

$$SR_i = \frac{\overline{r_i} - r_f}{\sigma_i} \quad (2)$$

where r_i denotes the mean return of asset *i*, r_f represents the risk free rate, and σ_i is the standard deviation of returns. In this study, the risk-free rate is proxied by the United States Treasury bill rate, converted to a daily equivalent to match the return frequency. Specifically, the proxy is the 3-month U.S. Treasury bill rate, transformed into a daily rate to align with the daily return frequency. As shown in Table 3, SOFI achieves a Sharpe ratio of 1.8568, while AFRM records a negative Sharpe ratio of −0.9895, indicating poor risk adjusted performance.

To evaluate downside risk exposure, maximum drawdown is computed as the largest peak to trough decline in cumulative returns over the sample period. Maximum drawdown is formally expressed as

$$MDD_i = \max_{t \in [0,T]} \left(\frac{Peak_t - Trough_t}{Peak_t}\right) \quad (3)$$

The drawdown statistics in Table 3 reveal extreme losses for several fintech stocks, with AFRM experiencing a maximum drawdown of −99.91 percent and COIN reaching −94.34 percent, highlighting substantial tail risk during the post pandemic period.

Systematic risk and abnormal performance are examined using the Capital Asset Pricing Model. The regression specification is given by

$$r_{i,t} - r_f = \alpha_i + \beta_i\left(r_{m,t} - r_f\right) + \varepsilon_t \quad (4)$$

Here, α_i captures abnormal return, while β_i measures sensitivity to market movements. The CAPM estimates, later reported in Table 5, show low beta values across fintech stocks, such as 0.1586 for SOFI and 0.0116 for COIN, indicating weak market dependence.

Correlation analysis is employed to further assess the degree of integration between fintech stocks and the market benchmark. Pearson correlation coefficients are calculated using daily returns to avoid spurious co movement driven by non stationary price levels. As summarized in Table 6, all fintech stocks exhibit very weak correlations with the market, ranging from 0.0031 to 0.0573, reinforcing the regression based evidence of limited systematic linkage.

To strengthen methodological reliability, multiple robustness checks are conducted. These include subsample analysis dividing the sample into two equal periods, winsorization at the 1 percent level to mitigate outlier influence, alternative benchmark comparisons, and out of sample prediction tests. The stability of Sharpe ratios across subsamples, as reported later, confirms that the core findings are not driven by short term anomalies or extreme observations.

4. Data Analysis and Empirical Results

Descriptive Characteristics of Fintech Stock Returns

The descriptive evidence summarized in Table 3 reveals clear and systematic heterogeneity in the post-pandemic performance of United States fintech stocks over the period July 2021 to December 2024. Mean daily returns range from a high of 0.5073 percent for SOFI to a low of −0.4007 percent for AFRM, compared with 0.0700 percent for the market benchmark. This dispersion provides initial support for the view that fintech innovation does not generate uniform return outcomes across firms, reflecting differences in business models and risk exposures.

Table 3. Descriptive Statistics of Fintech Stocks and Market Benchmark

Ticker	Mean (%)	Std (%)	Sharpe	Max DD (%)	Win Rate (%)	JB p-value
SOFI	0.5073	4.3376	1.8568	−58.75	55.49	0.3907
MARKET	0.0700	1.5675	0.7088	−34.06	50.90	0.3504
UPST	0.2012	6.4258	0.4971	−86.44	51.23	0.3106
COIN	0.1760	5.8262	0.4795	−94.34	50.67	0.9268
HOOD	0.1094	3.9631	0.4381	−80.32	51.57	0.1023
INTU	−0.0287	2.4159	−0.1889	−72.52	49.33	0.4238
PYPL	−0.0829	2.5497	−0.5159	−68.72	48.43	0.6500
LC	−0.1468	3.6780	−0.6335	−93.80	47.87	0.8405
AFRM	−0.4007	6.4280	−0.9895	−99.91	48.32	0.7176

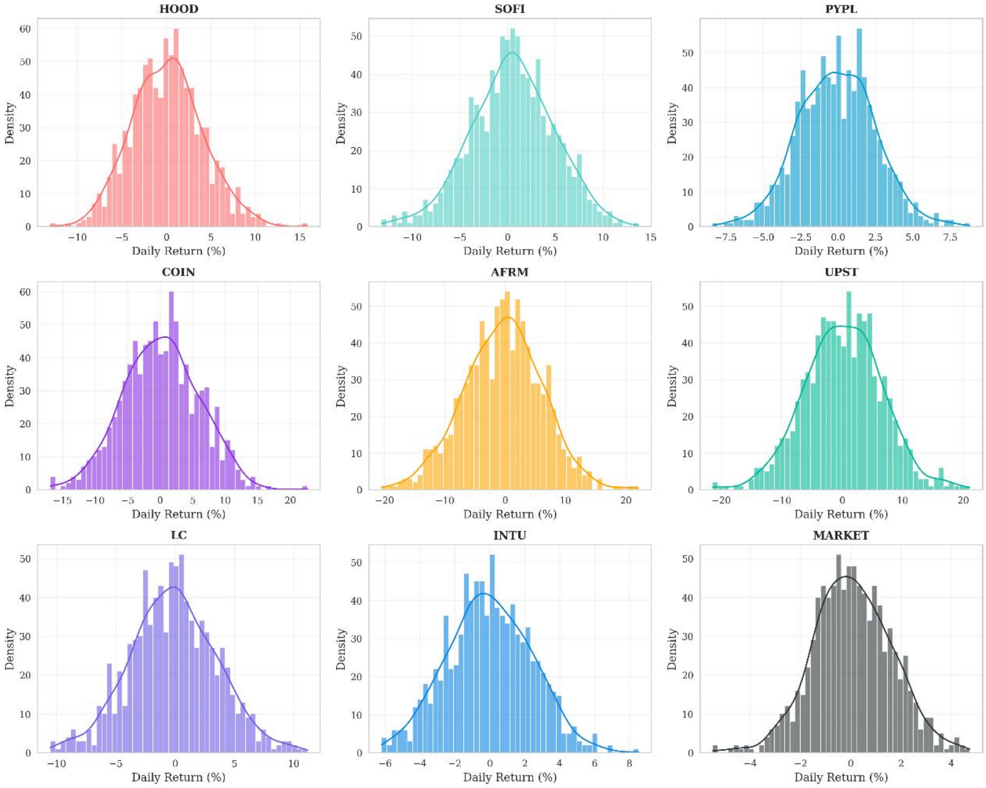
Source: own elaboration.

SOFI's positive average return contrasts sharply with the persistent losses observed for AFRM and LC, indicating substantial cross-sectional divergence within the fintech sector. These differences suggest that fintech firms respond unevenly to post-pandemic market conditions, with performance outcomes shaped by firm-specific characteristics rather than sector-wide innovation effects alone.

Return volatility further differentiates fintech stocks from the broader market. AFRM and UPST record standard deviations above 6.42 percent, substantially exceeding the market benchmark volatility of 1.5675 percent. INTU shows relatively lower volatility at 2.4159 percent, yet remains riskier than the market index. These figures confirm that fintech stocks embed structurally higher uncertainty, likely linked to revenue fragility, growth dependence, and innovation intensity.

Risk-adjusted performance reinforces this uneven pattern. SOFI achieves a Sharpe ratio of 1.8568, more than twice the market Sharpe ratio of 0.7088, indicating superior compensation for total risk. In contrast, AFRM posts a Sharpe ratio of −0.9895, implying that investors were not compensated for bearing elevated volatility. These results demonstrate that fintech innovation alone is insufficient to guarantee favorable risk-adjusted outcomes.

Figure 1. Distribution of Daily Returns for Fintech Stocks and Market Benchmark



Source: own elaboration.

Downside risk characteristics are particularly pronounced for several fintech firms. Maximum drawdowns reach −99.91 percent for AFRM and −94.34 percent for COIN, compared with −34.06 percent for the market benchmark. The return distributions illustrated in Figure 1 exhibit wide dispersion and heavier tails for fintech stocks, consistent with these drawdown magnitudes. Jarque–Bera p-values exceeding 0.10 across all assets, such as 0.3907 for SOFI and 0.9268 for COIN, indicate approximate normality and support the use of parametric methods, suggesting that the results are not driven by extreme non-normal behavior.

Comparative Performance Ranking and Value Creation

The comparative ranking reported in Table 4 demonstrates pronounced asymmetry in value creation among United States fintech stocks during the July 2021 to December 2024 period. Annualized returns range from 127.85 percent for SOFI to −100.97 percent for AFRM, while the market benchmark records a moderate return of 17.64 percent. This wide dispersion underscores that fintech innovation translates into shareholder value in a highly uneven manner, rather than delivering sector-wide performance gains.

Table 4. Performance Metrics and Ranking

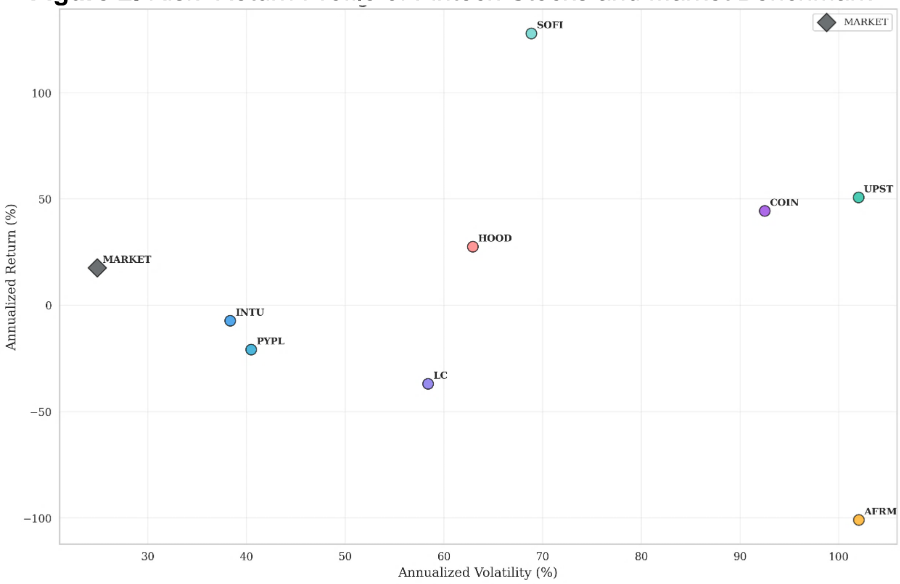
Rank	Ticker	Annual Return (%)	Sharpe	Information Ratio	Max DD (%)
1	SOFI	127.8509	1.8568	1.5337	−58.75
2	MARKET	17.6381	0.7088	N/A	−34.06
3	UPST	50.7124	0.4971	0.3138	−86.44
4	COIN	44.3463	0.4795	0.2791	−94.34
5	HOOD	27.5602	0.4381	0.1454	−80.32
6	INTU	−7.2443	−0.1889	−0.5323	−72.52
7	PYPL	−20.8807	−0.5159	−0.7960	−68.72
8	LC	−36.9906	−0.6335	−0.8646	−93.80
9	AFRM	−100.9677	−0.9895	−1.1325	−99.91

Source: own elaboration.

SOFI clearly dominates the ranking by combining a high annualized return of 127.85 percent with a Sharpe ratio of 1.8568 and an information ratio of 1.5337. This configuration signals both strong absolute performance and consistent benchmark outperformance, indicating robust value creation during the sample period. By comparison, the market benchmark ranks second with a Sharpe ratio of 0.7088, confirming that SOFI's performance exceeds that of the broader equity market on a risk-adjusted basis.

The intermediate performers, particularly UPST and COIN, illustrate a clear trade-off between return potential and downside exposure. Although UPST records an annualized return of 50.71 percent and COIN 44.35 percent, both experience severe maximum drawdowns of −86.44 percent and −94.34 percent, respectively. These outcomes suggest that higher returns are accompanied by substantial capital erosion, limiting their attractiveness for risk-averse investors.

Figure 2. Risk–Return Profile of Fintech Stocks and Market Benchmark



Source: own elaboration.

The dispersion in value creation is further visualized in Figure 2, which plots expected returns against volatility for fintech stocks and the market benchmark. The risk–return profile highlights SOFI's relatively favorable positioning, combining higher returns with comparatively controlled volatility, while AFRM and LC cluster in the high-risk, low-return region. This visual evidence reinforces the interpretation that fintech stocks occupy fundamentally distinct risk–return profiles rather than forming a homogeneous growth segment.

Systematic Risk and CAPM Evidence

The Capital Asset Pricing Model estimates reported in Table 5 provide direct evidence on the limited role of systematic market risk in explaining fintech stock returns during the July 2021 to December 2024 period. Across all firms, beta coefficients are economically small and statistically insignificant, indicating weak sensitivity to market movements. This pattern suggests that traditional market risk factors offer minimal explanatory power for fintech equity performance.

Table 5. CAPM Regression Results

Ticker	Beta	Alpha (%)	R-squared	Alpha Significance	Beta Significance
SOFI	0.1586	125.05	0.0033	Yes	No
AFRM	0.0514	−101.88	0.0002	No	No
LC	0.0294	−37.51	0.0002	No	No
COIN	0.0116	44.14	0.0000	No	No
HOOD	−0.0662	28.73	0.0007	No	No
UPST	−0.0663	51.88	0.0003	No	No
PYPL	−0.0682	−19.68	0.0018	No	No
INTU	−0.0770	−5.89	0.0025	No	No

Source: own elaboration.

SOFI records a beta of 0.1586 with an R-squared value of 0.0033, implying that less than 0.4 percent of its return variation is attributable to market fluctuations. Similar results are observed for COIN with a beta of 0.0116 and UPST with −0.0663, both accompanied by near-zero R-squared values. These magnitudes indicate a low degree of market integration across fintech stocks, consistent with firm-specific return dynamics. The presence of small negative beta coefficients for certain firms, such as UPST and HOOD, indicates that their daily return movements were not systematically synchronized with aggregate market fluctuations during the study period. However, given the extremely low R-squared values and statistical insignificance, these coefficients should not be interpreted as economically meaningful counter-cyclical exposures. Rather, they reinforce the dominance of firm-specific return drivers in the fintech segment. Such patterns may reflect speculative trading dynamics, short-term liquidity imbalances, or sensitivity to sector-specific news rather than structural inverse exposure to aggregate market risk.

The weak linkage between fintech returns and market risk challenges the applicability of conventional asset pricing assumptions in the context of innovation-driven firms. Fintech companies operate under distinct revenue structures, regulatory constraints, and technological uncertainties, which appear to dominate return behavior. As a result, market-wide risk factors fail to capture the primary sources of variation in fintech stock performance.

Alpha estimates further reinforce this interpretation. SOFI exhibits a statistically significant alpha of 125.05 percent, indicating substantial abnormal performance beyond market compensation. The magnitude of SOFI's estimated alpha reflects the annualized abnormal return derived from daily regressions within the sample period. Given the elevated volatility and valuation adjustments observed during the study window, this coefficient should be interpreted as sample-specific abnormal performance within the CAPM framework rather than as evidence of a structural long-term premium. The result reflects realized performance dynamics over the analyzed period. In contrast, AFRM reports a negative alpha of −101.88 percent, although not statistically significant. The wide dispersion in alpha values highlights the dominance of idiosyncratic factors in shaping fintech returns, rather than systematic market exposure.

Correlation Structure and Market Independence

The correlation structure reported in Table 6 provides additional confirmation of the weak linkage between fintech stock returns and the broader market benchmark. All correlation coefficients are close to zero, with the highest value observed for SOFI at 0.0573 and the lowest for COIN at 0.0031. These magnitudes indicate that fintech returns move largely independently of aggregate market fluctuations during the July 2021 to December 2024 period.

Table 6. Correlation with Market Benchmark

Ticker	Correlation	R-squared	Strength
SOFI	0.0573	0.0033	Very Weak
AFRM	0.0125	0.0002	Very Weak
LC	0.0125	0.0002	Very Weak
COIN	0.0031	0.0000	Very Weak
UPST	−0.0162	0.0003	Very Weak
HOOD	−0.0262	0.0007	Very Weak
PYPL	−0.0419	0.0018	Very Weak
INTU	−0.0499	0.0025	Very Weak

Source: own elaboration.

Several fintech stocks display negative correlations with the market benchmark, including PYPL at −0.0419 and INTU at −0.0499. While these values suggest occasional counter-cyclical behavior, their magnitudes remain economically small. The associated R-squared values are consistently below 0.003, indicating that such inverse movements explain only a negligible fraction of return variation.

The uniformly weak correlations observed across all fintech firms reinforce the conclusion that common market factors play a limited role in shaping fintech return dynamics. This pattern is consistent with earlier regression evidence and suggests that fintech stock performance is dominated by firm-specific characteristics rather than broad market co-movement.

Overall, the extremely low R-squared values across all firms confirm that market movements explain less than 0.3 percent of fintech return variation. This evidence supports the view that fintech equities offer limited diversification or hedging benefits during periods of market stress and further highlights the importance of firm-level risk assessment when evaluating fintech investments.

Robustness and Stability of Results

The robustness analysis provides strong support for the stability of the main empirical findings and mitigates concerns that the reported results are driven by sample-specific artifacts. Subsample analysis reported in Table 7 demonstrates that SOFI maintains consistently high risk-adjusted performance across both subperiods, with its Sharpe ratio declining only marginally from 1.9001 in the first half to 1.8128 in the second half. HOOD also exhibits stable performance, while PYPL shows moderate instability, indicating greater sensitivity to changing market conditions.

Table 7. Subsample Analysis of Sharpe Ratios

Ticker	Full Sample	First Half	Second Half	Stability
HOOD	0.4381	0.5604	0.3180	High
SOFI	1.8568	1.9001	1.8128	High
PYPL	−0.5159	−0.8944	−0.1383	Medium
MARKET	0.7088	0.2119	1.2205	Low

Source: own elaboration.

The robustness of downside risk patterns further reinforces these conclusions. Fintech firms differ markedly in their ability to absorb and recover from losses, with SOFI exhibiting drawdowns that, while substantial, remain comparatively contained relative to firms such as AFRM and LC, which experience extreme capital erosion exceeding −93 percent as documented earlier. This evidence underscores structural differences in resilience across fintech business models rather than transitory sample effects.

Sensitivity to extreme observations is assessed through winsorization at the 1 percent level. The results summarized in Table 8 show minimal changes in Sharpe ratios, with SOFI exhibiting a change of only 0.97 percent and HOOD 2.04 percent, while PYPL records a modest adjustment of −3.98 percent. These limited variations indicate that the observed performance patterns are not driven by outliers or isolated return realizations.

Table 8. Winsorization Sensitivity Analysis

Ticker	Original Sharpe	Winsorized Sharpe	Change (%)	Sensitivity
HOOD	0.4381	0.4470	2.04	Low
SOFI	1.8568	1.8748	0.97	Low
PYPL	−0.5159	−0.5364	−3.98	Low
MARKET	0.7088	0.7853	10.78	High

Source: own elaboration.

The robustness of relative performance comparisons is further examined through alternative benchmark analysis. As reported in Table 9, the market benchmark retains a Sharpe ratio of 0.7088, exceeding that of the alternative EWB benchmark at 0.3903 and the median benchmark at 0.6338. The near-zero correlations between these benchmarks and the market confirm that the relative ranking of fintech performance remains stable across different reference indices.

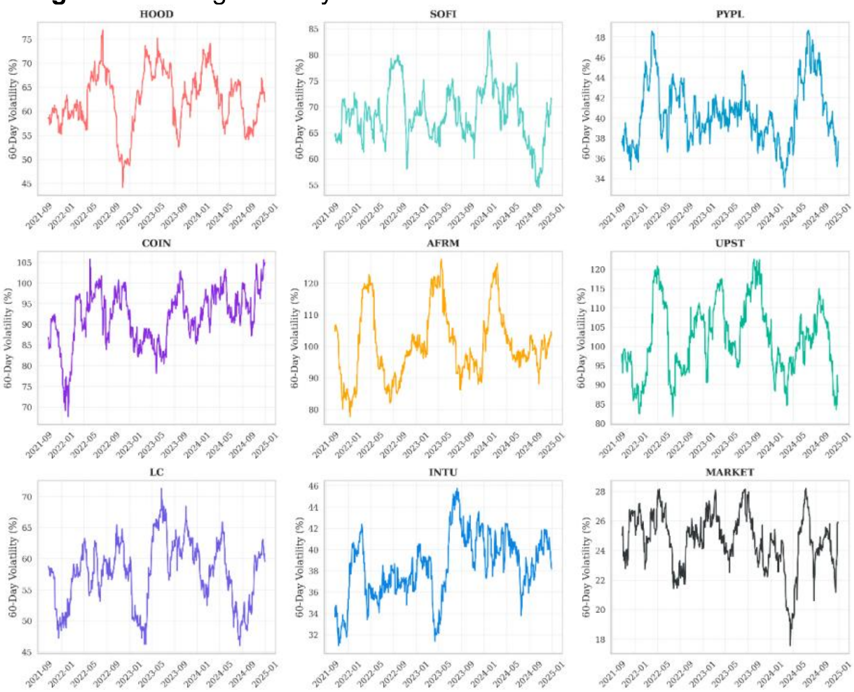
Table 9. Alternative Benchmark Comparison

Benchmark	Sharpe	Mean (%)	Std (%)	Correlation with Market
MARKET	0.7088	0.0700	1.5675	1.0000
EWB	0.3903	0.0419	1.7026	−0.0031
Median	0.6338	0.0659	1.6508	−0.0029

Source: own elaboration.

Risk dynamics over time are additionally evaluated using rolling volatility estimates. Figure 3 presents rolling volatility patterns for fintech stocks and the market benchmark, revealing sustained volatility clustering for firms such as AFRM and UPST, while SOFI exhibits comparatively smoother volatility dynamics. These patterns are consistent with earlier evidence on heterogeneous risk profiles across fintech firms.

Figure 3. Rolling Volatility of Fintech Stocks and Market Benchmark



Source: own elaboration.

Table 10. Out of Sample Prediction Accuracy

Ticker	In Sample Beta	Out Sample MSE	Out Sample MAE
HOOD	−0.1266	0.001599	0.031746
SOFI	0.0592	0.001877	0.033776
PYPL	−0.0666	0.000653	0.020664
COIN	−0.0414	0.003693	0.048688
AFRM	0.2324	0.004516	0.053553
UPST	−0.1020	0.003943	0.050200
LC	0.0631	0.001302	0.028655
INTU	−0.0503	0.000598	0.019771

Source: own elaboration.

Finally, the predictive relevance of market risk is assessed through out-of-sample tests. Table 10 reports out-of-sample prediction accuracy based on market beta, showing low mean squared errors across all firms, such as 0.001877 for SOFI and 0.000598 for INTU. The out-of-sample beta estimates differ slightly from in-sample coefficients reported in Table 5 due to the rolling estimation window applied in the prediction exercise. However, these low error magnitudes do not translate into meaningful forecasting power, reinforcing the conclusion that market beta offers limited explanatory and predictive value for fintech stock returns.

5. Discussions

Interpretation of Key Findings

The findings provide strong empirical support for H1, which posits heterogeneity in post-pandemic fintech market performance. While SOFI delivers an annual return of 127.85 percent and a Sharpe ratio of 1.86, firms such as AFRM and LC experience persistent negative returns and drawdowns exceeding 93 percent. This dispersion confirms that fintech firms do not constitute a homogeneous asset class, consistent with evidence on innovation-driven firm heterogeneity in financial markets (Melati, 2024; Thakor, 2020).

The results also strongly support H2, indicating that fintech stock returns are weakly explained by systematic market risk. CAPM estimates yield small and statistically insignificant beta coefficients, including 0.0116 for COIN and −0.0663 for UPST, with R squared values below 0.01. This pattern suggests that fintech returns are largely decoupled from aggregate market movements, aligning with asset pricing studies emphasizing the dominance of idiosyncratic risk in technology-intensive firms (Lyu, 2024; Pástor & Veronesi, 2009).

From a theoretical perspective, these outcomes reinforce models of innovation-based asset pricing in which learning dynamics, uncertainty, and heterogeneous beliefs drive return behavior. Fintech firms operate under rapidly evolving technological and regulatory conditions, causing return volatility that standard market risk factors fail to capture. This mechanism explains why fintech stocks display low beta yet high total volatility, consistent with findings in innovation-driven sectors such as biotechnology and platform-based firms (Xie, 2023).

Clear evidence also emerges in support of H3, highlighting the role of business model integration and regulatory alignment. SOFI’s superior risk-adjusted performance reflects its diversified platform combining lending, payments, and digital banking within a regulated framework. In contrast, fintech firms concentrated in consumer credit or crypto-related activities exhibit amplified volatility and deeper drawdowns during monetary tightening. This finding aligns with research emphasizing institutional embeddedness as a determinant of fintech resilience (Philippon, 2016; Thakor, 2020). This contrast becomes clearer when viewed through the business model classification presented in Table 1. Firms operating more diversified and institutionally embedded models, such as SOFI, exhibit comparatively stronger risk-adjusted outcomes, whereas firms concentrated in consumer credit expansion (AFRM, LC) or crypto-exchange exposure (COIN) display greater performance instability, reinforcing the structural interpretation underlying H3.

Correlation analysis further reinforces these interpretations. With correlations below 0.06 for all fintech stocks and near zero for COIN at 0.0031, fintech equities offer limited diversification benefits during market stress. This evidence does not support the view that fintech firms consistently function as defensive or countercyclical assets and instead suggests that fintech risk materializes independently of broad market dynamics, consistent with post-crisis evidence on digital asset mispricing (Ali et al., 2025; Talbi et al., 2024).

Comparison with Prior Literature

The findings partially diverge from early fintech literature that associates innovation with efficiency gains, productivity growth, and financial inclusion translating directly into firm value (Gomber et al., 2017). While such benefits are observable at the operational level, this study shows that market valuations remain highly sensitive to uncertainty and macrofinancial conditions. This divergence is consistent with evidence of valuation compression in high-growth technology firms following shifts in monetary policy regimes (Papanikolaou & Schmidt, 2022).

At the same time, the strong abnormal performance of SOFI supports more recent literature emphasizing business model maturity and regulatory alignment. Fintech firms that transition from experimental platforms to integrated financial intermediaries are more likely to achieve sustainable market performance. This study contributes new post-pandemic evidence showing that institutional structure, rather than innovation intensity alone, governs fintech value creation (Chuang & Shrestha, 2025; Thakor, 2020).

The negligible beta estimates also echo critiques of traditional asset pricing models in technology-driven contexts. Similar to prior findings in innovation-intensive industries, fintech stocks exhibit return dynamics weakly linked to systematic risk, suggesting the need for extended models incorporating innovation uncertainty and funding constraints. By documenting this phenomenon in the post-pandemic period, this study advances asset pricing evidence beyond pre-crisis settings (Pástor & Veronesi, 2009; Sandhya et al., 2024).

Implications for Investors, Policymakers, and Future Research

For investors, the results imply that treating fintech as a homogeneous sector entails substantial downside risk. Extreme drawdowns and negative risk-adjusted returns observed for several firms indicate that selective strategies based on business model structure, revenue diversification, and regulatory positioning are essential. Fintech stocks may increase portfolio risk exposure rather than provide diversification benefits during periods of systemic stress, particularly under tightening financial conditions.

From a policy perspective, the findings underscore the stabilizing role of regulatory clarity and institutional integration. Fintech firms operating within established supervisory frameworks demonstrate greater resilience and more stable performance. Conversely, the severe losses observed in credit-oriented fintech firms raise concerns regarding consumer protection and potential spillovers to financial stability, reinforcing the need for balanced and adaptive regulation.

Future research should build on these findings by employing multifactor asset pricing models that explicitly incorporate innovation intensity, regulatory exposure, and funding structure. Extending the analysis across countries and longer economic cycles would clarify whether fintech performance converges toward traditional financial institutions over time. Integrating machine learning-based risk indicators may further illuminate the nonlinear dynamics underlying fintech stock performance.

6. Conclusions

This study provides clear empirical support for the view that fintech innovation does not uniformly translate into superior market performance in the post-pandemic United States equity market. The results confirm substantial heterogeneity across fintech firms, where only a limited subset achieves sustained abnormal returns, while many experience persistent underperformance and severe downside risk. These findings validate the hypothesis that fintech firms should not be treated as a homogeneous asset class in capital market analysis.

The evidence further demonstrates that fintech stock returns are weakly explained by systematic market risk. Low and statistically insignificant beta coefficients, combined with minimal explanatory power of the Capital Asset Pricing Model, indicate that traditional market factors play a limited role in fintech valuation. This supports the argument that fintech performance is primarily shaped by firm-specific dynamics, including innovation uncertainty, funding dependence, and exposure to regulatory and technological shocks.

A key contribution of this study lies in identifying business model structure and regulatory integration as decisive determinants of risk-adjusted performance. Fintech firms operating diversified platforms within established regulatory frameworks exhibit greater resilience and more stable outcomes, whereas firms concentrated in consumer credit expansion or speculative digital assets display heightened volatility and extreme drawdowns. This evidence underscores the importance of institutional embeddedness in translating innovation into sustainable shareholder value.

Several limitations merit consideration. The analysis focuses on United States listed fintech firms and a relatively short post-pandemic period, which may limit generalizability across institutional settings and economic cycles. Future research should extend this framework to cross-country contexts, longer horizons, and multifactor asset pricing models that incorporate innovation intensity, regulatory exposure, and funding structure. Such extensions would further refine understanding of fintech innovation as a heterogeneous and risk-sensitive driver of market performance. In addition, the analysis relies on a deliberately small and heterogeneous comparative sample, which supports within-sample contrasts across business models but limits statistical generalization to the full universe of U.S. fintech firms.

The analysis includes firms with continuous daily data through December 2024. Consequently, fintech companies that were delisted or ceased operations during the study window are not captured in the sample. This may limit the representation of extreme downside outcomes within the broader fintech universe. Accordingly, the results may be subject to survivorship effects because the comparative set necessarily reflects firms with continuous listings and observable prices through the end of December 2024.

Furthermore, the study period overlaps with a phase of monetary tightening in the United States, which may interact with fintech-specific valuation sensitivity. While systematic market risk is captured through CAPM estimation, the model does not separately disentangle interest-rate channel effects from firm-level innovation dynamics.

7. References

Ali, S., Ali, H., & Tarek, A. (2025). Do stock prices deviate from their fundamental values during and after COVID-19? Evidence from Fintech firms. *Studies in Economics and Finance*, *42*(3), 510–531. https://doi.org/10.1108/SEF-04-2024-0191

Al-Matari, E. M., Mgammal, M. H., Senan, N. A. M., Kamardin, H., & Alruwaili, T. F. (2023). Fintech and financial sector performance in Saudi Arabia: An empirical study. *Journal of Governance and Regulation*, *12*(2), 43–65. https://doi.org/10.22495/jgrv12i2art5

Anguelov, K., & Stoyanova, T. (2025). Assessment of Factors Influencing Market Leadership and Innovation of FinTech Companies in the Digital economy. *Economics Ecology Socium*, *9*(3), 93–109. https://doi.org/10.61954/2616-7107/2025.9.3-7

Anifa, M., Ramakrishnan, S., Joghee, S., Kabiraj, S., & Bishnoi, M. M. (2022). Fintech Innovations in the Financial Service Industry. *Journal of Risk and Financial Management*, *15*(7), 287. https://doi.org/10.3390/jrfm15070287

Aziz Abdul Rahman, A., Ur Rahiman, H., Meero, A., & Rashad Amin, A. (2023). Fintech innovations and Islamic banking performance: Post-pandemic challenges and opportunities. *Banks and Bank Systems*, *18*(4), 281–292. https://doi.org/10.21511/bbs.18(4).2023.23

Bauer, M. D., Bernanke, B. S., & Milstein, E. (2023). Risk Appetite and the Risk-Taking Channel of Monetary Policy. *Journal of Economic Perspectives*, *37*(1), 77–100. https://doi.org/10.1257/jep.37.1.77

Ben Bouheni, F., Tewari, M., Salamon, A., Johnston, P., & Hopkins, K. (2025). *Credit Sales and Risk Scoring: A FinTech Innovation*. Business, Economics and Management. https://doi.org/10.20944/preprints202503.1216.v1

Bhatia, M. (2022). Fintech: The Innovation Benchmark. In M. Bhatia, *Banking 4.0* (pp. 295–304). Springer Nature Singapore. https://doi.org/10.1007/978-981-16-6069-6_13

Bin, Y. (2024). The Limitaitons and Alternatives of CAPM. *Advances in Economics, Management and Political Sciences*, *60*(1), 46–51. https://doi.org/10.54254/2754-1169/60/20231154

Boscia, V., Stefanelli, V., & Trinchera, M. (2021). Fintech & Risks. A Bibliometric Analysis. *Risk Management Magazine*, *16*(2), 68–74. https://doi.org/10.47473/2020rmm0091

Budinský, P., & Hütteroth, A. (2023). Correlation of European and U.S. Technology and Financial Stocks during COVID-19 Pandemic. *International Journal of Applied Research in Management and Economics*, *6*(4), 1–20. https://doi.org/10.33422/ijarme.v6i4.1134

Cai, J. L. (2025). The Impact of Fintech Levels on the Performance of Listed Companies. *Highlights in Business, Economics and Management*, *52*, 156–164. https://doi.org/10.54097/5mtx0742

Chellasamy, Dr. P., & Debnath, P. (2022). Performance analysis of post-pandemic initial public offering’s. *International Journal of Applied Research*, *8*(9), 242–246. https://doi.org/10.22271/allresearch.2022.v8.i9d.10161

Chen, T., Huang, Y., Lin, C., & Sheng, Z. (2022). Finance and Firm Volatility: Evidence from Small Business Lending in China. *Management Science*, *68*(3), 2226–2249. https://doi.org/10.1287/mnsc.2020.3942

Chi, H. (2024). The Current Situation and Development of Fintech. *Advances in Economics, Management and Political Sciences*, *132*(1), 104–109. https://doi.org/10.54254/2754-1169/2024.18450

Chi, J. D., & Su, X. (2017). The Dynamics of Performance Volatility and Firm Valuation. *Journal of Financial and Quantitative Analysis*, *52*(1), 111–142. https://doi.org/10.1017/S0022109016000788

Chuang, M. Y., & Shrestha, S. K. (2025). Fintech Converges with Investment and Risk: A Bibliometric Review. *Journal of Risk and Financial Management*, *18*(9), 517. https://doi.org/10.3390/jrfm18090517

Dar, A. A., Jain, A., Malhotra, M., Albalawi, O., & Shruti. (2024). Exploring the Factors Influencing the Capital Asset Pricing Model: In S. K. Kautish (Ed.), *Advances in Business Information Systems and Analytics* (pp. 220–237). IGI Global. https://doi.org/10.4018/979-8-3693-2823-1.ch011

Dodda, A. (2025). *Artificial Intelligence and Financial Transformation: Unlocking the Power of Fintech, Predictive Analytics, and Public Governance in the Next Era of Economic Intelligence*. Deep Science Publishing. https://doi.org/10.70593/978-81-988918-1-5

Erdilek Karabay, M., & Çağıl, G. (2017). Examining Financial Innovation and Performance in Financial Sector: A Comprehensive Review of Emerging Markets. In Ü. Hacioğlu, H. Dinçer, & N. Alayoğlu (Eds.), *Global Business Strategies in Crisis* (pp. 353–369). Springer International Publishing. https://doi.org/10.1007/978-3-319-44591-5_24

Erić, D. (2022). Innovation and Fintech. In D. B. Vukovic, M. Maiti, & E. M. Grigorieva (Eds.), *Digitalization and the Future of Financial Services* (pp. 19–39). Springer International Publishing. https://doi.org/10.1007/978-3-031-11545-5_2

Ferilli, G. B., Altunbas, Y., Stefanelli, V., Palmieri, E., & Boscia, V. (2024). Fintech governance and performance: Implications for banking and financial stability. *Research in International Business and Finance*, *70*, 102349. https://doi.org/10.1016/j.ribaf.2024.102349

Georgiev, L. (2024). Fintechs, Banks, and Financial Re-Intermediation. *Economic Alternatives*, *30*(3), 587–608. https://doi.org/10.37075/EA.2024.3.08

Ghanem, L. (2022). The economic essence of financial innovation and innovative transformation of financial services. *Economics and Management*, *28*(11), 1169–1180. https://doi.org/10.35854/1998-1627-2022-11-1169-1180

Giglio, F. (2021). Fintech: A Literature Review. *EUROPEAN RESEARCH STUDIES JOURNAL*, *XXIV*(Issue 2B), 600–627. https://doi.org/10.35808/ersj/2254

Gil-Corbacho, A., Miralles-Quirós, M. M., & Miralles-Quirós, J. L. (2023). Stock market performance differences between fintech and traditional financial firms. *Studies of Applied Economics*, *41*(1). https://doi.org/10.25115/sae.v41i1.9078

Gomber, P., Koch, J.-A., & Siering, M. (2017). Digital Finance and FinTech: Current research and future research directions. *Journal of Business Economics*, *87*(5), 537–580. https://doi.org/10.1007/s11573-017-0852-x

Goyal, N., Bajaj, P. K., & Saxena, D. (2025). Fintech Innovation, Financial Performance and Stability: A Systematic Literature Review and Bibliometric Analysis. *Abhigyan*, *43*(3), 227–238. https://doi.org/10.1177/09702385241299870

Hasan, I., Kwak, B., & Li, X. (2024). Financial technologies and the effectiveness of monetary policy transmission. *European Economic Review*, *161*, 104650. https://doi.org/10.1016/j.euroecorev.2023.104650

Imerman, M. B., & Fabozzi, F. J. (2020). A Conceptual Framework for Fintech Innovation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3543810

Jacobs, K., & Wang, K. Q. (2004). Idiosyncratic Consumption Risk and the Cross Section of Asset Returns. *The Journal of Finance*, *59*(5), 2211–2252. https://doi.org/10.1111/j.1540-6261.2004.00697.x

Jain, R., Kumar, S., Sood, K., Grima, S., & Rupeika-Apoga, R. (2023). A Systematic Literature Review of the Risk Landscape in Fintech. *Risks*, *11*(2), 36. https://doi.org/10.3390/risks11020036

Jarvis, R., & Han, H. (2021). FinTech Innovation: Review and Future Research Directions. *International Journal of Banking, Finance and Insurance Technologies*, *1*(1), 79–102. https://doi.org/10.61797/ijbfit.v1i1.126

Kapoor, A., Pokhriyal, S. K., & Kandpal, V. (2025). BALANCING VALUATION AND VALUE CREATION IN FINTECH STARTUPS. *ICTACT Journal on Management Studies*, *11*(3), 2156–2166. https://doi.org/10.21917/ijms.2025.0333

Kassamany, T., Naimy, V., & Dagher, G. (2025). *Impact of Fintech M&As on US and EU Acquirers' Market Performance: Evidence from COVID-19*. In Review. https://doi.org/10.21203/rs.3.rs-6002332/v1

Li, G. (2025). The Application of the Capital Asset Pricing Model in Corporate Risk Management. *Advances in Economics, Management and Political Sciences*, *158*(1), 162–168. https://doi.org/10.54254/2754-1169/2025.19766

Li, H. (2025). The Development of the Capital Asset Pricing Model and Its Applications in Modern Finance. *Advances in Economics, Management and Political Sciences*, *210*(1), 102–106. https://doi.org/10.54254/2754-1169/2025.BL26219

Li, W., & Ding, H. (2024). Research on the Impact of Technological Innovation on the Financial Services Industry. *Frontiers in Sustainable Development*, *4*(4), 109–119. https://doi.org/10.54691/8qneq173

Lin, X. (2014). Technology Adoption, External Financing Friction, and the Cross Sectional Returns. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2535409

Lu, L. (2024). Understanding Fintech. In L. Lu, *Global Fintech Revolution* (1st ed., pp. 11–44). Oxford University PressOxford. https://doi.org/10.1093/9780191884597.003.0002

Lyu, D. (2024). Analyzing the Risk-Return Trade-Off Relationship of Chinese New Energy Firms Using the Capital Asset Pricing Model. *Highlights in Business, Economics and Management*, *30*, 429–435. https://doi.org/10.54097/fwj7mr52

Maghyereh, A. I., & Cui, J. (2023). The Effect of Economic Policy Uncertainty on the Systemic Risk of Fintech Companies. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4476375

Matar, A. (2025). Dynamic Responses of Fintech Equity Returns to Financial Shocks, Geopolitical Risks, and Market Volatility. *International Journal of Advances in Soft Computing and Its Applications*, *17*(2). https://doi.org/10.15849/IJASCA.250730.18

Melati, Y. A. (2024). Fintech and financial performance in the banking industry: A literature review. *Asian Journal of Economics and Business Management*, *3*(1), 357–361. https://doi.org/10.53402/ajebm.v3i1.385

Moosa, I. (2022). *Fintech: A Revolution or a Transitory Hype?* Edward Elgar Publishing. https://doi.org/10.4337/9781802206340

Moro-Visconti, R., & Cesaretti, A. (2023). FinTech and Digital Payment Systems Valuation. In R. Moro-Visconti & A. Cesaretti, *Digital Token Valuation* (pp. 411–458). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-42971-2_13

Natarajan, B., & Ramkumar, A. (2024). Financial Technology during and beyond Covid-19 Era—An Evaluation. *Shanlax International Journal of Management*, *12*(1), 7–13. https://doi.org/10.34293/management.v12i1.7770

Nkatekho, B. (2024). The Impact of Fintech Innovations on Traditional Banking Systems. *International Journal of Finance*, *9*(4), 48–61. https://doi.org/10.47941/ijf.2116

Panova, G., Larionova, I., & Lengyel, I. (2021). Technological Revolution in Financial Intermediation. In I. Stepnov (Ed.), *Technology and Business Strategy* (pp. 51–68). Springer International Publishing. https://doi.org/10.1007/978-3-030-63974-7_4

Papanikolaou, D., & Schmidt, L. D. W. (2022). Working Remotely and the Supply-Side Impact of COVID-19. *The Review of Asset Pricing Studies*, *12*(1), 53–111. https://doi.org/10.1093/rapstu/raab026

Pástor, Ľ., & Veronesi, P. (2009). Technological Revolutions and Stock Prices. *American Economic Review*, *99*(4), 1451–1483. https://doi.org/10.1257/aer.99.4.1451

Petruk, O. M., Burtsev, Ya. I., Zaschipas, S. M., & Popov, O. H. (2023). Fintech as a concept of functional economic science. *Problems of Theory and Methodology of Accounting, Control and Analysis*, *3(53)*, 48–53. https://doi.org/10.26642/pbo-2022-3(53)-48-53

Philippon, T. (2016). *The FinTech Opportunity* (No. w22476; p. w22476). National Bureau of Economic Research. https://doi.org/10.3386/w22476

Qiang, X. (2024). Digital Transformation in the Financial Sector Through Fintech. *Advances in Economics, Management and Political Sciences*, *76*(1), 226–234. https://doi.org/10.54254/2754-1169/76/20241656

Qiu, B. (2025). A Review of the Theory and Development of the Capital Asset Pricing Model. *Advances in Economics, Management and Political Sciences*, *205*(1), 100–106. https://doi.org/10.54254/2754-1169/2025.BJ25531

Qiu, S. (2024). Analyzing the Impact of Fintech Innovation on Company Valuation. *Advances in Economics, Management and Political Sciences*, *99*(1), 8–16. https://doi.org/10.54254/2754-1169/99/2024OX0180

Rahman, A. A. A., Rahiman, H. U., Meero, A., & Amin, A. R. (2022). *FinTech Innovations and Islamic Banking Performance: Post pandemic Challenges and Opportunities*. In Review. https://doi.org/10.21203/rs.3.rs-1272120/v1

Reinganum, M. R. (1981). Misspecification of capital asset pricing. *Journal of Financial Economics*, *9*(1), 19–46. https://doi.org/10.1016/0304-405X(81)90019-2

Reshma, M., Jahnavi, B., Cherishma, A., & Hope, T. (2024). The Impact of Fintech Innovations on Stock Market Efficiency. *International Journal of Advanced Multidisciplinary Research and Studies*, *4*(6), 168–171. https://doi.org/10.62225/2583049X.2024.4.6.3410

Ruof, C. (2023). Fintech—What's New About It (and What Isn't)? In C. Ruof, *Regulating Financial Innovation* (pp. 105–152). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-32971-5_5

Sagala, I. Y. A., Sihite, M., & Napitupulu, M. (2023). The Effect of Financial Technology and Innovation on Financial Performance in The Digital Age. *Jurnal Sistem Informasi, Akuntansi Dan Manajemen*, *3*(2), 243–253. https://doi.org/10.54951/sintama.v3i2.566

Saha, S., & Kansal, A. (2022). FinTech: The New Normal Functioning of Financial Sector. *ECS Transactions*, *107*(1), 17143–17151. https://doi.org/10.1149/10701.17143ecst

Sánchez-Gutiérrez, J., Cabanelas, P., Lampón, J. F., & González-Alvarado, T. E. (2019). The impact on competitiveness of customer value creation through relationship capabilities and marketing innovation. *Journal of Business & Industrial Marketing*, *34*(3), 618–627. https://doi.org/10.1108/JBIM-03-2017-0081

Sandhya, A., Reddy, Dr. R., & (Dean Academics of AIMS IBS B-School). (2024). Capital Asset Pricing Model: Analysis, Flaws & Solutions. *International Scientific Journal of Engineering and Management*, *03*(12), 1–6. https://doi.org/10.55041/IJSREM39490

Sanyaolu, T. O., Adams Gbolahan Adeleke, Chidimma Francisca Azubuko, & Olajide Soji Osundare. (2024). Exploring fintech innovations and their potential to transform the future of financial services and banking. *International Journal of Scholarly Research in Science and Technology*, *5*(1), 054–072. https://doi.org/10.56781/ijsrst.2024.5.1.0033

Son, D., & Yoo, T. (2025). Wage Volatility and Firm Performance: The Roles of Foreign Ownership and Firm Growth Opportunities for Performance. *Academic Journal of Interdisciplinary Studies*, *14*(1), 1. https://doi.org/10.36941/ajis-2025-0001

Sophia, S. (2021). Financial Literacy and Financial Innovation, FinTech. *Journal of the International Academy for Case Studies*, *27*(1S), 1–1.

Talbi, M., Ferchichi, M. M., Ismaalia, F., & Samil, S. (2024). Unveiling COVID-19's impact on Financial Stability: A Comprehensive Study of Price Dynamics and Investor Behavior in G7 Markets. *International Journal of Economics and Financial Issues*, *14*(1), 216–232. https://doi.org/10.32479/ijefi.15643

Thakor, A. V. (2020). Fintech and banking: What do we know? *Journal of Financial Intermediation*, *41*, 100833. https://doi.org/10.1016/j.jfi.2019.100833

Thesmar, D., & Thoenig, M. (2011). Contrasting Trends in Firm Volatility. *American Economic Journal: Macroeconomics*, *3*(4), 143–180. https://doi.org/10.1257/mac.3.4.143

Thorbecke, W. (2023). The Impact of Monetary Policy on the U.S. Stock Market since the COVID-19 Pandemic. *International Journal of Financial Studies*, *11*(4), 134. https://doi.org/10.3390/ijfs11040134

Tien, P. P., & My, N. T. H. (2022). Performance measurement for fintech company. *HO CHI MINH CITY OPEN UNIVERSITY JOURNAL OF SCIENCE - ECONOMICS AND BUSINESS ADMINISTRATION*, *13*(1), 169–184. https://doi.org/10.46223/HCMCOUJS.econ.en.13.1.2100.2023

Tomar, S. (2015). Firm Volatility and IT. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2912440

Tompo, J. (2023). Exploring Asset Pricing Models and Market Efficiency. *Advances in Economics & Financial Studies*, *1*(3). https://doi.org/10.60079/aefs.v1i3.221

Toumi, A., Najaf, K., Dhiaf, M. M., Li, N. S., & Kanagasabapathy, S. (2023). The role of Fintech firms' sustainability during the COVID-19 period. *Environmental Science and Pollution Research*, *30*(20), 58855–58865. https://doi.org/10.1007/s11356-023-26530-3

Tsanis, K., & Stouraitis, V. (2022). Global Fintech Market: Recent Performance and the Effect of COVID-19 – Investigating the Impact of the Pandemic in the Financial Technology Sector. In H. C. Webb & H. Al Numairy (Eds.), *Advances in Human Resources Management and Organizational Development* (pp. 1–23). IGI Global. https://doi.org/10.4018/978-1-7998-8346-3.ch001

Varga, D. (2017). Fintech, the new era of financial services. *Vezetéstudomány / Budapest Management Review*, *48*(11), 22–32. https://doi.org/10.14267/VEZTUD.2017.11.03

Wan, Z. (2025). The Limitations and Evolution of the CAPM Model. *Advances in Economics, Management and Political Sciences*, *210*(1), 140–144. https://doi.org/10.54254/2754-1169/2025.BL26763

Wei, X., & Han, L. (2021). The impact of COVID-19 pandemic on transmission of monetary policy to financial markets. *International Review of Financial Analysis*, *74*, 101705. https://doi.org/10.1016/j.irfa.2021.101705

Xiang, C. (2025). Evaluating CAPM: Strengths, Limitations, and Alternative Asset Pricing Models. *Advances in Economics, Management and Political Sciences*, *145*(1), 37–41. https://doi.org/10.54254/2754-1169/2024.LD19020

Xie, Z. (2023). A Literature Study on the Capital Asset Pricing Model. *BCP Business & Management*, *40*, 162–166. https://doi.org/10.54691/bcpbm.v40i.4375

Xu, L., Liu, Q., Li, B., & Ma, C. (2022). Fintech business and firm access to bank loans. *Accounting & Finance*, *62*(4), 4381–4421. https://doi.org/10.1111/acfi.13023

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance Research Letters*, *36*, 101528. https://doi.org/10.1016/j.frl.2020.101528

Zhao, X. (2024). The Application of the Capital Asset Pricing Model (CAPM) in the Field of Asset Management. *Advances in Economics, Management and Political Sciences*, *71*(1), 144–149. https://doi.org/10.54254/2754-1169/71/20241459