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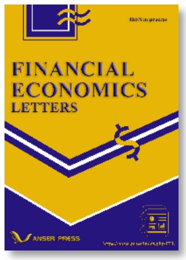


# The Impact of Economic Policy Uncertainty on Systemic Risk in the Fintech Industry: Evidence from Crisis Events and the COVID-19 Pandemic

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## ABSTRACT

This paper investigates the effect of economic policy uncertainty (EPU) on the systemic risk of the fintech industry. To achieve this goal, we first estimate the evolution of system-wide systemic risk using the CatFin method. We further examine whether EPU significantly affects systemic risk. Our findings demonstrate that the systemic risk of the fintech industry is time-variant and sensitive to major crisis events. Systemic risk tends to increase after major crises, especially the outbreak of the COVID-19 pandemic. EPU has a considerable impact on systemic risk, notably during periods of turmoil.

## KEYWORDS

Fintech industry; Systemic risk; CatFin; Economic policy uncertainty; COVID-19

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## 1. Introduction

The dynamic evolution of the FinTech sector, characterized by its technological innovations and disruptive impact on the traditional financial services industry, prompts an in-depth exploration of the potential risks it introduces to the broader financial system (FSB, 2019; Fung et al. 2020; Chaudhry et al. 2022). As FinTech continues to redefine financial services by offering faster, more cost-effective, and more accessible solutions, the rapid pace of innovation also brings forth new challenges. This paper focuses on the risks inherent in the FinTech sector, specifically addressing potential systemic risks arising from its interconnected nature.

The identified sources of systemic risk within the FinTech sector encompass cybersecurity threats, operational risks, platform concentration, regulatory arbitrage, and liquidity risk. The sector's dependence on digital platforms and processes makes it susceptible to cyber-attacks, which could disrupt financial services and lead to systemic risks (FSB, 2019). Concentration of market power in dominant platforms, such as payment processing and peer-to-peer lending, raises concerns about single points of failure and potential financial distress, amplifying systemic risks. Additionally, liquidity risk emerges as a significant threat, given the sector's operation with thin capital buffers and reliance on short-term funding. In the event of a sudden loss of investor confidence, these firms may struggle to meet their funding needs, leading to a liquidity crisis and disrupting the entire sector (Boukherouaa et al. 2021).

Recent unprecedented events, referred to as "Black Swan" occurrences, including the European debt crisis, the COVID-19 pandemic, and geopolitical conflicts like the Russia-Ukraine war, have cast uncertainties on the economic landscape. Recent studies document that uncertainty in economic policies related to the lack of clarity surrounding future government policies and regulatory frameworks adversely impacts economic activities (i.e. Baker et al. 2016; Shabir et al. 2021), corporate investment and profitability (i.e., Jory et al. 2020; Dreyer and Schulz, 2022); corporate investment in R&D (i.e., Borghesi and Chang, 2020; Cui et al. 2021); stock market risk (i.e., Kundu and Paul, 2022; Wang et al. 2022); and bank systematic risk (i.e., Nguyen, 2021; Duan et al. 2021, 2022; Shabir et al. 2021, 2023).

Despite the exponential expansion of fintech companies, the research pays scant attention to assessing the aggregate systematic risk of these companies or the impact of economic policy uncertainty on fintech systematic risk. One exception is Chaudhry et al. (2022), who have examined and compared the systemic risk of large FinTech companies to that of finance companies. Therefore, the purpose of this paper is to bridge that gap by analyzing the aggregate macro-level fintech systemic risk and identifying whether economic policy uncertainty adversely influences the fintech sector's systemic risk. One way that economic policy uncertainty can increase the systemic risk of fintech companies is by increasing the likelihood of a financial crisis. During times of economic uncertainty, investors may become more risk-averse and pull their investments from fintech companies. This can lead to a liquidity crunch, which can exacerbate the systemic risk of the fintech sector. Furthermore, when there is economic policy uncertainty, it can also lead to changes in regulations and policies for fintech companies. These changes can increase the costs of doing business or limit their market power, potentially leading to lower profitability, which in turn can increase the level of systemic risk in the industry. reater political and regulatory scrutiny during a period of high economic policy uncertainty in areas such as antitrust, data privacy, and cybersecurity can also further increase systemic risk in the industry.

This paper endeavours to undertake an examination with dual objectives. Firstly, it seeks to investigate the profound impact of recent unprecedented "Black Swan" events, notably the 2011 European debt crisis, the far-reaching COVID-19 pandemic, and the geopolitical tensions surrounding the 2022 Russia-Ukraine war, on the systemic landscape of the fintech industry. By scrutinizing the aftermath of these transformative events, the study aims to discern whether they have engendered substantial systemic risks within the fintech sector, thereby providing insights into the sector's resilience and vulnerabilities in the face of external shocks. Secondly, the paper aims to scrutinize the relationship between policy uncertainty and systemic risk within the fintech industry. The investigation will shed light on the interplay between policy-related uncertainties and the sector's systemic risk, offering valuable insights for regulators, policymakers, and industry stakeholders aiming to navigate and enhance the sector's resilience in the face of dynamic and uncertain economic environments.

To achieve our goals, we first estimate the evolution of system-wide systemic risk using the CatFin (Catastrophic Risk in the Financial Sector) method developed by Allen et al. (2012). Unlike institution-specific risk measures, the technique comprises a comprehensive framework for measuring collective catastrophic (tail) risk (Jalan and Matkovskyy, 2023). It incorporates various components of systemic risks, such as contagion, concentration, and interconnection. For robustness checks, employ the Turbulence Index (TI) developed by Kritzman and Li (2010). It provides a quantitative measure of the degree to which the financial markets are turbulent, considering drastic price swings, fragmentation of correlated assets, and asset market convergence. We use the novel quantile cross-spectral approach (QCSD) of Baruník and Kley (2019) to assess how policy uncertainty affects systemic risk. This approach enables us to measure variable structure dependence across quantiles (e.g., at high, normal, and low market stability) and time frequencies (e.g., short-term, medium-term, and long-term). Thus, compared to other methodologies that did not account for tail-dependency, the QCSD is more supportive at times of turbulence and during different economic statuses.

Our research makes noteworthy contributions to the existing literature in several crucial dimensions. Firstly, it pioneers the investigation into systemic risk dynamics within the fintech sector, providing a foundational understanding of its vulnerabilities to systemic shocks. Secondly, our research introduces an innovative empirical framework that unravels the intricate interactions between systemic risk and economic policy uncertainty. By accounting for complexities like nonlinearity and structural breaks, our study offers a nuanced perspective on the intertwining dynamics of economic policy uncertainty and systemic risk in the fintech sector.

The implications of our research extend far beyond the realm of academia. This study holds significant relevance for regulators and policymakers entrusted with shaping the regulatory landscape of the fintech industry. By uncovering the interplay between economic policy uncertainty and systemic risk, our findings empower regulators to formulate more informed and adaptive regulatory frameworks. Additionally, industry stakeholders in the fintech sector stand to benefit from our research, gaining valuable insights into the sector's resilience, vulnerabilities, and potential areas for strategic enhancement. Overall, our paper advances the understanding of systemic risk in fintech, offering actionable insights for practical decision-making within the industry.

## 2. Data

The sample consisted of the daily stock returns of the top thirty publicly traded fintech companies in the U.S. based on capitalization from January 3, 2011 to February 30, 2023, a time during which the fintech industry in the U.S. experienced significant development. The sample is drawn from the components of the KBW Nasdaq Financial Technology Index. The list of fintech companies included in the sample and summary statistics of their stock returns are provided in Table A1 of Appendix A.

To represent US economic policy uncertainty (EPU), we use the daily US EPU index constructed by Baker et al., (2016). It is constructed based on the frequency and tone of newspaper articles that mention economic policy uncertainty, as well as other indicators such as stock market volatility, tax code changes, and other economic policy-related data.

## 3. Methodology

### *3.1. Industry-level systemic risk*

The CatFin method is employed for estimating the systemic risk of the fintech industry. This approach utilizes the arithmetic average of three distinct Value at Risk (VaR) measures. Specifically, two of these measures are based on parametric distributions, namely the eneralized Pareto Distribution ( $\vartheta_{\mathrm{GPD}}$) and the Skewed eneralized Error Distribution ($\vartheta_{\mathrm{SGED}}$). The third measure utilizes a nonparametric VaR based on the cross-sectional distribution ($\vartheta_{\mathrm{NP}}$).

At a loss probability level of $\alpha$ for a sample size $N$, the VaR threshold ($\vartheta_{\mathrm{GPD}}$) is defined as:

$$\vartheta_{GPD} = \mu\left(\frac{\sigma}{\gamma}\right)\left[\left(\frac{\alpha N}{n}\right)^{-\gamma} - 1\right] \tag{1}$$

where $n$ is number of extremes losses of excess daily returns (lower tail) for fintech firms, $\mu$ and $\sigma$ are the mean and standard deviation of excess stock returns respectively, and $\gamma$ is the shape parameters of the PD.

To estimate the VaR threshold for the SED ($\vartheta_{\mathrm{SGED}}$) at a loss probability level of $\alpha$, we used the following equation:

$$\vartheta_{\mathrm{SGED}} = \int_{-\infty}^{\vartheta_{\mathrm{SGED}}} f_{\mu,\sigma,k,\gamma}\,(r_i)dr_i \tag{2}$$

where $f_{\mu,\sigma,k,\gamma}\,(r)$ is the probability density function, $\mu, \sigma$ are the excess stock return $r$, and $k$ and $\gamma$ are the tails and skewness parameters, respectively. Finally, the nonparametric VaR ($\vartheta_{\mathrm{NP}}$) is computed using the left tail of the empirical excess returns' distribution without placing any constraints on the density moments. Finally, the nonparametric VaR ($\vartheta_{\mathrm{NP}}$) is computed using the left tail of the empirical excess returns' distribution without placing any constraints on the density moments. In particular, the 1% nonparametric VaR ($\vartheta_{\mathrm{NP}}$) in a given month, is determined as the threshold for the lowest one percentile of the monthly excess returns on fintech firms.

Hence, in line with Allen et al. (2012), the definition of CatFin is as follows:

$$CatFin = \frac{\vartheta_{\mathrm{GPD}} + \vartheta_{\mathrm{SGED}} + \vartheta_{\mathrm{NP}}}{3} \tag{3}$$

As a robustness test, we calculate the Turbulence Index (TI) developed by Kritman and Li. (2010). The TI measures a state in which the behavior of financial markets is highly uncertain and unpredictable, characterized by extreme price movements, high volatility, and frequent changes in the direction of prices. Formally, the TI is defined as

$$TI_t = (r_t - \mu)\Sigma^{-1}(r_t - \mu)' \tag{4}$$

where $r_t$ is the vector of returns of fintech firms, and μ and $\Sigma$ are the sample average and variance-covariance matrix of historical returns, respectively.

## *3.2. Quantile cross-spectral (QCSD)*

As in Baruník and Kley (2019), let a set of $X_{t,T} = \left(x_{t,j1}, x_{t,j2}\right)^T$ are two strictly stationary process, the quantile coherency ($\Re^{j_1,j_2}$) can be written as[1]

$$\Re^{j_1,j_2}(\omega;\tau_1,\tau_2) := \frac{f^{j_1,j_2}(\omega;\tau_1,\tau_2)}{\left(f^{j_1,j_1}(\omega;\tau_1,\tau_1)f^{j_2,j_2}(\omega;\tau_2,\tau_2)\right)^{1/2}} \tag{5}$$

[1] For more details see Maghyereh and Abdoh (2020, 2021, 2022).

where $\epsilon(-\pi < \omega < \pi)$ and $(\tau_1, \tau_2) \in [0,1]$ are the time-frequency and τth quantiles, respectively. The quantile cross-spectral density $f^{j_1,j_2}$, $f^{j_1,j_1}$ and the quantile spectral densities $f^{j_2,j_2}$ are derived by taking the Fourier transform of the matrix of quantile cross-covariance kernels $\Gamma(\tau_1, \tau_2) := \left(f(\omega; \tau_1, \tau_2)\right)_{j_1,j_2}$, where

$$\gamma_k^{j_1,j_2} \coloneqq Cov\left(I\{X_{t+k,j_1,} \leq q_{j_1(\tau_1)}\}, I\{X_{t+k,j_2,} \leq q_{j_2(\tau_2)}\}\right) \quad (6)$$

For $j \in \{1, \dots, d\}$, $k \in \mathbb{Z}, \tau_1, \tau_2 \in [0,1]$, and I{A} is the event A indicator function. To calculate serial and cross-sectional dependence, we experiment with different values of K and restrict $j_1 \neq j_2$. This produces the following matrix in the frequency domain:

$$f^{j_1,j_2}(\omega; \tau_1, \tau_2) \coloneqq (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1,j_2}(\tau_1, \tau_2) e^{-ik\omega} \quad (7)$$

The smoothed quantile cross-periodograms are then used to estimate the quantile coherency. In accordance with Barunk and Kley (2019), we estimate the coherency matrices for the combinations of the three different quantiles $(0.05, 0.5, 0.95)$. These correspond, respectively, to the lowest, middle, and higher quantiles. We also provide the interdependence throughout a range of three timescales, from the very short-term (one week) to the more extended (one month) to the very long-term (one year), all of which correspond to $\omega \in 2\pi\{1/5, 1/22, 1/250\}$.

## 4. Results

### 4.1. Systemic risk

Figure 1 illustrates the evolution of systemic risk as estimated by CatFin. The figure reveals that systemic risk exhibits noteworthy time-varying attributes. Specifically, we observe a substantial increase in the risk measure during mid-2011, which coincides with the occurrence of the European debt crisis that had significant ramifications for economic policy uncertainty. Additionally, we identify another noteworthy upsurge in the CatFin metric after the emergence of the COVID-19 pandemic in early 2020. This unprecedented global health crisis has greatly amplified the transmission of risk across various financial markets, as documented by several scholars (Antonakakis et al., 2023; Yousaf et al., 2023, among others). The COVID-19 pandemic has expedited the implementation of digital technology within the financial industry, precipitating an unparalleled call for digital financial services. [2] However, the COVID-19 pandemic has also presented certain operational and funding impediments to the fintech sector. Indeed, several scholarly investigations have also ascertained an escalation in risk within the fintech domain during the COVID-19 pandemic, as evidenced by Zhou and Li (2022), Bhatti et al. (2022), and others.

In summary, our study highlights that systemic risk within the fintech industry exhibits a relatively stronger presence during times of extreme market conditions as compared to regular situations. This observation underscores the notion that systemic risk tends to amplify during recent "Black Swan" events, thereby emphasizing the need for investors, portfolio managers, and regulators to exercise dynamic monitoring of systemic risk in the fintech sector, especially during turbulent periods. Using TI, we find similar results (see Fig. 2), demonstrating the robustness of our findings.

[2] https://www.weforum.org/agenda/2020/10/covid-19-financial-technology-fintech-regulation/.

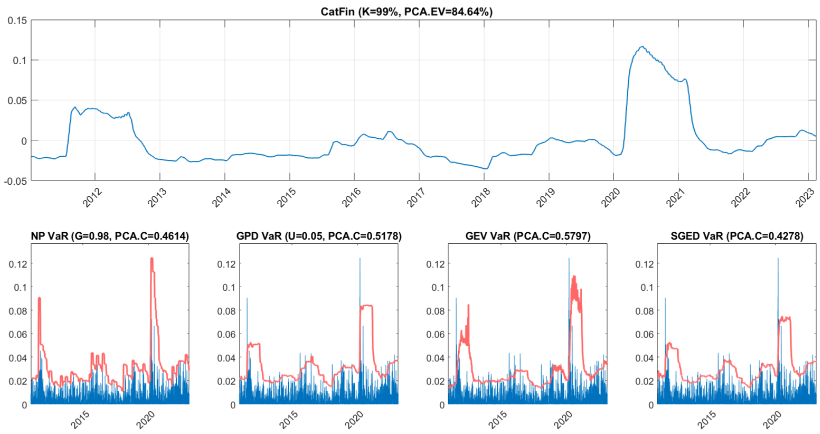


**Figure 1.** CatFin at 1% VaR.

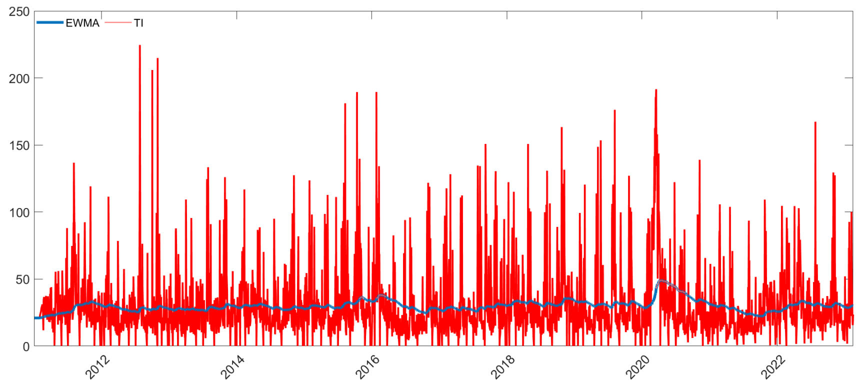


**Figure 2.** Turbulence Index (TI).

*Notes: EWMA is the exponentially weighted 30-day moving average of TI.*

## 4.2. Quantile cross-spectral results

To avoid spurious results, we conduct the stationarity test statistic for the variables before our empirical estimation. Table 1 shows the summary of descriptive statistics and unit root test results. The stationarity is examined using ADF (Augmented Dickey-Fuller) and PP (Phillips Perron) unit root tests and concludes that all variables are stationary, therefore meeting the conditions of the QCSD.

**Table 1.** Descriptive statistics and unit root tests.

| | CatFin | US EPU index | TI |
|---|---|---|---|
| Mean | 1.39E-17 | 121.3713 | 30.4963 |
| Median | -0.0111 | 98.4800 | 23.2310 |
| Maximum | 0.1285 | 807.6600 | 224.5762 |
| Minimum | -0.0358 | 3.3200 | 0.0455 |
| Std. Dev. | 0.0324 | 86.9203 | 25.5289 |
| Skewness | 1.9957 | 2.4686 | 2.5736 |
| Kurtosis | 6.6048 | 11.8466 | 12.2889 |
| Jarque-Bera | 3813.30*** | 13531.08*** | 14867.82*** |
| ADF | -3.2026** | -5.2536*** | -5.0299*** |
| PP | -3.1274** | -34.2023*** | -5.8812*** |

*Notes: **, *** denote statistical significance at 5% and 1% levels, respectively.*

Figure 3 shows the quantile coherency estimations. Our analysis reveals a relatively robust coherence (0.3) between CatFin and EPU for the upper quantiles of high returns (0.95|0.95) over a long-term period (yearly frequency). Conversely, the dependence between CatFin and EPU is comparatively weaker for the lower (0.05|0.05) and median return quantiles (0.5|0.5), although it is worth noting that the dependency for low return quantiles is somewhat stronger than for median return quantiles over the long-term horizon. These results suggest that the strength of the reliance between EPU and CatFin seems to be stronger during extreme market circumstances (i.e., at the tails of the distribution) than normal conditions (i.e., around the median of the distribution) over the long-term horizon.

For the mid-term (monthly frequency) and short-term (weekly frequency) horizons, the coherency for the high return quantiles (0.95|0.95) between CatFin and EPU is also the highest. This suggests that EPU has exerted more significant impacts on the systemic risk of the fintech industry during the upturn market conditions (i.e., upper quantiles of the joint distribution). This finding is supported by several studies. For instance, Zhang et al., (2022), Tiwari et al. (2022), Chen et al. (2022), and Mensi et al. (2023) found that the systemic risk spillovers among different financial markets are stronger during bullish market conditions.

For robustness, we also examine the quantile coherency between TI and EPU. We find that the coherency between TI and EPU for the median return quantiles (0.5|0.5) is the strongest in the long-term horizon (yearly frequency), followed by the extremely low return quantiles (0.05|0.05) as well as the extremely high return quantiles (0.95|0.95). When it comes to the mid-term (monthly frequency), the coherency for the high return quantiles (0.95|0.95) becomes the strongest. Further, as for the short-term horizon (weekly frequency), the coherency between TI and EPU is highest for the extremely low return quantiles (0.05|0.05), followed by the extremely high quantiles (0.95|0.95) and median quantiles (0.5|0.5). We find that the quantile coherency results in the unreal parts also confirm this finding, i.e., the strength of the dependence seems to be stronger during extreme market circumstances than in normal conditions.

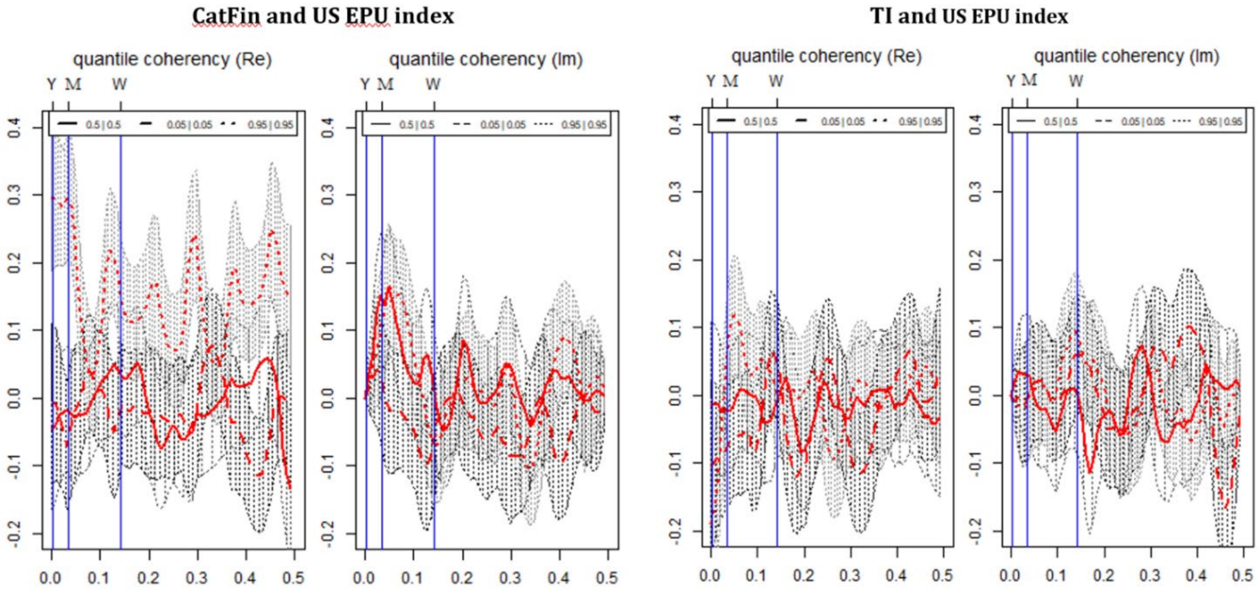


**Figure 3.** Quantile coherency.

*Notes: The figures show the real (left) and imaginary (right) components of the quantile coherency estimates at 0.05, 0.5, and 0.95 quantiles, with 95% confidence intervals. W, M, and Y stand for the weekly, monthly, and yearly, respectively.*

### *4.3. Additional test*

As a robustness test for our findings, we conducted the wavelet coherence analysis, introduced by Whitcher and Craigmile (2004). This methodology allows us to investigate how strongly two-time series are linked through time and across frequencies.[3]

The wavelet coherence is shown in Figure 4 for various time scales, from one day at the top of the plot to 1024 at the bottom. Time intervals are shown along the horizontal axis, while the scale is shown along the vertical axis. Significant dependency at 5% is shown by areas within the thick black line. The degree of dependency is indicated by coherency, which has values ranging from 0 to 1. Higher coherence is represented by the warmer red patches, whereas poor coherence is represented by the cooler blue parts. An arrow pointing right-up (left-down) indicates that the US EPU index positively (negatively) leads CatFin, while arrows facing right-down (left-up) indicate that CatFin positively (negatively) leads CatFin.

The findings show in the figures that CatFin is relatively highly coherent with both the US EPU index and TI, particularly during the European financial crisis and the COVID-19 outbreak over the long term. A rightward and upward arrow pattern suggests that the US EPU index has positive interconnectedness with CatFin and TI, with the US EPU index leading. Overall, our findings largely validate the QS approach's findings, demonstrating that the dependency between the US EPU index and both CatFin and TI is significant during crises and on a longer time scale.

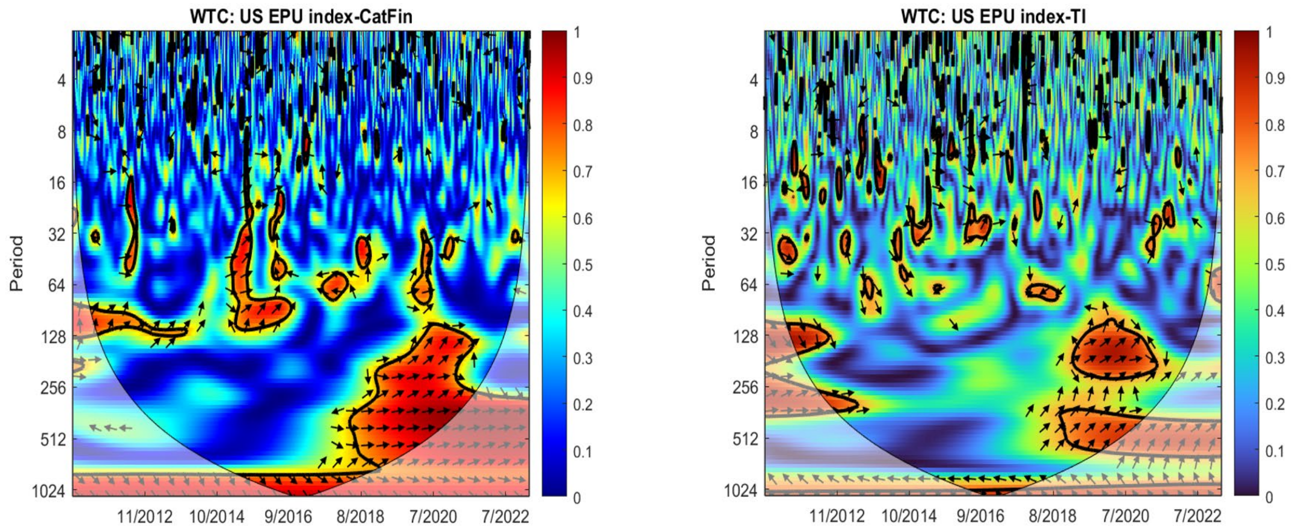


**Figure 4.** Wavelet coherence.

*Notes: The horizontal axis represents time, while the vertical axis represents frequency.*

## 5. Conclusion

Our findings reveal the time-dependent and precarious nature of systemic risk in the fintech domain, with a notable susceptibility to significant crisis events, notably the latest "Black Swan" episodes. Specifically, the degree of systemic risk within the fintech sector exhibits higher levels during extreme market conditions in contrast to normal circumstances. Furthermore, our research indicates that EPU has a considerable impact on systemic risk, notably during times of turmoil. Specifically, in the long run, the coherence between EPU and CatFin is stronger during extreme market conditions compared to normal situations. Our results demonstrate that EPU has a relatively high degree of coherence with both CatFin and TI, with EPU leading the systemic risk of the Fintech sector, especially

[3] It accounts for nonlinear structures, breaks, and cyclical patterns in dynamic variable interactions. For further details, see allegati (2008), Maghyereh et al. (2020), and Cui and Maghyereh (2023a,b).

during significant crises over the long term.

Our empirical results hold significant practical implications for investors, regulators, and policymakers. iven the time-variant and sensitive nature of systemic risk within the fintech industry, it is crucial for these stakeholders to dynamically monitor systemic risk, particularly during periods of crisis. In light of the substantial impact of EPU on systemic risk, investors with a long-term investment horizon are recommended to incorporate EPU into their fintech investment strategies. Moreover, regulators and policymakers should pay special attention to EPU in their risk management practices.

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## Conflict of interest

All the authors claim that the manuscript is completely original. The authors also declare no conflict of interest.

## Author contributions

Conceptualization: Aktham Maghyereh; Methodology: Aktham Maghyereh; Formal analysis: Aktham Maghyereh, Jinxin Cui; Writing – original draft: Aktham Maghyereh; Writing – review & editing: Aktham Maghyereh, Jinxin Cui.

## Appendix

**A1.** The list of the sample fintech companies and summary statistics of their stock returns.

| Company name | Ticker | Mean | Maximum | Minimum | Std. Dev. | Skewness | Kurtosis | Jarque-Bera |
|---|---|---|---|---|---|---|---|---|
| ACI Worldwide, Inc | ACIW | 1.43E-04 | 0.0634 | -0.0894 | 0.0090 | -0.3096 | 13.2113 | 13796.98 |
| WEX Inc. | WEX | 3.49E-04 | 0.0770 | -0.1561 | 0.0115 | -0.8977 | 20.1787 | 39330.06 |
| lobal Payments Inc. | PN | 2.56E-04 | 0.0513 | -0.0443 | 0.0061 | -0.2238 | 10.4107 | 7266.477 |
| Fiserv, Inc. | FISV | 3.30E-04 | 0.1219 | -0.1085 | 0.0111 | 0.0414 | 24.7134 | 62156.74 |
| Thomson Reuters Corp. | TRI | 1.09E-04 | 0.1201 | -0.1183 | 0.0115 | 0.3908 | 22.1834 | 48595.56 |
| Envestnet, Inc., | ENV | 2.00E-04 | 0.1110 | -0.1603 | 0.0086 | -0.8029 | 71.1692 | 612975.3 |
| Jack Henry and Associates | JKHY | 1.50E-04 | 0.0486 | -0.0883 | 0.0068 | -1.1121 | 21.3152 | 44875.11 |
| CoStar roup, Inc. | CSP | 3.55E-04 | 0.0689 | -0.0706 | 0.0085 | 0.2380 | 11.3337 | 9185.667 |
| Fair Isaac Corporation | FICO | 2.53E-04 | 0.0836 | -0.0737 | 0.0097 | -0.1003 | 12.1743 | 11101.52 |
| SS&C Technologies Holdings | SSNC | 2.42E-04 | 0.0605 | -0.0695 | 0.0073 | -0.6271 | 15.5672 | 21028.49 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Visa Inc. | V | 1.86E-04 | 0.0857 | -0.1872 | 0.0109 | -1.5993 | 37.6811 | 159915.4 |
| Western Union Company | WU | 4.62E-04 | 0.1176 | -0.1008 | 0.0093 | 0.8585 | 26.0763 | 70591.7 |
| Total System Services, Inc.. | TSS | 2.81E-04 | 0.0513 | -0.0792 | 0.0065 | -0.6985 | 16.4000 | 23929.16 |
| LendingTree, Inc.. | TREE | 2.67E-04 | 0.0643 | -0.0553 | 0.0083 | 0.1064 | 9.7655 | 6040.256 |
| Equifax Inc. | EFX | -1.52E-04 | 0.1479 | -0.4106 | 0.0155 | -7.3175 | 189.0384 | 4591027 |
| CoreLogic, Inc. | CLX | 2.20E-04 | 0.0852 | -0.0924 | 0.0082 | -0.3273 | 17.4240 | 27484.44 |
| JACK HENRY | JKHY | 2.39E-04 | 0.0404 | -0.0599 | 0.0059 | -0.6639 | 13.3291 | 14297.84 |
| Cardtronics PLC. | CATM | 3.84E-04 | 0.0667 | -0.0591 | 0.0075 | 0.2210 | 12.0934 | 10927.08 |
| Broadridge Financial Solutions, Inc. | BR | 3.92E-04 | 0.0650 | -0.0556 | 0.0088 | -0.0596 | 8.9745 | 4707.655 |
| SEI Investments Company | SEIC | 3.60E-04 | 0.0720 | -0.1357 | 0.0083 | -1.4274 | 32.2282 | 113698.3 |
| Nasdaq, Inc. | NDAQ | 2.73E-04 | 0.0565 | -0.0595 | 0.0069 | -0.1389 | 12.8200 | 12723.09 |
| MarketAxess Holdings Inc. | MKTX | 2.50E-04 | 0.0524 | -0.0775 | 0.0080 | -0.5842 | 12.6522 | 12462.3 |
| MSCI Inc. | MSCI | 1.29E-04 | 0.0500 | -0.0589 | 0.0073 | -0.6506 | 11.7534 | 10324.61 |
| reen Dot Corporation | DOT | 2.04E-04 | 0.1531 | -0.1513 | 0.0149 | 0.1765 | 15.6812 | 21216.89 |
| TOTAL SYS SERVS | TSS | 2.93E-04 | 0.0565 | -0.0693 | 0.0051 | -0.4322 | 23.1243 | 53489.47 |
| THOMSON REUTERS | TRI | 1.61E-04 | 0.0436 | -0.0509 | 0.0054 | -0.3873 | 12.1547 | 11127.87 |
| VISA INC-CLASS A | V | 3.49E-04 | 0.0607 | -0.0632 | 0.0068 | 0.2170 | 12.7226 | 12486.86 |
| VERISK ANALYTI | VRSK | 2.25E-04 | 0.0542 | -0.0490 | 0.0060 | -0.3488 | 14.9218 | 18801.58 |
| WEX INC | WEX | 1.94E-04 | 0.0962 | -0.1123 | 0.0101 | -0.5754 | 19.7844 | 37313.95 |
| WESTERN UNION | WU | -4.17E-05 | 0.0465 | -0.1488 | 0.0075 | -2.9506 | 57.6147 | 397818.7 |

*Notes: The sample daily stock prices are collected from the Thomson Datastream database. The stock returns are calculated as first difference of log daily prices.*

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