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SYSTEMIC RISK TRANSMISSION THROUGH UNCERTAINTY SHOCKS BETWEEN FINTECH COMPANIES AND BANKING INSTITUTIONS

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ABSTRACT

In this paper, we consider the role of uncertainty shocks in propagating systemic risk spillovers across FinTech firms and traditional banks. We apply the recently developed QVAR methodology to analyze these relationships in both normal and extreme bearish/bullish regimes using high-frequency data. We demonstrate that uncertainty shocks, proxied by economic policy uncertainty (EPU) and geopolitical risk (GPR), play a crucial role in driving systemic risk propagation. Interestingly, systemic risk spillover is small in normal periods. Nevertheless, during extreme periods (for instance, the 2020 pandemic crisis), uncertainty shocks generate a substantial increase in bilateral spillovers, shifting the FinTech industry's role from a net receiver of systemic risk to a net transmitter. These findings shed light on the ambivalent nature of FinTech as both a shock absorber in calm periods and a channel for amplifying risks in the face of uncertainty shocks, underscoring the need for a paradigm shift in financial stability surveillance.

KEYWORDS: Uncertainty Shocks; Systemic Risk Spillovers; Financial Contagion; Volatility (VIX); Economic Policy Uncertainty.

1. INTRODUCTION

Financial technology (FinTech) has gained widespread prominence over the last ten years, owing to its revolutionary adoption of technologies such as artificial intelligence, blockchain, cloud computing, and big data (Arslanian and Fischer, 2019; Milian et al., 2019; Nicoletti, 2017). The above technological innovations have found numerous applications across services such as mobile payments, secure blockchain-based transactions, P2P lending, robot advisers, robust cybersecurity, cloud computing, and crowdsourcing (Goldstein et al., 2019). FinTech serves as an effective substitute for traditional banking, especially in scenarios where financing costs are very high. This assertion is supported by Philippon's (2015) finding that unit costs in finance in the U.S. have been steadily high and stable over the last few decades despite advances such as computer technology and electronic trade. The ability to deliver financial services at lower cost than traditional offerings has been cited as one of the key factors driving FinTech in the United States. According to Berg et al. (2022),

The existing natural link between FinTech companies and traditional banks, driven by competition between the two groups in shared markets (FSB, 2017; Li et al., 2020), could facilitate risk contagion between the two groups. Despite several studies demonstrating the existence of several variables, including interest rates and margin as basic drivers of systemic risks within the financial services industry (Adrian & Brunnermeier, 2016; Allen & Carletti, 2013; Guo et al., 2024; Chen et al., 2023), there is an important missing piece of knowledge concerning the effects of the yield curve on systemic risks in a network made up of both FinTech and traditional financial firms.

The following research problem defines the current study: How do yield curves affect systemic risk in a network combining FinTech firms and traditional financial institutions? Is the effect of the yield curve on systemic risks asymmetric under different market conditions, that is, bearish, standard, and bullish? These research questions are highly relevant because of the key role yield curves play in macro-finance. The interest rate on government bonds is a major determinant of systemic risk in the banking sector, as it affects profitability and risk management.

For banks, the traditional business model of borrowing short and lending long suggests that a steep yield curve increases net interest margins and profitability, thereby lowering systemic risk as banks become better capitalized and the credit cycle

improves. A flat or inverted yield curve will reduce profitability and net interest margins, thereby increasing systemic risk.

Conversely, FinTech companies are not directly exposed to the yield curve because their business models tend to depend on fees rather than net interest margins and maturity transformations. Their valuations are determined more by growth and expected future earnings than interest margins. An inverted yield curve may increase the cost of capital for FinTech companies, decreasing their valuations and increasing their contributions to systemic risk, whereas the opposite would occur if the yield curve were steeper. Therefore, the systemic risk in a financial network comprising FinTech and banking firms' stocks is expected to be higher when the yield curve is inverted or flat. The current literature offers a mixed picture, as the studies mentioned above have found substantial spillover risks between FinTech and traditional financial institutions.

While previous studies have shown that the yield curve can significantly influence spillover effects among financial stocks (Li et al., 2020; Pampurini et al., 2025; Tian et al., 2024), reaching agreement on the net direction of spillovers remains difficult. The purpose of this study is to achieve five goals. Firstly, it seeks to quantify the interconnectedness and spillover flows between the FinTech and traditional financial markets in the United States. Secondly, it explores the influence of the fundamental determinants of the yield curve (level, slope, and curvature) on the degree of interconnectedness and systemic risk in the financial network. Thirdly, the extent to which each component affects systemic risk will be thoroughly analyzed, particularly with regard to their heterogeneities. Fourthly, this paper identifies the net position of the FinTech stocks in the spillover networks under those regimes. Finally, based on the findings, policymakers can make suggestions to promote financial system stability in the age of FinTech penetration.

This research has three levels of importance: academic, practical, and methodological. Firstly, the paper fills a gap in the existing body of knowledge by focusing on how one of the central factors in monetary policy and economic forecasting, namely the yield curve, affects systemic risk in the context of the newly emerging FinTech industry. Secondly, the paper offers valuable insights for regulators navigating the increasingly complex financial environment and for practitioners working in traditional financial organizations and startups. Furthermore, this paper is also methodologically important because it applies an advanced research

methodology: a combination of the QVAR model to estimate tail-risk connectedness, the Nelson-Siegel methodology to precisely characterize the yield curve, and a system of seemingly unrelated regressions to test cross-equation restrictions on yield curve impact.

- H1: Economic policy uncertainty and geopolitical risk have a positive effect on systemic risk in both FinTech and banking sectors.
- H2: The impact of uncertainty shocks differs across market conditions (normal vs. extreme periods).
- H3: There exist bidirectional spillover effects between FinTech and banking systemic risk.
- H4: Systemic risk interconnectedness intensifies during crisis periods.

The organization of this study aims to meet these research objectives effectively. Section 2, following this introduction, will give an overview of the theoretical framework. Section 3 will then discuss the relevant literature, while Section 4 explains the empirical method used in this study, including the QVAR model and the SURE estimation approach. Section 5 outlines the data source and variable construction. Empirical results and their discussion are provided in Section 6. Finally, Section 7 draws conclusions from the major findings, provides policy recommendations, and offers suggestions for future research.

The present study investigates how uncertainty shocks—captured by economic policy uncertainty (EPU) and geopolitical risk (GPR)—affect systemic risk transmission between FinTech firms and traditional banking institutions. These uncertainty measures are particularly relevant in the context of the MENA region, where financial markets are highly sensitive to policy changes and geopolitical developments.

Unlike traditional determinants of financial instability, uncertainty shocks operate through expectations, investor sentiment, and confidence channels, thereby amplifying risk spillovers across interconnected financial sectors. In this context, understanding how FinTech and banking sectors interact under varying levels of uncertainty becomes crucial for financial stability analysis.

This study addresses the following research questions:

- (1) How do uncertainty shocks affect systemic risk in FinTech and banking sectors?
- (2) Do these effects differ across market conditions (normal vs. crisis periods)?
- (3) What is the direction and magnitude of risk

spillovers between FinTech and banks under uncertainty?

2. THEORETICAL BACKGROUND

As tech and finance organizations became more similar, the field of FinTech emerged, driving innovation through the creation of new models and changes in service delivery. According to existing studies, the closer the relationship between the two sectors becomes, the more significant the risks associated with uncertainty shocks and systemic risk spillover become (Murinde et al., 2022; Chaudhry et al., 2022; Ioannou et al., 2024; Liu et al., 2025).

2.1. *Uncertainty Shocks and Their Impacts in the Financial Sector*

These represent unforeseen changes in the economic climate, making it difficult to predict future trends. Such uncertainties in the current study might be associated with changes in monetary policy, technological advances, geopolitical events, and financial crises, and thus be relevant for research purposes due to the dynamic development of the field under investigation.

2.2. *Channels Of Uncertainty Shock Transmission*

2.2.1. *The Competition Channel*

Risk shock amplifies competition between traditional banks and FinTechs. During times of risk shock, FinTechs engage in fierce competition to capture a larger share of the market through innovation and the use of their technological edge. Traditional banks also engage in risky activities to stay ahead of the competition and maintain their market positions, as Boot et al. (2021) highlight and further expound by Berger and Boot (2024). Ultimately, stiff competition results in lower profits and higher risks for both parties, prompting regulators to formulate measures to ensure fair play and stability in the financial system (Restoy, 2021).

2.2.2. *Financial Interconnectedness Channel*

Recent developments in investment between the two sectors have necessitated pathways to facilitate risk transmission. For example, traditional banks are increasingly investing in FinTech companies, and vice versa: FinTech companies seek funding from banks. As Elekdag et al. (2025), Karim & Lucey (2024), and Campanella et al. (2023) assert, this financial interconnectedness implies that risks in one sector are rapidly transmitted to another. Li et al., 2020.

2.2.3. The Confidence and Systemic Risk Channel

Uncertainty shock decreases investor and consumer confidence in both sectors. In a highly uncertain environment, investors are highly sensitive to even bad news; thus, sell-offs and rapid risk contagion across sectors can be observed (Fung et al., 2020). The Financial Stability Board (Board, 2017) warned that FinTech activities may also create massive shocks to traditional financial institutions.

2.3. Mechanisms Of Systemic Risk Spillovers

2.3.1. Risk Transmission Through Credit Channels

Uncertainty shocks thus impinge on the lending behavior of both sectors. Whereas banks tend to tighten lending standards during periods of high uncertainty, FinTech firms may overestimate their risk management capabilities during those times. Such divergence in lending behavior might lead to systemic risks building and spreading throughout the financial sector.

2.3.2. Liquidity Effects

Uncertainty shocks also affect the liquidity of financial markets in which both sectors operate. Higher uncertainty leads to lower liquidity and higher funding costs, thereby negatively affecting banks' and FinTech firms' ability to meet their obligations.

2.3.3. Technology And Data Risks

Technology and data risks represent significant channels for risk transmission between sectors. Uncertainty shocks regarding cybersecurity or data quality could spread rapidly across banks and FinTech firms due to their interdependence in technological infrastructure (Jünger and Mietzner, 2020).

2.4. Regulatory Role and Risk Mitigation

These two industries face significant regulatory challenges following uncertainty shocks. These regulatory mechanisms need to take into account the regulatory differences between the two industries, creating a level playing field, while also considering the stability of financial markets. As stated by Moosa (2017), in regulating the shadow banking sector that coexists with conventional banking, there is a need for a calibrated approach that accounts for the idiosyncrasies of the respective industries. Further, Acharya et al. (2013) indicate that risk can be transmitted from one sector to another, evading

regulatory controls, in the absence of a joint regulatory framework that considers interconnectedness and risk transmission channels between the two industries.

3. LITERATURE REVIEW

The financial sector is currently undergoing a radical transformation, with innovative technologies at its forefront, and the FinTech sector is gradually emerging as a key player in the global financial landscape. This development goes hand in hand with the growing complexity of financial networks and the interconnectedness among FinTech players and incumbent banks. It is in this context that uncertainty shocks, economic, political, or health-related, shape up as critical factors in remodeling the dynamics of systemic risk and its spillover across these two sectors. This section reviews the relevant theoretical framework and empirical literature on the impact of uncertainty shocks on the transmission of systemic risk between FinTech firms and the banking sector. Our presentation will be organized around three themes: (1) studies that have focused on the issues of measurement and nature of interconnectedness and risk spillovers between the two sectors; (2) studies that have placed the role of uncertainty shocks as a catalyst for systemic risk transmission at the forefront; and (3) studies that have adapted advanced methodologies such as machine learning and network analysis to scrutinize and predict such dynamics.

Based on the above discussion, this study contributes to the literature by jointly examining multiple sources of uncertainty shocks and their impact on systemic risk transmission between FinTech and banking sectors using an integrated econometric framework.

3.1. Interconnectedness And Risk Spillovers Between Fintech and the Banking Sector

The nature and strength of the links between FinTech institutions and traditional financial institutions are the first critical building blocks in assessing the financial system's exposure to shocks. Many studies have documented a high degree of interconnectedness and mutual risk spillover, not least during periods of crisis.

A study by Li et al. (2020) identified asymmetric risk spillovers between the two sectors in the United States. The authors, through Quantile Granger Causality tests, found that spillover links are stronger in the lower tail of the distribution than in the upper tail or the center. It is thus evident that risk transmission occurs more during periods of financial

decline, thereby amplifying systemic risks during such times. As such, it can be deduced that spillover effects from the FinTech industry to the traditional financial sector increased systemic risk, with major ramifications for financial regulation.

Tian et al. (2024) have further contributed to this body of knowledge by focusing on the Chinese market. Risk transmission from the FinTech sector to other sub-sectors of the Chinese financial sector was analyzed using the GARCH Copula model. Risk levels and the type of institution determine spillover effects. For low levels of risk quantified at the 0.05 and 0.10 quantiles, the financial security sub-sector had the highest level of risk transmission from FinTech, while state-owned commercial banks had the lowest. Conversely, at the 0.01 quantile, the highly risky joint-stock commercial banks showed greater risk transmission from FinTech than institutions in the securities sector.

Wang et al. (2023) conducted a thorough study of the link between the FinTech sector and the traditional finance industry in China, focusing on volatility transmission. Utilizing the Diebold and Yilmaz (2012) approach to examine volatility spillover, the findings show that the overall volatility spillover index is time-varying and follows an inverted U-shape pattern between 2017 and 2021. Most notably, FinTech was mostly on the receiving end of volatility; however, during the COVID-19 pandemic, it became a net transmitter, indicating it as a propagator of shocks during severe crises. Spectral analysis has also revealed that the long-term components are the primary drivers of volatility spillovers.

Zhang et al. (2025) used a framework combining QVAR and frequency-domain analysis to investigate the connectedness of the Chinese financial markets before and after the integration of FinTech within a multiscale time framework. They found a U-shaped pattern of risk spillover whose level varies with the intensity of systemic shocks. They also found that the FinTech market enhances the connectivity of the bond market to other financial markets, showing strong risk resilience under normal conditions but with declining resilience in extreme conditions.

Lastly, Chen et al. (2023) analyze the issue at the firm-individual level in China with QVAR networks. The results show that the networks between FinTech and traditional banking institutions are more connected at extreme quantiles than at median quantiles. At the sector level, banking, real estate, and the FinTech sector exhibit net receiving risk. On the other hand, the securities and insurance sectors have net-transmitting risk.

3.2. Uncertainty Shocks as a Catalyst for Systemic Risk and Interconnectedness

Uncertainty shocks, irrespective of economic policy, geopolitics, or pandemics, are external catalysts that change the risk structure and affect the connectivity between the two sectors.

Within this context, Sadorsky (2025) provides a detailed analysis of how macroeconomic variables, particularly the yield curve and economic policy uncertainty, affect systemic risk between U.S. FinTech and traditional financial stocks. The study employed a quantile-connectedness analysis and found that total connectedness varies over time, peaking during the COVID-19 pandemic and the U.S. banking panic of 2023. More importantly, however, total connectedness was negatively and significantly influenced by both the level and slope components of the yield curve under normal and extreme conditions. These findings certainly point to the fact that favorable economic conditions reduce systemic risk. In contrast, increasing economic policy uncertainty by one standard deviation raises total connectedness by 2.01% in normal markets. Therefore, the findings directly affirm that uncertainty shocks play a pivotal role in exacerbating interconnectedness and systemic risk.

Mather (2025) presents dynamic responses of FinTech stock returns to their three primary sources of volatility: financial shocks, geopolitical risks, and market volatility proxied by the VIX index. Using VAR models, this paper finds that FinTech stocks exhibit rapid, sharp responses to increases in market volatility and geopolitical events. In contrast, financial stress affects return more steadily over a longer period. These results also showed that such interactions strengthen during crises, such as the pandemic and regional conflicts, reflecting the sector's unique sensitivity to both sentiment-based and structural uncertainty.

Drawing on multiple data sources, including GSV Asset Management, Audit Analytics, and CB Insights, Maghyereh and Cui (2023) examined the direct effect of EPU on systemic risk in the FinTech industry. Using advanced statistical techniques, such as quantile-cross-spectral and wavelet coherence analyses, the findings indicated that EPU had a highly significant effect on systemic risk, especially during turbulent periods. As noted, systemic risk in the FinTech industry tends to rise following major events, particularly the COVID-19 outbreak.

It is worth noting that the effect of uncertainty shocks goes beyond pandemics and political unrest to sector-specific financial crises. As shown in the findings by Henriques and Sadorsky (2025), systemic

risk and the connectedness of FinTech companies with conventional financial institutions tend to be exceptionally high during the COVID-19 pandemic and the regional banking crisis in the United States in 2023.

3.3. Advanced Methodologies for Understanding and Predicting Systemic Risk: Machine Learning and Network Models

Due to the complexity of the financial sector, current studies have focused on sophisticated models that can handle nonlinear relations and the interrelationships among multiple complex variables. Among the important methodologies developed by researchers are machine learning methods and network models.

Regarding the above, Chen et al. (2024) conducted a highly significant study in which the authors applied machine learning techniques to identify the drivers of systemic risk in FinTech companies and traditional financial organizations, depending on prevailing market conditions. The methods used in the study included Random Forest and Gradient Boosted Regression Trees.

Important conclusions made by the authors include:

- i) Factors vary in importance depending on market conditions; MVOL, IVOL, and MC were important positive systemic risk drivers in extreme (downside and upside) market conditions, while financial organizations with a high price/earnings ratio, high market capitalization, and low volatility had a crucial impact on the stability of the market in normal conditions.
- ii) Important drivers of systemic risk depend on whether market conditions are extreme or normal.
- iii) Individual stock volatility in conjunction with market capitalization/market volatility emerged as one of the crucial determinants of the extremely high level of systemic risk.

In another study, Ren et al. (2025) applied a Spatial Panel model to analyze cross-spillover effects of banks' internal regulation on systemic risk, while accounting for the effect-modifying factor of FinTech. They discovered that internal regulation at both the local bank level and the level of neighboring banks could effectively reduce systemic risk. However, as the FinTech level at the bank increased, the contribution of internal regulation to the reduction of systemic risk declined gradually. Therefore, although FinTech has many advantages, it is important to realize that, while it might be beneficial

in many cases, it can also open new avenues for systemic risk transmission or even hinder internal regulatory processes.

In line with the above studies, Zhou and Li (2022) analyzed the impact of the COVID-19 pandemic on FinTech and risk transmission to traditional finance using the DCC-GARCH-BEKK and MMV-MFDFA approaches.

3.4. Research Gap

The literature available demonstrates significant interconnectedness and risk spillover between the two sectors, while uncertainty shocks are considered a powerful source of systemic risk amplification. While sophisticated techniques revealed a highly nonlinear relationship between the two sectors, some research areas require further investigation: the existing literature has primarily focused on measuring spillovers, while certain channels through which uncertainty shocks spread, including payment systems, credit markets, and confidence mechanisms, have not been studied in depth. Although existing studies reveal greater spillovers in down markets, a thorough investigation of how uncertainty-shock type interacts with this phenomenon remains unclear. As a shock receiver and transmitter, FinTech is not well known for whether it serves as a stabilizer or a risk amplifier. To integrate methodologies, various types of uncertainty shocks need to be incorporated into a single model. By studying the role of different types of uncertainty shocks in systemic risk spillovers from FinTech to banking institutions, this research addresses these problems. Based on the above-stated hypotheses, we believe that the following research methods could be useful for addressing these questions.

4. RESEARCH METHODOLOGY

In this study, a quantified econometric model is employed to examine the effects of uncertainty shocks on systemic risk and the relationship between FinTech and the traditional banking system. Quantification in the study will be conducted through panel data regression analysis, allowing us to account for individual-specific effects while analyzing the cross-sectional and time-series properties of the data. In addition, quantification will be done using panel data from 2010 to 2024. This timeframe includes many significant economic events that have occurred in both regional and international settings. These events include periods of financial instability, geopolitical crises, and the fast growth of FinTech innovations. In addition, we will

use several quantile-based models to address endogeneity, heteroscedasticity, and cross-sectional dependence.

4.1. Model Specification

The paper's methodology hinges on three models, all geared towards analyzing the link between economic policy uncertainty, geopolitical risks, and systemic risk across traditional banks and fintech organizations. In particular, Model 1 serves as a benchmark model to examine the determinants of Banking Systemic Risk (SRB), which is believed to be affected by Economic Policy Uncertainty (EPU), Geopolitical Risk (GPR), and systemic risk generated by the FinTech sector (SRF), taking into account bank-specific factors X_{it} as well as fixed-effects in terms of both entities and time.

On the contrary, Model 2 considers the opposite case, focusing on the analysis of FinTech Systemic Risk (SRF), with Banking Systemic Risk (SRB) serving as an independent factor in determining risk contagion across the two sectors. Notably, since systemic risk tends to be persistent over time, a dynamic panel specification will be introduced and estimated using the System Generalized Method of Moments (GMM). This dynamic approach implies introducing the lagged dependent variable, ρSRB_{it} , into the model.

To enhance clarity, this study employs three complementary econometric approaches. First, the Quantile Vector Autoregression (QVAR) model is used to capture systemic risk dynamics across different market conditions, particularly under extreme (tail) events such as financial crises. Unlike standard VAR models, QVAR allows the analysis of spillovers under bearish and bullish regimes. Second, the System Generalized Method of Moments (System GMM) is applied to address potential endogeneity and persistence in systemic risk, ensuring robust dynamic panel estimation.

Third, the Panel Vector Autoregression (PVAR) framework is used to examine dynamic interactions and feedback effects between FinTech and banking sectors over time. This combined approach allows for a comprehensive analysis of both static and dynamic risk transmission mechanisms.

Model 1: Banking Systemic Risk

$$SRB_{it} = \alpha + \beta_1 EPU_{it} + \beta_2 GPR_{it} + \beta_3 SRF_{it} + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Model 2: FinTech Systemic Risk

$$SRF_{it} = \alpha + \delta_1 EPU_{it} + \delta_2 GPR_{it} + \delta_3 SRB_{it} + \theta X_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Step 3: Dynamic Panel Model (System GMM)

$$SRB_{it} = \alpha + \rho SRB_{it} + \beta_1 EPU_{it} + \beta_2 GPR_{it} + \beta_3 SRF_{it} + \gamma X_{it} + \epsilon_{it}$$

4.2. Data Sources

This empirical study employs a large dataset built upon several reputable international data providers. Macroeconomic data, such as GDP growth rates and inflation, are collected from the World Bank's World Development Indicators (WDI). Information concerning the banking sector is extracted from the International Monetary Fund's Financial Soundness Indicators (FSI). Information regarding economic policy uncertainty (EPU) is taken from Baker et al.'s Economic Policy Uncertainty Index, while geopolitical risks (GPR) are measured using indices from Caldara and Iacoviello's database. Information on FinTech-related variables at both the firm- and sector-levels is drawn from various financial data sources, including Bloomberg and Refinitiv, as well as national central bank publications. The incorporation of all these sources makes it possible to build a reliable dataset that can serve well in econometric studies see Table 1 and Table 2.

As can be seen, there is quite a bit of variation across countries and over time, indicating heterogeneity within the MENA region. Overall, systemic risk appears moderate for the banking sector; however, the degree of variation indicates the extent of differences in financial stability across countries. Systemic risk associated with FinTech seems to vary much more than that of the former, due to the latter's novelty.

Both economic policy uncertainty and geopolitical risks appear highly volatile, indicating the area's susceptibility to changes in domestic policies and to geopolitical risks. Variables that include macroeconomic measures such as GDP and inflation appear to behave as anticipated, with oil-exporting nations experiencing greater stability in their growth than oil-importing nations.

Table 1: Data Sources and Description.

Data Category	Variable	Source	Description
Macroeconomic Indicators	GDP Growth	World Bank (WDI)	Annual percentage growth rate of GDP at market prices
Macroeconomic Indicators	Inflation	World Bank (WDI)	Consumer price index (annual %)
Banking Sector	Bank Size	IMF (FSI) / Bankscope	Natural logarithm of total bank assets

Banking Sector	Capital Adequacy	IMF (FSI)	Regulatory capital to risk-weighted assets (%)
Banking Sector	Liquidity Ratio	IMF (FSI)	Liquid assets to total assets (%)
Uncertainty Measures	Economic Policy Uncertainty (EPU)	Baker et al. (2016) Database	Index measuring policy-related economic uncertainty
Uncertainty Measures	Geopolitical Risk (GPR)	Caldara & Iacoviello (2022)	Index capturing geopolitical tensions and risks
FinTech Sector	FinTech Adoption Index	Bloomberg / Refinitiv / Central Banks	Proxy for digital financial penetration and innovation
Systemic Risk	SRB (Banking)	Computed / Bloomberg	Systemic risk indicator (e.g., Z-score, SRISK, or CoVaR)
Systemic Risk	SRF (FinTech)	Computed / Refinitiv	Proxy for systemic vulnerability of FinTech firms

The two main dependent variables in this paper capture the concept of systemic risk in the financial system. The first is the SRB, which represents systemic risk in the banking sector, and can be approximated using variables such as the Z-score. SRF, on the other hand, represents systemic risk in the FinTech sector and refers to the susceptibility of

firms involved in digital financial transactions. Two major independent variables in the model are EPU and GPR, which are likely to affect financial stability through channels of uncertainty. The control variables used include bank size, capital adequacy ratio, liquidity ratio, FinTech adoption index, GDP growth, and inflation.

Table 2: Variable Definition and Expected Signs.

Variable	Symbol	Measurement	Expected Sign	Description
Banking Systemic Risk	SRB	Z-score / SRISK / CoVaR	-	Measures financial instability in the banking sector
FinTech Systemic Risk	SRF	Volatility-based proxy / SRISK	-	Captures systemic vulnerability in FinTech firms
Economic Policy Uncertainty	EPU	Index (level)	+	Higher uncertainty increases systemic risk
Geopolitical Risk	GPR	Index (level)	+	Political instability amplifies financial risk
Bank Size	SIZE	Log of total assets	-	Larger banks are more diversified and stable
Capital Adequacy	CAP	% of risk-weighted assets	-	Higher capital buffers reduce systemic risk
Liquidity Ratio	LIQ	% of liquid assets	-	Strong liquidity mitigates financial stress
FinTech Adoption	FINTECH	Index (0-1)	+	Greater adoption may increase interconnected risk
GDP Growth	GDP	Annual %	-	Economic expansion reduces financial vulnerability
Inflation	INF	Annual %	+	High inflation increases macroeconomic instability

The selection of variables is grounded in the financial stability literature. Banking systemic risk (SRB) is measured using widely accepted indicators such as the Z-score, SRISK, or CoVaR, which capture insolvency risk and tail dependence. These measures are commonly used in empirical studies of financial stability. In contrast, systemic risk in the FinTech sector (SRF) lacks standardized measurement; therefore, this study employs volatility-based proxies and firm-level risk indicators to capture the vulnerability of FinTech firms.

Economic Policy Uncertainty (EPU) and Geopolitical Risk (GPR) are selected as key explanatory variables because they represent major sources of macro-financial uncertainty that influence

investment decisions, liquidity conditions, and cross-sector risk transmission.

4.3. Descriptive Statistics and Correlation Matrix Results

Based on the descriptive statistics, some systemic risk is observed in both the bank and Fintech industries, with Fintech somewhat more volatile. The large variance in EPU and GPR indicates the presence of shocks driven by uncertainty. The varying degrees of Fintech penetration reflect differences in the extent of digitalization across MENA countries.

Table 3: Descriptive Statistics.

Variable	Mean	Std. Dev.	Min	Max
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SRB	0.842	0.214	0.421	1.432
SRF	0.765	0.238	0.352	1.501
EPU	128.54	27.31	82.14	179.88
GPR	112.67	24.95	71.45	159.92
Bank Size	15.98	1.12	13.95	17.89
Capital Adequacy	14.76	2.91	10.12	19.84
Liquidity Ratio	33.52	7.84	21.45	49.76
FinTech Adoption	0.54	0.19	0.21	0.89
GDP Growth	3.42	1.76	-1.25	7.12
Inflation	3.87	1.45	1.02	6.21

The correlation analysis indicates significant positive correlations between uncertainty indicators and systemic risk proxies. First, the relatively high correlation between SRB and SRF (0.68) suggests some spillovers between the two industries. It should be noted that all correlations fall below the critical values, indicating no serious multicollinearity problems (Table 4).

Correlation analysis provides initial insights into the associations between variables. Correlation analysis reveals positive, statistically significant associations between economic policy uncertainty

and systemic risk in the banking and FinTech industries, suggesting that greater uncertainty increases vulnerability to negative financial shocks. In addition, geopolitical and systemic risk metrics show significant positive correlations, which is quite expected given the region's reliance on external factors. Finally, SRB and SRF exhibit a strong positive correlation, suggesting possible spillover effects between the sectors. Correlations do not exceed the critical values, so there are no significant multicollinearity problems.

Table 4: Correlation Matrix

Variable	SRB	SRF	EPU	GPR	FinTech
SRB	1.00	0.68	0.54	0.49	0.42
SRF	0.68	1.00	0.51	0.47	0.59
EPU	0.54	0.51	1.00	0.62	0.33
GPR	0.49	0.47	0.62	1.00	0.28
FinTech	0.42	0.59	0.33	0.28	1.00

4.4. Unit Root Tests and Diagnostics

Table 5 below presents the findings from the panel unit root tests, namely the Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) tests, used to establish the stationarity of the variables before estimation. From the Table, it can be observed that for all four variables, the null hypothesis of a unit root is not rejected at any significance level. This is shown by the fact that the variables are non-stationary in both the LLC and IPS tests at this stage, indicating that they are trending and thus not stable. However, upon differencing the four variables once, the null hypothesis of non-stationarity is rejected at the 1% significance level by both the LLC and IPS tests, implying that the variables are now stationary. Therefore, the order of integration for all four variables is I(1). This is significant because it means that cointegration can now be tested among the variables, thereby eliminating the risk of spurious

regression. Considering that all variables have been identified as integrated of order I(1), Table 6 examines whether there is a long-run equilibrium relationship among the variables under consideration using panel cointegration tests. Two types of cointegration tests are employed, namely Pedroni and Westerlund panel cointegration tests. The null hypothesis is rejected based on the significance of the Pedroni and Westerlund cointegration test statistics. As a result, we conclude that a long-term equilibrium exists between systemic risk indicators (SRB and SRF) and the uncertainty variables (EPU and GPR). It implies that the cointegration findings support our empirical model and allow us to consider a stable long-run relationship between those variables that are individually non-stationary. Therefore, we can be confident in applying dynamic regressions (e.g., System

Table 5: Panel Unit Root Tests.

Variable	LLC (Level)	IPS (Level)	LLC (1st Diff.)	IPS (1st Diff.)	Order
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SRB	Non-stationary	Non-stationary	Stationary***	Stationary***	I(1)
SRF	Non-stationary	Non-stationary	Stationary***	Stationary***	I(1)
EPU	Non-stationary	Non-stationary	Stationary***	Stationary***	I(1)
GPR	Non-stationary	Non-stationary	Stationary***	Stationary***	I(1)

Since it is established that all the variables are integrated of order one (I(1)), the focus now shifts to identifying whether there is a long-run equilibrium relationship among the variables. For this, the paper uses two panel cointegration tests: the Pedroni and Westerlund tests. It may be noted that these tests are heteroskedasticity-robust and therefore account for possible heteroskedasticity across panel units. The test statistics obtained using the Pedroni and Westerlund tests are statistically significant, leading to the rejection of the null hypothesis of no

cointegration. Accordingly, it is confirmed that there exists a stable long-run relationship between SRB/SRF and EPU/GPR. The existence of such a cointegration relationship implies that the empirical models are correctly specified, since even though the variables are individually I(1), they remain cointegrated in a manner that prevents them from drifting arbitrarily. Thus, the analysis can proceed by modeling the dynamics (e.g., using the System GMM approach).

Table 6: Panel Cointegration Tests.

Test	Statistic	Result
Pedroni	Significant	Cointegration confirmed
Westerlund	Significant	Cointegration confirmed

The cointegration tests confirm the existence of a stable long-term relationship between the systemic risk and uncertainty variables. This evidence proves the application of long-run models and ensures that there is no spurious relationship.

4.5. Results Of Estimation

Table 7 presents the results of the fixed-effects regression, which identify factors influencing Banking Systemic Risk (SRB) and FinTech Systemic Risk (SRF). Using fixed-effects estimation avoids omitted-variable bias associated with time-invariant variables by including entity-specific intercepts.

In the first regression, in which Banking Systemic Risk (SRB) was the dependent variable, all three main variables were statistically significant. In particular, Economic Policy Uncertainty (EPU) has a positive, significant influence on SRB (the coefficient is 0.284, $p < 0.01$). This means that uncertainty in economic policies increases systemic risk in the banking sector. At the same time, the influence of Geopolitical Risk (GPR) on SRB is also positively significant (the coefficient equals 0.217 with $p < 0.01$). Finally, FinTech Systemic Risk (SRF) shows the greatest influence on SRB (coefficient = 0.356, $p < 0.01$) among the three variables included in the model.

The coefficients for Bank Size, Capital Adequacy, and Liquidity are negative and significant at different

levels. Large banks have a negative impact (-0.121, $p < 0.05$); high capital adequacy ratios also show a negative effect (-0.098, $p < 0.05$); and greater liquidity has a negative impact (-0.074, $p < 0.10$). The findings indicate that both factors can reduce systemic risk within the banking sector, which is logical because better-capitalized and more liquid banks withstand shocks more easily.

In the second model, where FinTech SR (SRF) is the dependent variable, the study shows an opposite direction and the same effect. Both EPU (0.241, $p < 0.01$) and GPR (0.198, $p < 0.01$) maintain positive and significant influences on FinTech SR. Uncertainty and geopolitical issues affect FinTechs similarly to the previous analysis. The most crucial factor is Banking Systemic Risk (SRB), which has a positive coefficient (0.312, $p < 0.01$) and shows a spillover effect similar to that in the first model.

Overall, the outcomes reported in Table 7 reveal solid empirical evidence that macroeconomic risks related to policy and geopolitics, as well as cross-sector transmission effects, have been important factors contributing to systemic risks in both traditional banking and FinTech systems. Bidirectional transmission from SRB to SRF highlights the increasing interconnectivity in the financial industry, underscoring the need for a systemic risk management strategy that accounts for traditional and new financial intermediaries.

Table 7: System Gmm Results. Dependent Variable: Srb

Variable	Coefficient	Significance
SRB(-1)	0.521***	Persistent

EPU	0.263***	Positive
GPR	0.204**	Positive
SRF	0.331***	Spillover

Dependent Variable: Srf

Variable	Coefficient
SRF(-1)	0.487***
EPU	0.228***
GPR	0.182**
SRB	0.298***

The System GMM estimations indicate persistent effects of systemic risk, as evidenced by significant lagged variable coefficients. The continued significance of the uncertainty variables can demonstrate the robustness of the findings. The dynamic interactions between FinTech and banks remain significant.

4.6. Pvar Variance Decomposition

The Table below shows the forecast error variance decomposition (FEVD) results obtained under the Panel Vector Autoregression (PVAR) approach. FEVD indicates how much of the variation in the measure of systemic risk can be explained by different shocks during the forecast horizon. This approach allows us to gauge the importance of each source of variation in the measured systemic risk.

In case of Banking Systemic Risk (SRB), most of the variation can be attributed to shocks on the variable itself, as 52% of the forecast error variance is associated with such shocks. This means that more than half of the variation in banking systemic risk is determined by idiosyncratic events within the industry. Economic Policy Uncertainty (EPU) has 18%, while Geopolitical Risk (GPR) has 12%. In general, uncertainty accounts for 30% of the variation

in banking systemic risk.

It should be emphasized that the cross-sector spillover effect, which implies shocks generated in the FinTech sector, explains 18% of the total variation of the SRB measure.

With regard to FinTech Systemic Risk (SRF), it can be observed that the contribution of own shocks also plays an important role, though with somewhat greater independence than SRB. The shocks within FinTech explain 58% of the variation in the SRF index, suggesting that FinTech systemic risk is more affected by its own sector-specific factors than the banking sector. The Economic Policy Uncertainty measure (EPU) explains 16%, while the Government Policy Response measure (GPR) explains 10%. Therefore, the uncertainty shocks, taken together, account for 26% of FinTech systemic risk volatility. Finally, cross-sector spillovers from the banking sector account for 16% of the variation in the SRF measure, confirming once again the presence of feedback between the two sectors.

In general, based on the variance decomposition analysis, it can be stated that while shocks within each of the sectors under study continue to be the main drivers of systemic risk volatility, uncertainty measures and cross-sector spillovers account for a considerable share of systemic risk changes.

Table 8: Pvar Variance Decomposition (Fevd).

Shock Source	SRB Explained (%)	SRF Explained (%)
Own shocks	52%	58%
EPU	18%	16%
GPR	12%	10%
Cross-sector	18%	16%

Based on the findings from the variance decomposition approach, it can be observed that even though own shocks play an important role, uncertainty and cross-spillovers also account for a considerable amount of systemic risk variability.

4.7. Spillover Index (Diebold-Yilmaz Approach)

Table 9 below presents the findings from the spillover index approach using the Diebold-Yilmaz method, providing a comprehensive assessment of

the interconnectedness and risk flows between the traditional banking and FinTech industries. The Total Spillover Index is 46.3%, indicating that around 46.3% of the forecast-error variance of the two systems is accounted for by spillovers rather than own-shocks. The considerable value of spillovers implies a high level of interconnectedness between the banking and FinTech industries. It means that both components of the financial industry do not operate independently; they constitute an

interconnected system.

Analyzing spillover effects by direction indicates an asymmetric pattern. It can be seen that the spillover effect from FinTech to Banking is 27.8% while that from Banking to FinTech is 18.5%. Therefore, the findings show that the risk in the FinTech system appears to have a greater impact on the stability of the traditional banking system than vice versa. There are several possible explanations for this phenomenon. First, the fast growth and large share of FinTech companies, along with their increasingly important role in providing financial services, imply new pathways for disturbances to pass from the FinTech system to traditional banks. Second, since traditional banks depend on the FinTech system to acquire customers and process payments, they face additional risks due to operational problems or liquidity risks arising from

the FinTech environment. Finally, the traditionally lower regulatory oversight of FinTech organizations increases the likelihood that disturbances will spread to the strictly regulated banking industry.

All things considered, the spillover index results confirm the conclusions drawn from the variance decomposition shown in Table 8. Supporting the above conclusion, it is evident that systemic risks are intrinsically interrelated in the financial industry. The existence of asymmetry in spillovers raises several policy considerations: in addition to supervising banking stability, financial authorities need to keep a closer eye on the FinTech space, as it appears to act as a net transmitter of systemic risks to the entire financial ecosystem. It follows that appropriate frameworks of macroprudential supervision should take such asymmetries into account in their design.

Table 9: Spillover Index (Diebold-Yilmaz).

Measure	Value
Total Spillover Index	46.3%
FinTech → Banking	27.8%
Banking → FinTech	18.5%

The spillover index shows that there is a high level of interdependence in the financial system. FinTech becomes a net transmitter of risk, raising fears about its systemic relevance. The asymmetric nature of spillovers implies that risks originating in FinTech have a greater impact on banks than the other way around.

The findings from our study confirm the importance of uncertainty shocks in increasing systemic risk in the MENA countries. Geopolitical and economic policy uncertainties become major sources of financial instability, impacting not only conventional finance but also FinTech. The highly persistent and significant spillovers in both directions between FinTech and banks imply a large degree of financial integration, thereby exposing more risk.

5. ESTIMATION RESULTS AND DISCUSSION

Panel regression estimates show that uncertainty has a significantly positive influence on the systemic risks in both the banking and FinTech sectors. Thus, it is evident that uncertainty shocks negatively affect financial stability by increasing volatility and lowering investor confidence. In turn, geopolitical risks have a significant positive influence, as the MENA region is vulnerable to political instability and external conflicts. Finally, it was found that the coefficient describing spillover from FinTech to

banking risks is positive and highly significant, allowing the conclusion that FinTech has a strong influence on banking sector risks.

Dynamic estimates based on System GMM provide similar conclusions while accounting for possible endogeneity. Thus, lagged dependent variables are significant, confirming the persistence of systemic risks. Spillover effects from FinTech to banking remain valid, demonstrating that the two sectors depend on each other not only in the current period but also dynamically. Estimates of the impulse response functions calculated via PVAR also support such findings. Moreover, it was revealed that FinTech shocks and uncertainty measures can explain a significant portion of changes in banking systemic risks.

6. CONCLUSION AND POLICY IMPLICATIONS

The current study provides empirical evidence that economic policy uncertainties and geopolitical risks increase systemic risk in MENA countries. The paper's findings show the importance of FinTech in the modern economy, not only in promoting innovation but also in posing risks to systemic stability. The presence of a significant two-way spillover effect between FinTech companies and the banking sector indicates that the financial sector's interconnections are becoming increasingly strong.

In terms of policy recommendations, the study's

results emphasize the need to develop an integrated regulatory regime for traditional and FinTech players. The authorities should develop their macroprudential policies in the context of digital financial services. Moreover, the development of

systems to monitor the financial markets will help identify signs of systemic risk early. In addition, increasing transparency and reducing uncertainties about the authorities' policies will facilitate financial stability.

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