Vol. 33, No. 4 (2023) | DOI: 10.37190/ord230402

OPEN ACCESS

Operations Research and Decisions

www.ord.pwr.edu.pl

OPERATIONS RESEARCH AND DECISIONS QUARTERLY

Has the pandemic changed the relationships between fintechs and banks?

Barbara Będowska-Sójka[1] Agata Kliber[2*] Laivi Laidroo[3]

[1]*Department of Econometrics, Poznań University of Economics and Business, Poznań, Poland*
[2]*Department of Applied Mathematics, Poznań University of Economics and Business, Poznań, Poland*
[3]*Department of Economics and Finance, Tallinn University of Technology, Tallinn, Estonia*
[*]*Corresponding author, email address: agata.kliber@ue.poznan.pl*

Abstract

We examine the impact of COVID-19 on the banking and fintech sectors based on the relationships of the respective stock indices from December 2017 to April 2022. We analyse dynamic correlations within multivariate GARCH models and relationships in tails with the quantile coherency approach. Returns of fintech and banks dropped simultaneously at the beginning of the pandemic, but the analysis of cumulative returns and draw-downs reveals that the former recovered faster. Banks and fintechs experienced sharp declines together and fintech experienced extreme growth during the downfalls in the banking sector. However, the latter relationship disappears when we analyze only the banks from the USA and Eurozone. Thus, integrating with fintech may be especially beneficial for banks outside those regions. The ability of fintech to resurface and continue to grow demonstrates its importance in the financial system and confirms the shift toward a digital economy in financial markets.

Keywords: *fintech, banks, COVID-19, cumulative return, MGARCH model, quantile coherency*

1. Introduction

The recent decade has witnessed the emergence of an increasing number of companies, called fintechs, using or providing innovative digital solutions for the provision of financial services [25]. Following their appearance, some scholars have warned that such firms could pose a competitive threat to banks, their stability, and innovations in the industry [5, 26, 33]. Such results could occur if, over time, fintech services replace those provided by traditional financial intermediaries [34]. There exists some evidence that the emergence of fintech has already begun to harm the performance of financial intermediaries in some countries [30]. Still, it may also happen that traditional financial intermediaries catch up by adopting the same innovative technologies as fintechs. Several studies have already shown that the integration

Received 29 October 2022, accepted 17 August 2023, published online 22 December 2023
ISSN 2391-6060 (Online)/

The costs of publishing this issue have been co-financed by the program *Development of Academic Journals* of the Polish Ministry of Education and Science under agreement RCN/SP/0241/2021/1

of fintech by traditional financial institutions is associated with lower credit risk of the bank and superior profitability [9, 10, 37]. Traditional financial intermediaries may also be more resilient to shocks, as the risks in the fintech sector have been shown to remain higher than in the traditional finance industry [39].

The COVID-19 pandemic has impacted the performance of companies in various sectors (see, e.g., [4, 16, 29]). Constraints on physical mobility have contributed to an increase in the use of digital solutions, which have become the backbone of fintech activity. As fintech companies provide or operate services similar to banks, this may have increased the substitutability of traditional financial services to fintech services. Fu and Mishra [14] showed that in 71 countries, finance mobile app downloads increased between 29 and 33% during the lockdown. Similarly, Tut [35] reported an increase in mobile banking transactions and mobile banking accounts in Kenya with a simultaneous decrease in traditional electronic fund transfers. Najaf et al. [28] also found that the pandemic has increased customers' willingness to take longer-term, unverified P2P loans at higher interest rates. On the other hand, Chaundhry et al. [8] found that technology firms are riskier than traditional finance firms in terms of extreme tail risk. Thus fintechs may remain more vulnerable to the crisis [7, 23]. If the pandemic did not change customers' behaviour as indicated by Vasenska et al. [36], fintech performance would not have necessarily improved.

As noted by Schildbach and Schneider [32], the banking sector has not suffered considerably from the coronavirus slowdown. It was not affected directly by lockdown measures nor problems with broken supply chains. On the contrary, the demand for credit has grown, and trading activity in capital markets increased. However, the sector has been affected by reduced revenues in other areas and a surge in loan loss provisions.

This paper aims to determine whether the pandemic has triggered a significant structural change in financial markets that would empower already developing fintechs at the expense of banks. Assuming that the fintechs could have exercised their technological superiority, we test the hypothesis that fintechs and banks reacted to the pandemic similarly versus the alternative, that fintechs outperformed banks during the pandemic.

We examine the relationship between the fintech and banking sectors before and during the COVID-19 pandemic by analyzing the returns of indices representing the two sectors and investigating the dynamics of their interdependence. We use the iSTOXX Global Fintech 30 Index to represent the fintech sector and STOXX Global 3000 Banks Index, which represents the banking sector. The data sample starts on 01.12.2017 and ends on 11.04.2022.

We prefer using market indices to other performance measures for the following reasons. First, market indices capture the aggregate sector performance, which is also forward-looking. Second, while the activities of fintechs and banks cannot be directly compared on a company-by-company basis, market pricing allows for an assessment of developments. Third, identifying fintechs for a large sample survey would be complicated by the lack of industry classification for this area. Using market indices, we focus on the most significant players who have been identified as being involved in fintech.

We contribute to the fintech literature during the COVID-19 pandemic [14, 28, 35, 36] by taking an aggregate forward-looking view on the developments in the fintech sector. More specifically, we find evidence that although the returns of fintechs and banks dropped severely at the beginning of the pandemic, the former better adapted to the crisis and recovered faster.

We find that the correlation between fintech and bank indices was time-varying, with a remarkable but short-time increase at the beginning of the pandemic. That growth demonstrates that the two sectors reacted similarly to the crisis - but only in its initial phase. We also observe a long-lasting change in relationships between the extreme returns of the indices. More precisely, we reveal significant and positive coherence in the lower tails of the joint distribution, suggesting that, on average, declines in both sectors were synchronized starting from the pandemic. We also find a positive relationship between the asymmetric quantiles across various frequencies, which means that declines in the banking sector and increases in the fintech accompanied one another. The latter demonstrates better flexibility of the fintechs and their ability to adjust to the crisis. That indicates that the facilitation of fintech development and increased integration of fintech by traditional financial institutions could improve the resiliency of the financial sector to external shocks.

Nonetheless, the relationships disappear when we retain only American and Eurozone banks with the highest capitalization in the sample. That suggests that the abovementioned integration may be especially beneficial for enterprises outside these regions and could increase their market competitiveness.

To our knowledge, no previous study has compared differences in the performance of fintechs and traditional financial intermediaries before and during the COVID period. The exceptions are the work of Le et al. [21] and [22], who investigated the volatility transmission on financial markets and performed similar exercises for fintechs, green bonds, and cryptocurrencies. They show that Bitcoin and KBW NASDAQ financial technology index received more volatility spillovers during the COVID-19 pandemic than traditional financial assets, such as gold and currency. Our approach is different because we focus on the relationships between two types of enterprises offering similar financial services, fintechs and banks. We analyse the performance of these two sectors based on a time series analysis of their respective indices, and our main objective is to determine whether the pandemic has changed their mutual dependencies.

In the paper, Section 2 provides an overview of the method, and Section 3 describes the data. The results are provided in Section 4, with a robustness check in Section 5. Section 6 delivers the discussion and conclusions.

2. Methods

We study two types of relationships. First, we concentrate on volatility and time-varying correlation (MGARCH-DCC model). Then, we broaden the analysis by investigating relationships in the tails of the joint distribution. We use the estimates of volatilities obtained in the first research step to calculate the latter.

2.1. Dynamic conditional correlation models

As we examine the dependency between stock indices, the dynamic conditional correlation model appears to be a suitable choice. We apply the specification of [11], according to which the covariance matrix is specified in the following way:

$$H_t = D_t R_t D_t \tag{1}$$

where for the conditional constant correlation $R = (\rho_{ij})$ is a symmetric positive definite matrix with $\rho_{ii} = 1$ for each i, and

$$D_t = \mathrm{diag}(h_{11,t}^{1/2}, \ldots, h_{NN,t}^{1/2}) \tag{2}$$

In a general case, $h_{ii,t}$ can be defined by any univariate GARCH model.

The introduction of the dynamics into the conditional correlation requires R to be specified in the following way [20]:

$$R_t = \mathrm{diag}(q_{11,t}^{-1/2} \cdots q_{NN,t}^{-1/2}) Q_t \mathrm{diag}(q_{11,t}^{-1/2} \cdots q_{NN,t}^{-1/2}) \tag{3}$$

where Q_t is a symmetric positive definitive matrix such as

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha a_{t-1} a_{t-1}^{'} + \beta Q_{t-1} \tag{4}$$

$\overline{Q}$ is the $N \times N$ unconditional variance matrix of a_t, which are the residuals from the conditional mean equations, while α and β are nonnegative scalar parameters satisfying $\alpha + \beta < 1$.

2.2. Quantile coherency

We apply the quantile coherency measure proposed by Baruník and Clay [2]. The method allows an understanding of the behaviour of joint quantiles in return distributions and across frequencies. We study returns standardised by their volatility. The latter is approximated by GARCH-class models, estimated in the first step of the research. We investigate the behaviour of the fintech and bank indices. We apply a non-parametric quantile coherency method to study the dependence in quantiles across different frequencies of the data.

Let us denote by $(\mathbf{X}_t)_{t \in Z}$ the d-variate strictly stationary process with components $X_{j,t}$, where $j = 1, \ldots, d$. Let F_j denote the marginal distribution function, and $q_{j,t}(\tau)$ the corresponding quantile function, i.e., $F^{-1}(\tau) = \inf\{q \in R : \tau \leq F_j(q)\}, \tau \in < 0;\ 1 >$.

As a measure of cross-dependency structure of $(\mathbf{X}_t)_{t \in Z}$ we apply the matrix of quantile cross-covariance kernels $\mathbf{\Gamma}_k(\tau_1,\ \tau_2) = \gamma_k^{j_1, j_2}(\tau_1, \tau_2)_{j_1, j_2 = 1, \ldots, d}$, where:

$$\gamma_k^{j_1, j_2}(\tau_1, \tau_2) = \mathrm{Cov}\left(\mathbf{I}\{X_{t+k, j_1} \leq q_{j_1}(\tau_1), \quad \mathbf{I}\{X_{t+k, j_2} \leq q_{j_2}(\tau_2)\}\right) \tag{5}$$

The symbol $\mathbf{I}(A)$ denotes the indicator function that takes value 1 for $x \in A$ and 0 otherwise.

Barunik and Kley extend the concept to the frequency domain and define (under appropriate mixing conditions) the matrix of quantile cross-spectral density kernels

$$\mathfrak{f}\left(\omega; \tau_1, \tau_2\right) := \left(\mathfrak{f}^{j_1, j_2}\left(\omega; \tau_1, \tau_2\right)\right)_{j_1, j_2 = 1, \ldots, d}$$

where:

$$\mathfrak{f}^{j_1, j_2}\left(\omega; \tau_1, \tau_2\right) := (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \gamma_k^{j_1, j_2}\left(\tau_1, \tau_2\right) \mathrm{e}^{-\mathrm{i}k\omega} \tag{6}$$

Subsequently, the authors propose a quantile coherency kernel – the quantity that can be used as a measure for the dynamic dependence of the two processes:

$$\mathfrak{R}^{j_1, j_2}\left(\omega; \tau_1, \tau_2\right) := \frac{\mathfrak{f}^{j_1, j_2}\left(\omega; \tau_1, \tau_2\right)}{\left(\mathfrak{f}^{j_1, j_1}\left(\omega; \tau_1,\ \tau_1\right) \mathfrak{f}_{2,\ j_2}\left(\omega; \tau_2, \tau_2\right)\right)^{1/2}} \tag{7}$$

The authors define the estimator for the quantile cross-spectral density as the collection:

$$I_{n, R}^{j_1, j_2}\left(\omega; \tau_1, \tau_2\right) := \frac{1}{2\pi n} d_{n, R}^{j_1}\left(\omega; \tau_1\right) d_{n, R}^{j_2}\left(-\omega; \tau_2\right) \tag{8}$$

and call it the rank-based copula cross-periodograms, shortly, the CCR-periodograms, where:

$$d^{j}_{n,R}(\omega;\tau) := \sum_{t=0}^{n-1} I\left\{\hat{F}_{n,j}\left(X_{t,j}\right) \leq \tau\right\} \mathrm{e}^{-\mathrm{i}\omega t} = \sum_{t=0}^{n-1} I\left\{R_{n;t,j} \leq n\tau\right\} \mathrm{e}^{-\mathrm{i}\omega t} \tag{9}$$

$\hat{F}_{n,j}(x) := n^{-1}\sum_{t=0}^{n-1} I\left\{X_{t,j} \leq x\right\}$ denotes empirical distribution function of $X_{t,j}$, while $R_{n;t,j}$ – the maximum rank of $X_{t,j}$ among $X_{0,j}, \ldots, X_{n-1,j}$.

Let us denote the matrix of CCR-periodograms by:

$$\boldsymbol{I}_{n,R}\left(\omega;\tau_1,\tau_2\right) := \left(I^{j_1,j_2}_{n,R}\left(\omega;\tau_1,\tau_2\right)\right)_{j_1,j_2=1,\ldots,d} \tag{10}$$

Kley et al. [17] show that the CCR periodograms fail to estimate $\mathfrak{f}^{j_1,j_2}\left(\omega;\tau_1,\tau_2\right)$ consistently. Therefore, Baruník and Kley [2] propose to smooth $I^{j_1,j_2}_{n,R}\left(\omega;\tau_1,\tau_2\right)$ across frequencies. For this purpose, they consider:

$$\hat{G}^{j_1,j_2}_{n,R}\left(\omega;\tau_1,\tau_2\right) := \frac{2\pi}{n}\sum_{s=1}^{n-1} W_n(\omega - 2\pi s/n) I^{j_1,j_2}_{n,R}\left(2\pi s/n,\tau_1,\tau_2\right) \tag{11}$$

where W_n denotes a sequence of weight functions. The matrix of smoothed CCR periodograms is denoted as in [2]:

$$\hat{\mathfrak{R}}^{j_1,j_2}_{n,R}\left(\omega;\tau_1,\tau_2\right) := \frac{\hat{G}^{j_1,j_2}_{n,R}\left(\omega;\tau_1,\tau_2\right)}{\left(\hat{G}^{j_1,j_1}_{n,R}\left(\omega;\tau_1,\tau_1\right)\hat{G}^{j_2,j_2}_{n,R}\left(\omega;\tau_2,\tau_2\right)\right)^{1/2}} \tag{12}$$

and the estimators of quantile coherency are given by:

$$\hat{\boldsymbol{R}}_{n,R}\left(\omega;\tau_1,\tau_2\right) := \left(\hat{\mathfrak{R}}^{j_1,j_2}_{n,R}\left(\omega;\tau_1,\tau_2\right)\right)_{j_1,j_2=1,\ldots,d} \tag{13}$$

3. Data sources

Our dataset consists of one fintech index and one banking index. The data source for all series used in the study is Refinitiv (former Thompson Reuters). The iSTOXX Global Fintech 30 Index (hereafter STXFT3P, Refinitiv ticker: STXFT3P) comprises the 30 largest companies associated with fintech in the global market [31]. As an index approximating the condition of the banking sector, we chose the STOXX Global 3000 Banks Index (STOXXG, ticker: SXG83P). STOXXG includes banks from all over the world.

The sample period starts on 01.12.2017 and ends on 11.04.2022. Since we aim to compare the dependencies before and during the pandemic, we need to set the threshold date. Based on the observations of the returns and drawdowns of the indices (see Section 4.1.), we chose 10.02.2020 as the date that divides the entire study period into two sub-periods. This day precedes the deep price declines caused by the pandemic. We will explain this choice in more detail in the Results section.

Thus, we divide our sample period into two subperiods to reflect that threshold, i.e., from 01.12.2017 to 09.02.2020 and from 10.02.2020 to 11.04.2022. Figure 1 displays the dynamics of prices of all indices. The grey boxes indicate the second – pandemic sub-period.

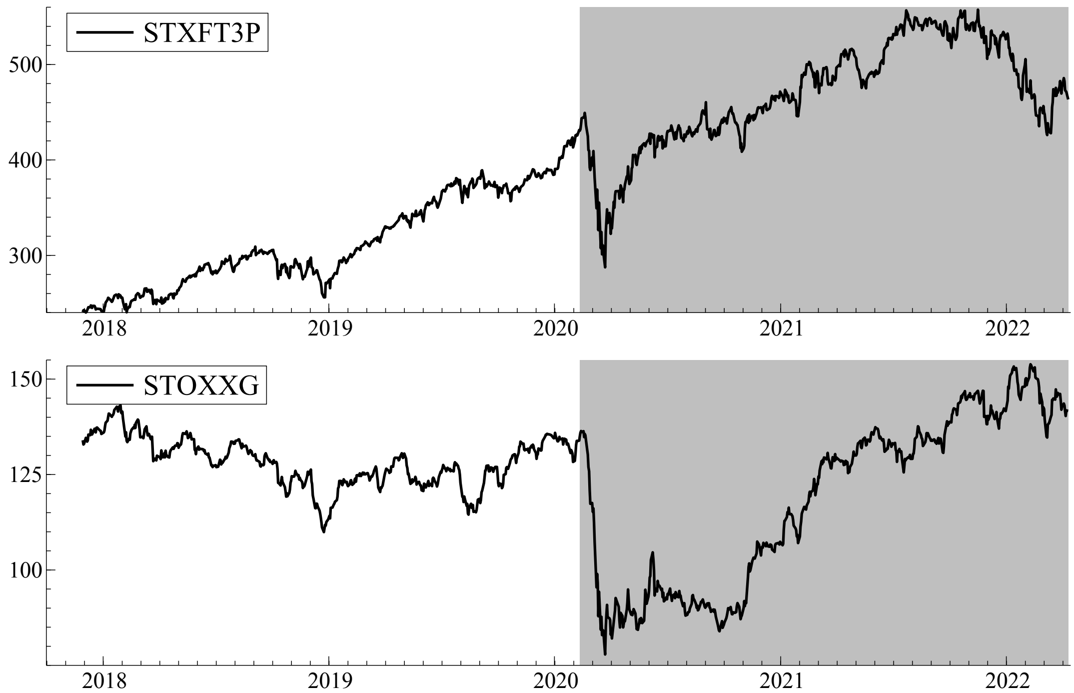

Figure 1. The prices of the fintech and bank indices.
The sample period starts on 1.12.2017 and ends up on 30.11.2021. The prices are recalculated to obtain price for all indices on 10.02.2020 – the date of the conventional beginning of the pandemic in our study. STXFT3P is for iSTOXX Global Fintech30, and STOXXG is for the STOXX Global 3000 Banks Index

4. Results

Our study is divided into three steps. We start by presenting the descriptive statistics, cumulated returns, and drawdowns within the sample period. Then, to examine measures of dependence, we estimate conditional correlations between the indices in our sample and check the strength of the correlations and whether they are time-varying. In the last step, we estimate the quantile coherency regressions and thus obtain the dependency measures in the case of extreme returns.

4.1. Descriptive statistics of the series and the cumulative returns

We examine the descriptive statistics of the log-returns in the whole period and in two subsamples and present them in Table 1. If the entire sample is considered, in both series the averages are not statistically significantly different from zero, and the returns from STOXXG are less volatile than those from STXFT3P. Both series are skewed to the left, and their excess kurtosis is higher than in the normal distribution, implying long tails and outliers. We also checked stationarity – according to the Kwiatkowski –Phillips–Schmidt–Shin statistics [18], both return series are stationary.

The comparison of the descriptive statistics in the subperiods shows that volatility approximated with the standard deviation is higher in the pandemic period than in the pre-pandemic one for both indices. There is a difference between the skewness observed for the pre- and pandemic subsample - STXFT3P has a lower value, while STOXXG has a higher value in the second period. The excess kurtosis for both series is much higher in the pandemic subsample than in the pre-pandemic; for both series, the minimum and maximum values in the whole period come from the pandemic subperiod.

Table 1. Descriptive statistics of the fintech and bank indices

Index[1]	Mean	Standard deviation	Skewness	Excess kurtosis	Min	Max
Whole period: 01.12.2017 to 11.04.2022, No. of observations: 1122						
STXFT3P	0.06	1.54	–0.58	13.99	–14.47	12.17
STOXXG	0.00	1.34	–1.23	16.52	–11.82	8.86
1st subperiod: 01.12.2017 to 09.02.2020, No. of observations: 561						
STXFT3P	0.10	1.10	–0.55	3.22	–5.21	5.73
STOXXG	0.00	0.77	–0.44	1.25	–3.00	2.42
2nd subperiod: 10.02.2020 to 11.04.2022, No. of observations: 561						
STXFT3P	0.02	1.87	–0.48	11.64	–14.47	12.17
STOXXG	0.01	1.73	–1.11	10.81	–11.82	8.86

[1] STXFT3P stands for iSTOXX Global Fintech30, while STOXXG is for the STOXX Global 3000 Banks Index.

Table 2 presents the comparison of the cumulative returns in the whole period and two subsamples (details referring to indices and time periods cf. Table 1). We find higher cumulative returns in the case of the fintech index, independently of the period analysed.

Table 2. The cumulative returns in the whole sample and subsamples [%]

Period	STXFT3P	STOXXG
Whole sample	65.58	5.59
Subperiod 1	57.10	–0.18
Subperiod 2	8.48	5.57

Our approach is complemented by the drawdown analysis, which shows the peak-to-through decline and thus indicates when, for a given period, the most significant drops in prices have begun. Such examination is intended to indicate the approximate date of the beginning of the pandemic. It also allows us to count the time it took for prices to recover. We perform the drawdown analysis for December 2019 and June 2021 and present the results in Table 3.

Table 3. The highest through-peak of the indices from December 2019 to April 2022[1]

Index	From	Trough	To	Depth	TT	Recovery
STXFT3P	20.02.2020	23.03.2020	04.02.2021	–0.38	23	224
STOXXG	13.02.2020	23.03.2020	02.06.2021	0.45	27	384

[1] From and Through mean the dates of the peak and the lowest values for the first biggest drawdown from 01.12.2019 to 30.11.2021. At To – the prices achieved the initial level (highest watermark) before the drawdown. Depth – the overall drop in prices, and TT shows how many days it takes to drop toward the lowest level (trough). Recovery – the number of days from the lowest point toward recovery.

For STXFT3P, pandemic-induced declines started on 20.02.2020. The end of the period of the largest losses (which accounted for 38%) was on 23.03.2020, while the recovery required 224 days. For STOXXG, the highest drawdowns began on 14.02.2020 with the most considerable loss of 45%. Both indices reached the lowest price level (Through) on the same day, 23.03.2020. In the case of the latter index, the price recovered on 02.06.2020 after 384 trading days. Based on this analysis, we chose the pandemic start date as the beginning of the week of the observed earliest highest peak[1].

4.2. Estimates of the dynamic conditional correlation models

To analyse the dependency between fintech and bank indices, we apply the multivariate conditional correlation models in a two-step procedure. First, we examined various univariate specifications and based on the information criteria, we chose ARMA(1-0)-GJR-GARCH(1,1) with skewed Student distribution. The estimates are presented in Table 4.

Table 4. The estimates from univariate ARMA-GJR-GARCH models with skewed Student t-distribution[1]

Index	μ	ϕ	ω	α	β	γ	Asymm.	Tail
				STXFT3P				
Coefficient	0.06	–0.03	0.08	0.02	0.83	0.22	0.80	8.46
Standard error	0.03	0.03	0.02	0.03	0.04	0.05	0.04	1.86
				STOXXG				
Coefficient	–0.01	0.11	0.03	0.04	0.88	0.14	0.87	6.74
Standard error	0.03	0.03	0.01	0.02	0.03	0.04	0.04	1.41

μ is a constant in the conditional mean equation, ϕ – an autoregressive term, ω – the constant in the conditional variance equation, α – the ARCH parameter, β – the GARCH parameter, γ – the leverage effect, Asymm. – the estimate of the symmetry (for a symmetric distribution $Asymm. = 1$), Tail – an estimate for the degrees of freedom within the skewed Student distribution.

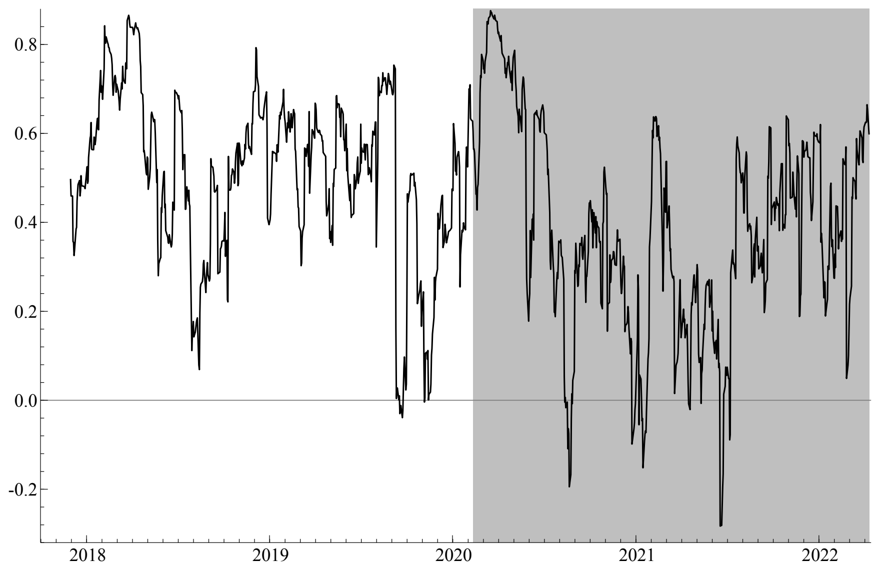

Figure 2. The conditional dynamic correlations estimated within the DCC model of [11] between fintech and bank indices. The vertical red line shows the date of 10.02.2021 which contractually signifies the beginning of the pandemic

[1]The actual date of the pandemic outbreak varies from study to study. Some researchers follow the WHO report [1] and indicate 31.12.2019 is the start date, while others tend to favour the timing of the restrictions [3, 6]. However, the latter were introduced on different dates and with different intensities. That makes it difficult to establish a single consistent date for all markets and instruments. We also took into account the dynamics of the Stringency Index (SI) calculated according to the Oxford Coronavirus Government Response Tracker (OxCGRT) report [15]. Its values indicate that the first restrictions were introduced in Asian countries in January, while in Europe and the Americas since early February.

Secondly, we estimated the multivariate GARCH dynamic conditional correlation model, MGARCH -DCC, in which we considered the multivariate Student distribution. To verify the goodness of fit, we conduct standard tests for autocorrelations in standardised and squared standardised residuals, both for univariate and multivariate specifications. We also apply Engle and Sheppard's test [12], which allows us to verify the correlation's stability over time. The null hypothesis states that the conditional correlation is constant, while the alternative is that the correlation is dynamic. We reject the null for our pair of indices as the p-value in the Engle-Sheppard test is < 0.001.

Figure 2 shows the dynamic conditional correlations between returns of the STXFT3P and STOXXG indices. We note the increase in the dynamic conditional correlation at the beginning of the pandemic period, which ends in mid-March (17.03.2020), with a correlation of 0.88. After that day, the dynamic conditional correlation starts to decrease.

4.3. The quantile coherency estimates

We also estimated the quantile coherency for the analysed pair to get more insight into the joint dynamics of the studied indices. It is well-known that time-varying volatility can create peaks in quantile spectral density [2, 24]. Therefore, to estimate the quantile coherency, we use residuals standardised with conditional standard deviations from the univariate GARCH models computed in the previous step of the research. Next, we estimate quantile coherency between the fintech and banking indices. With this approach, we discover the behaviour in the tails of the joint distribution of the indices. Additionally, we study the dynamics across various frequencies, which can be interpreted as investment horizons.

We estimate the smoothed periodograms (according to equation (12)) and the quantile coherency between the fintech and banking indices (equation (13)). That allows us to analyse interdependencies between the downfalls of both indices below their 0.05 quantile and their growths exceeding 0.95 quantiles, before and during the pandemic. Eventually, we study the coherence between the extreme negative returns in the banking sector and excessive positive returns in the fintech one.

In all graphs, we report the real part of the quantile coherency estimates of the joint distribution across different frequencies. The figures present the 95% confidence intervals. We interpret the relationship as significant if the interval does not include 0. The daily cycles over the interval $< 0; 0.5 >$ are presented on the X-axis. The Y-axis shows the co-dependence of the analysed series. We focus on three investment horizons: two days (2D), one week (1W), and one month (1M). For instance, the frequency $1/2 = 0.5$ means that there is a 0.5 cycle per day; hence, the whole cycle covers two days. Analogously, the frequency $1/5 = 0.2$ denotes five days (one week), and the frequency $1/22 \approx 0.045$ – 22-day period, which approximates one month. The frequencies are denoted in figures by red lines.

We present the results in Figure 3. There was no positive coherence between the most extreme negative returns in the pre-COVID period which means that the extreme drops did not occur at the same time (Figure 3a). Since during financial crises, the interrelationships between jointly affected markets tend to synchronize [13], we expected to see an increase in coherency between extreme negative returns during the COVID-19 period. That would imply crisis transmission across sectors. Indeed, we observe such relationships, but only for investment horizons shorter than a week (Figure 3b). When it comes to the joint increases, we do not observe such a situation in the pre-COVID but it appears during the COVID period for a short investment horizon (Figure 3c, d).

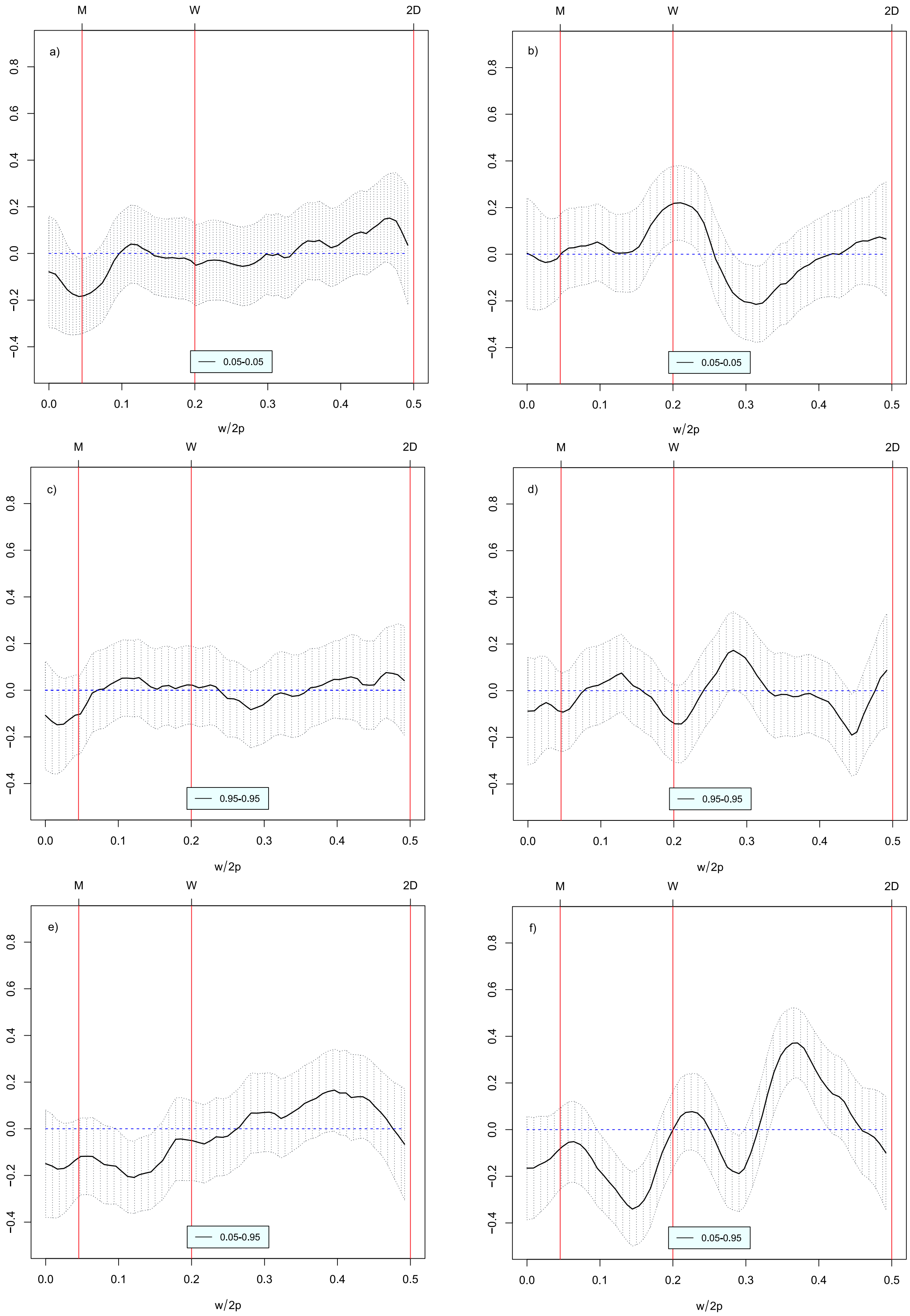

Figure 3. Quantile coherency estimates for the combination of quantiles STOXXG-SXFT3P:
a), b) 0.05-0.05 quantiles, c), d) 0.95-0.95 quantiles, e), f) 0.05-0.95 quantiles. 2D denotes the frequency for 2 days, W – weekly frequency, while M – monthly frequency. The left panel shows the pre-pandemic period, while the right panel shows the pandemic one

Ultimately, the most interesting analysis is the possibility of extreme increases in the fintech sector during extreme decreases in the banking sector. As we are aware that the latter did not suffer much during the current crisis, the extreme growth of the fintech sector during the short periods of decline in the banking sector would denote that fintechs took their chance during the pandemic. Indeed, in the pre-COVID period, we observed positive coherency between the 0.05-0.95 quantiles only for the short-term investment horizon between 2 days and a week. The situation changes during COVID, as the positive coherency interval covers a much wider set of short-term frequencies (Figure 3f). We observe intriguing changes in the tails of their joint distribution, suggesting that the fintech sector flourished during the pandemic.

5. Robustness check

As a robustness check, we calculate similar dependencies for a broader set of bank indices. In particular, we replace STOXXG with the MSCI World Banks Industry Index, which is composed of large and mid-cap stocks across 23 Developed Markets countries[2] and can be interpreted as another worldwide bank index. We also include two regional bank indices: ESTOXX – the Eurozone Banking Index (composed of 22 stocks[3]) and KBW Nasdaq Bank Index (KBWB). The latter is the oldest one in the banking sector listed since 1991. It includes 24 American largest regional and nationwide banking companies selected as representatives of this industry group. The index focuses specifically on banking and excludes components that would be heavily insurance-related or investment-oriented. Similar to others, the KBWB takes into account only the large-capitalization stocks. The source of the data of all indices is Refinitiv.

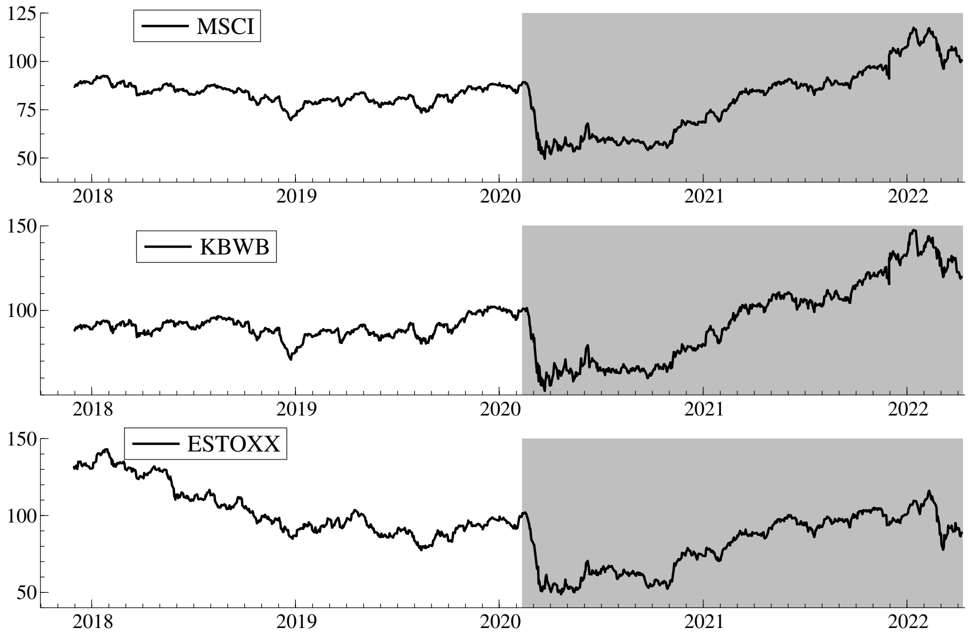

Figure 4. The prices of three bank indices: MSCI, KBWB and ESTOXX

[2]Those markets are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK, and the US [27].

[3]Data for November 2021

Figure 4 presents the series of these three indices while Table 5 presents the descriptive statistics for the bank indices included for the robustness check. The conditional correlations and the results of the constant conditional tests are presented in Table 6. All correlations between banking indices and the fintech index are dynamic.

Table 5. Descriptive statistics of the fintech index and remaining bank indices[1]

Index	Mean	Standard deviation	Skewness	Excess kurtosis	Min	Max
Whole period: 01.12.2017–11.04.2022, No. of observations: 1122						
MSCI	0.01	1.59	–0.51	17.92	–13.65	12.53
KBWB	0.03	2.19	–0.33	12.48	–18.36	14.52
ESTOXX	–0.04	2.05	–0.77	11.00	–18.12	13.02
1st subperiod: 01.12.2017–09.02.2020, No. of observations: 561						
MSCI	0.00	0.87	–0.33	1.16	–3.26	2.98
KBWB	0.02	1.28	–0.40	1.57	–4.91	5.12
ESTOXX	–0.05	1.31	0.03	0.64	–4.53	4.31
2nd subperiod: 10.02.2020–11.04.2022, No. of observations: 561						
MSCI	0.00	0.87	–0.33	1.16	–3.26	2.98
KBWB	0.02	1.28	–0.40	1.57	–4.91	5.12
ESTOXX	–0.05	1.31	0.03	0.64	–4.53	4.31

[1] MSCI is an abbreviation for the MSCI Banks Industry Index, KBWB is for KBW Nasdaq Bank Index, and ESTOXX denotes Euro STOXX Banks Index.

Table 6. The estimates of the constant conditional correlations and p-valuesin the stability test of Engle and Sheppard [12]

	STOXXG	MSCI	KBWB	ESTOXX
STXFT3P	0.50	0.47	0.49	0.24
p-value	(0.00)	(0.00)	(0.00)	(0.00)

[1] The values in the table represent the estimated of constant correlations between indices. In the brackets there are p-values of [12] constant correlation tests. The null hypothesis state that a correlation is constant versus the alternative that the correlation is dynamic.

In Figure 5, we present the relationships between the joint declines of fintech and banking indices. We note some differences between the American and European banks regarding their relationships with the fintech sector. We observe positive coherency between the joint declines of the American banks and the fintech sector for a much shorter interval of frequencies than in the Eurozone. That result supports the findings of [32], who note that major US banks have survived the crisis better than their European counterparts (in particular, they remained moderately profitable, despite setting aside far more funds to cover future loan losses).

In Figure 6, we present coherences between the joint increases above 0.95 quantiles. In the pre-pandemic period, the relationships were insignificant or negative for all pairs (except for Eurozone banks but for a very short interval of short frequencies). We observe synchronization of the extreme growths at some frequencies during the pandemic for all the pairs except STXFT3P–KBWB. We also point out that the frequency intervals of negative relationships (returns moving in opposite directions) during the pandemic were observed only for American banks paired with the fintech index.

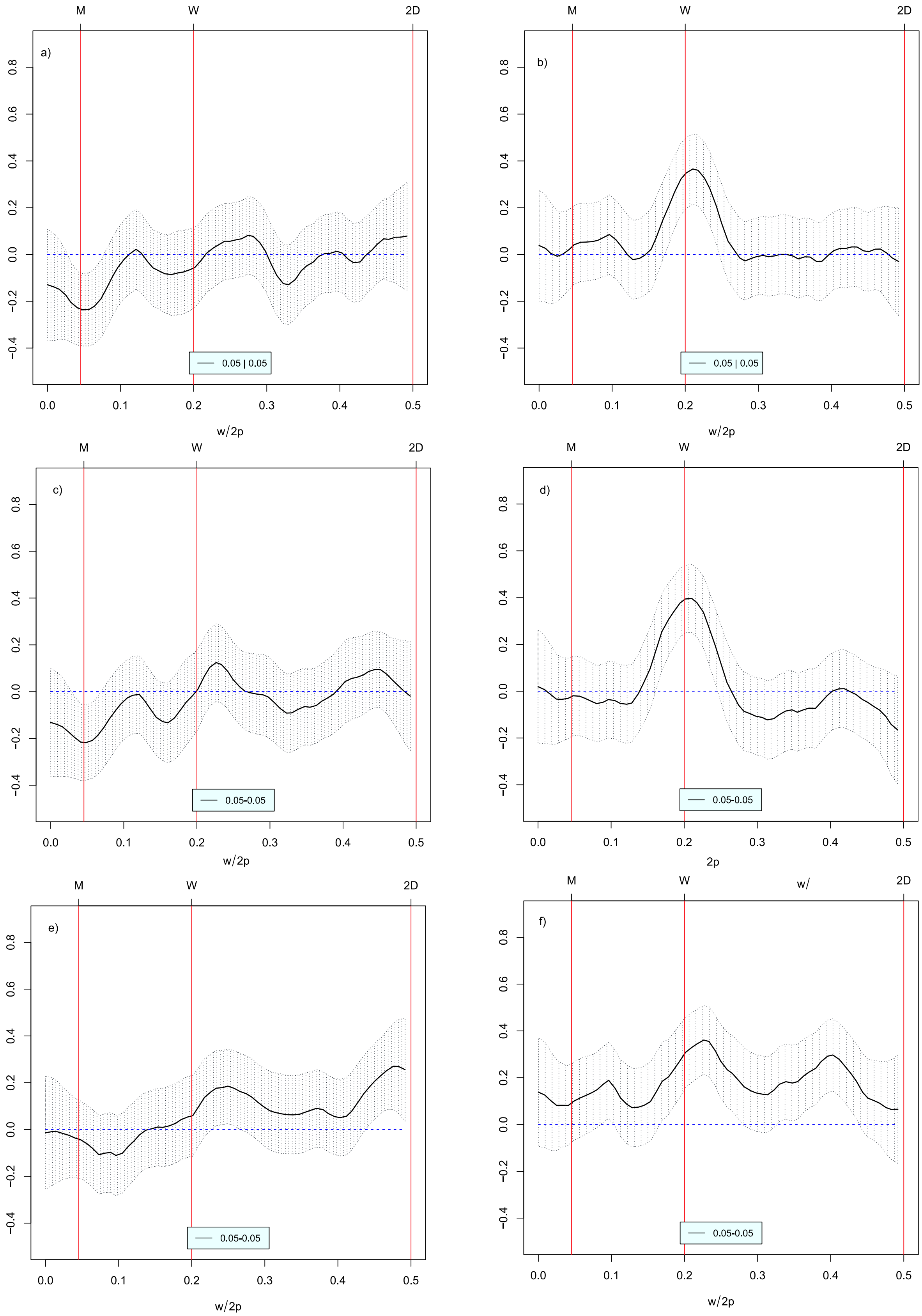

Figure 5. Quantile coherency estimates for the combination of 0.05 and 0.05 quantiles: a), b) are for SXFT3P-MSCI, c), d) for STXFT3P-KBWB, and e), f) for STXFT3P-ESTOXX. 2D denotes the frequency for 2 days, W – weekly frequency, M – monthly frequency. Left panel shows the pre-pandemic period, the right panel – the pandemic one

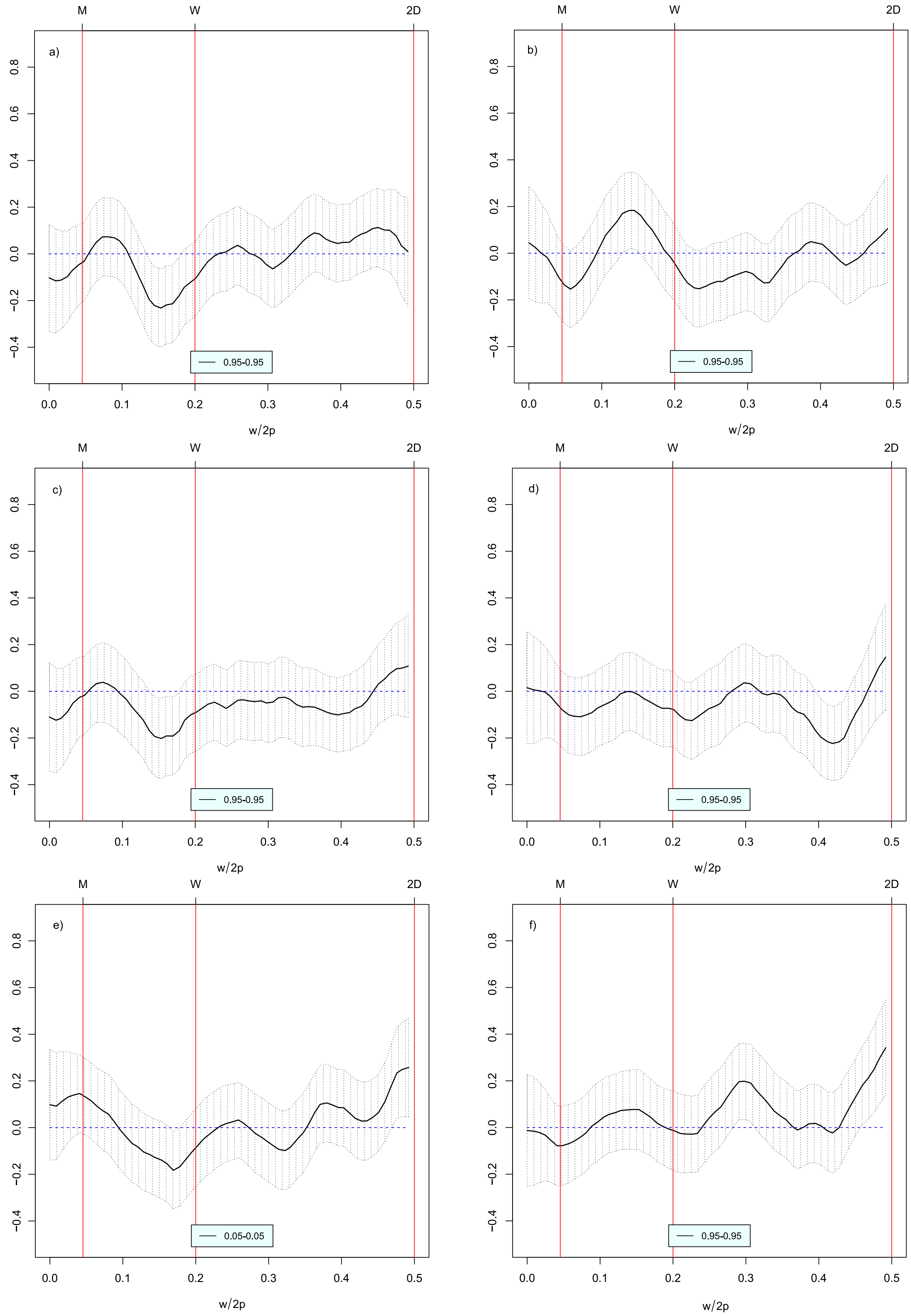

Figure 6. Quantile coherency estimates for the combination of 0.95 and 0.95 quantiles: a), b) for SXFT3P-MSCI indices, c), d) for STXFT3P-KBWB, and e), f) for STXFT3P-ESTOXX. 2D denotes the frequency for 2 days, W – weekly frequency, M – monthly frequency. Left panel shows the pre-pandemic period, while the right panel – the pandemic one

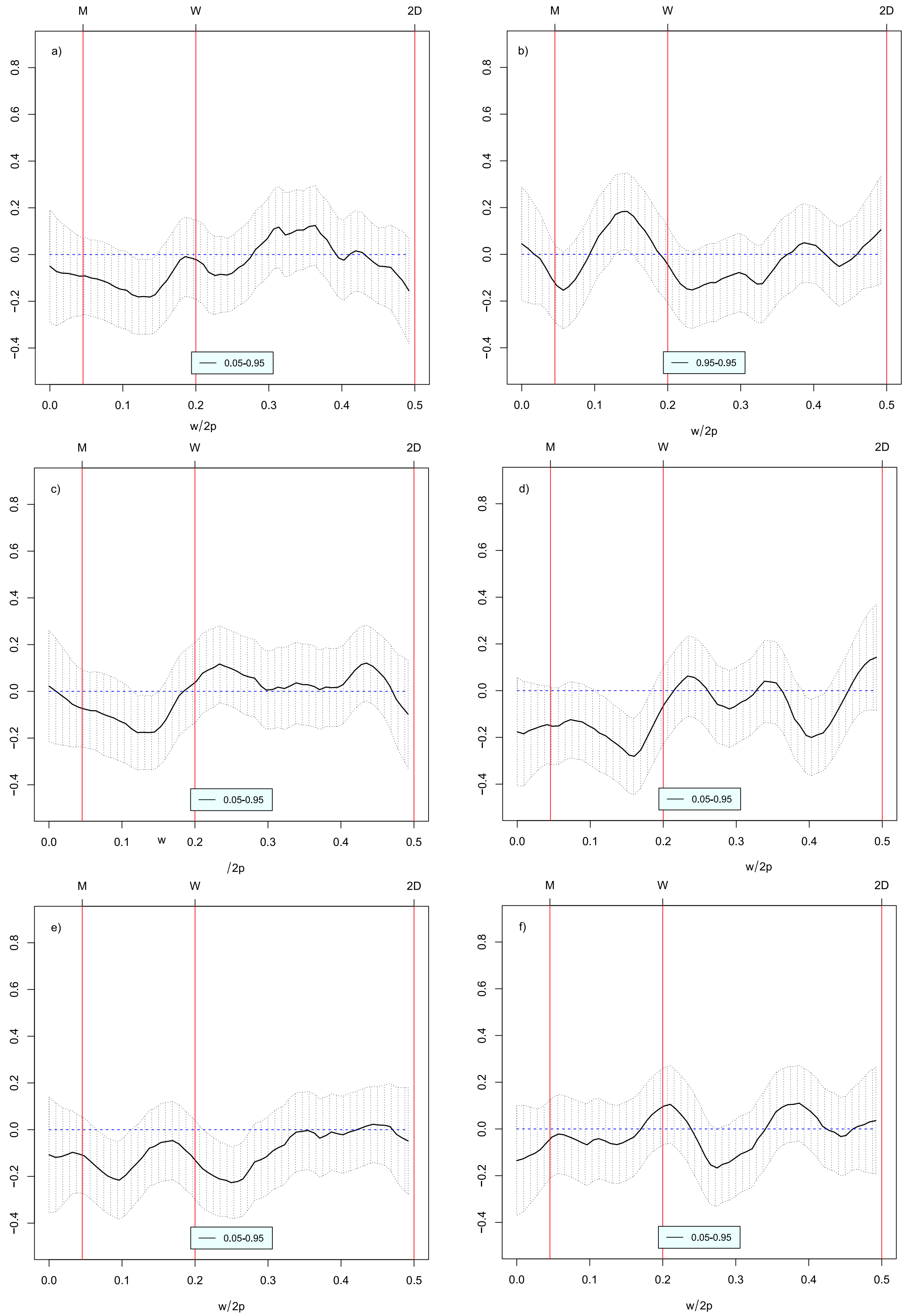

Figure 7. Quantile coherency estimates for the combination of 0.05 and 0.95 quantiles:
a), b) are for SXFT3P-MSCI indices, c), d) for STXFT3P-KBWB, and e), f) for STXFT3P-ESTOXX.
2D denotes the frequency for 2 days, W – weekly frequency, M – monthly frequency.
The left panel shows the pre-pandemic period, while the right panel shows the pandemic one

Based on the results presented in Figure 7, we suppose that there were episodes when excessive drops in the fintech sector accompanied the extreme increases in the American banks. Again, that confirms that the American banking sector is different to the European one. Eventually, in Figure 7, we present the coherence of the chances that the bank index falls below its 0.05th quantile, and at the same time, the fintech index jumps above its 0.95th quantile. No such relationships were present before the pandemic. During the pandemic, the results varied across the bank indices concerning the frequency when negative coherency was present. Nevertheless, regardless of the region studied, there were no such periods during which banks experienced drastic declines and - at the same time - fintechs experienced abnormal growths.

We note that this result differs from the one obtained for the STOXXG index, which encompasses the broadest set of banks. The MSCI, KBWB and ESTOXX indices include only a subset of the largest banks in the region or worldwide. Thus, the result suggests that banks' reactions to the crisis differed depending on their geographical location and size. It further implies that the cooperation between the fintech and banking sectors might be especially beneficial for banks outside the Eurozone and the US and smaller enterprises.

6. Discussion and conclusions

In this article, we show how the investment opportunities in the banking and fintech sectors have changed during the pandemic. Thus, we assess indirectly how the market valuation of the fintech sector as compared to the banking one has changed in the new reality. We analyse the returns of the fintech index SXFT3P and the banking index STOXX Global 3000. Three different banking indices, EuroSTOXX, MSCI World Banks, and KBW Nasdaq Bank Index, are used for robustness check. In the first step, we model the volatility of each instrument and analyse the changes in the dynamic correlations between each pair. We observe that, in each case, the correlation followed an upward trend from the beginning of the pandemic until mid-March 2020 and a downward one until September 2020.

The observed initial increase in correlation between fintechs' and banks' returns after the pandemic outbreak suggests that volatility transmission between the sectors had occurred or that both types of entities reacted similarly to the crisis. Nevertheless, the subsequent decline in the correlation signifies that one industry has performed better than the other during further phases of the pandemic.

To study the joint performance of both sectors in detail, we apply the quantile coherency method. The outcomes of this approach reveal that during the pandemic, the downfalls in the two sectors occurred simultaneously. At the same time, joint increases were less common and present only in the European market. For a relatively large set of frequencies, we also find a positive and statistically significant coherence between the increases in the fintech sector and decreases in the banking sector. The latter conclusion, however, does not apply to the largest banks, especially from the American market, which experienced abnormal growth during the episodes of extreme downfalls in the fintech sector.

It is often believed that the 2008 financial crisis was a stimulus for the development of the fintech sector [19]. Our results show that a short-term crisis in 2020 could have been a second driver of its accelerated growth. We demonstrate that fintech companies recovered faster than most of the banks during the COVID-19 pandemic. The phenomenon may stem from the greater adaptability of fintech firms to the changing conditions. Fintechs revolutionized the world of payments and lending, previously dominated by banks. This adaptability allowed them to experience higher growth in firm value compared to banks. From the policy perspective, it indicates that although the risks in the fintech sector may be higher [8], their presence may contribute to the enhanced stability of the financial sector as a whole immediately following the crisis. That can be achieved through the greater adaptability of fintech firms compared to slower-reacting traditional financial services providers. Therefore, the resiliency of the financial sector to external shocks could be enhanced through the facilitation of the development of the fintech sector while putting in place sufficient but not too strict risk controls. It also indicates that the increased integration of fintech by traditional financial institutions could potentially enable them to achieve the same aim. The latter might be especially beneficial for the banks outside the Eurozone and the US.

One can expect that the current crisis along with the increasing demand for digitization, will speed up further development of the fintech sector. Indeed, the various fintech reports confirmed the accelerated growth of this market. For instance, according to *The Global Covid-19 FinTech Market Rapid Assessment Report* [40], over the first and second quarters of 2020, fintech firms reported, on average, a year-on-year increase in their transaction numbers and volumes of 13% and 11%, respectively. Furthermore, the more stringent the COVID-19-related measures applied, the faster the growth of fintech firms was.

The *Report* also reveals that, due to the digital nature of the fintech delivery model, they could have reached unbanked and underbanked populations and, in this way, enhanced financial inclusion. Fintech companies reported that a large proportion of the clients were new customers and from groups that had traditionally faced challenges in accessing financial services.

Eventually, we observe differences in the relationship between the Eurozone and the American banking sector with fintech. Our results quantitatively support the observation that the major American banks have survived the crisis better than their European counterparts [32]. This can be because European banks – already before the pandemic outbreak – have been smaller and less profitable. Moreover, the US banks have consistently invested in technology in their capital markets businesses, which has not always been the case in Europe [38].

To summarize, fintechs seized their opportunity during the current crisis and overtook at least the smaller banks. There is also a piece of good news for those banks - although their recovery has taken much longer, we have observed that all banks' indices performed better in 2021. From the policy perspective, the facilitation of fintech development and increased integration of fintech by traditional financial institutions could improve the resiliency of the financial sector to external shocks.

Acknowledgement

The authors acknowledge the support of the Minister of Science and Higher Education of Poland through the Regional Initiative for Excellence programme, years 2019–2022, grant No. 004/RID/2018/19, financing 3,000,000 PLN. Barbara Będowska--Sójka acknowledges the support from Action CA19130-Fintech and Artificial Intelligence in Finance. Towards a Transparent Financial Industry (https://www.cost.eu/actions/CA19130/).

References

[1] Akhtaruzzaman, M., Boubaker, S., Lucey, B. M., and Sensoy, A. Is gold a hedge or a safe-haven asset in the COVID–19 crisis? *Economic Modelling 102*, (2021), 105588.

[2] Baruník, J., and Kley, T. Quantile coherency: A general measure for dependence between cyclical economic variables. *The Econometrics Journal 22*, 2 (2019), 131–152.

[3] Będowska Sójka, B., and Kliber, A. Impact of Covid-19 on sovereign risk: Latin America versus Asia. *Finance Research Letters 47* (2022), 102582.

[4] Brania, K., and Gurgul, H. Contagion effects on capital and forex markets around GFC and COVID-19 crises: A comparative study. *Operations Research and Decisions 31*, 2 (2021), 59–92.

[5] Bunea, S., Kogan, B., and Stolin, D. Banks versus FinTech: At last, it's official. *Journal of Financial Transformation 44* (2016), 122–131.

[6] Caferra, R., and Vidal-Tomás, D. Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the Covid-19 pandemic. *Finance Research Letters 43* (2021), 101954.

[7] Carlini, F., Del Gaudio, B. L., Porzio, C., and Previtali, D. Banks, FinTech and stock returns. *Finance Research Letters 45* (2021), 102252.

[8] Chaudhry, S. M., Ahmed, R., Huynh, T. L. D., and Benjasak, C. Tail risk and systemic risk of finance and technology (FinTech) firms. *Technological Forecasting and Social Change 174* (2022), 121191.

[9] Chen, X., You, X., and Chang, V. FinTech and commercial banks' performance in China: A leap forward or survival of the fittest? *Technological Forecasting and Social Change 166* (2021), 120645.

[10] Cheng, M., and Qu, Y. Does bank FinTech reduce credit risk? Evidence from China. *Pacific-Basin Finance Journal 63* (2020), 101398.

[11] Engle, R. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics 20*, 3 (2002), 339–350.

[12] Engle, R. F., and Sheppard, K. *Theoretical and Empirical Properties of Dynamic Conditional Correlation Multivariate GARCH*. Working Paper No. 8554, National Bureau of Economic Research, Cambridge MA, USA, 2001.

[13] Forbes, K. J., and Rigobon, R. No contagion, only interdependence: Measuring stock market comovements. *The Journal of Finance 57*, 5 (2002), 2223–2261.

[14] Fu, J., and Mishra, M. Fintech in the time of Covid-19: Technological adoption during crises. *Journal of Financial Intermediation 50* (2022), 100945.

[15] Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., Webster, S., Cameron-Blake, E., Hallas, L., Majumdar, S., and Tatlow, H. A global panel database of pandemic policies (Oxford Covid-19 government response tracker). *Nature Human Behaviour 5* (2021), 529–538.

[16] Just, M., and Echaust, K. Dynamic spillover transmission in agricultural commodity markets: What has changed after the Covid-19 threat? *Economics Letters 217* (2022), 110671.

[17] Kley, T., Volgushev, S., Dette, H., and Hallin, M. Quantile spectral processes: Asymptotic analysis and inference. *Bernoulli 22*, 3 (2016), 1770–1807.

[18] Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., and Shin, Y. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics 54*, 1-3 (1992), 159–178.

[19] Laidroo, L., and Avarmaa, M. The role of location in FinTech formation. *Entrepreneurship & Regional Development 32*, 7-8 (2020), 555–572.

[20] Laurent, S. *Estimating and Forecasting ARCH Models using G@RCH™ 8*. Timberlake Consultants Ltd, London, 2018.

[21] Le, L.-T. N., Yarovaya, L., and Nasir, M. A. Did COVID-19 change spillover patterns between Fintech and other asset classes? *Research in International Business and Finance 58* (2021), 101441.

[22] Le, L.-T. N., Abakah, E. J., A., and Tiwari, A. K. Time and frequency domain connectedness and spill-over among fintech, green bonds and cryptocurrencies in the age of the fourth industrial revolution. *Technological Forecasting and Social Change 162* (2021), 120382.

[23] Lee, C.-C., Li, X., Yu, C.-H., and Zhao, J. Does fintech innovation improve bank efficiency? Evidence from China's banking industry. *International Review of Economics & Finance 74* (2021), 468–483.

[24] Lee, J., and Rao, S. S. The quantile spectral density and comparison based tests for nonlinear time series, 2012. Technical report available from arXiv: https://arxiv.org/abs/1112.2759.

[25] Liu, J., Li, X., and Wang, S. What have we learnt from 10 years of fintech research? A scientometric analysis. *Technological Forecasting and Social Change 155* (2020), 120022.

[26] Locke, T. (7 April 2021). JPMorgan Chase CEO Jamie Dimon: Fintech is an 'enormous competitive' threat to banks (accessed on 19 June 2021).

[27] MSCI. (2022). MSCI World Banks Index (accessed on 11 April 2022).

[28] Najaf, K., Subramaniam, R. K., and Atayah, O. F. Understanding the implications of FinTech Peer-to-Peer (P2P) lending during the COVID-19 pandemic. *Journal of Sustainable Finance & Investment 12*, 1 (2022), 87–102.

[29] Olbryś, J., and Majewska, E. Regularity in stock market indices within turbulence periods: The sample entropy approach. *Entropy 24*, 7 (2022), 921.

[30] Phan, D. H. B., Narayan, P. K., Rahman, R. E., and Hutabarat, A. R. Do financial technology firms influence bank performance? *Pacific-Basin Finance Journal 62* (2020), 101210.

[31] QONTIGO. (2022). iSTOXX®Methodology Guide (accessed on 25 November 2022).

[32] Schildbach, J., and Schneider, S. European banks suffer more than US peers in the corona crisis. *Deutsche Bank EU Monitor*, (2020), 1–8.

[33] Siek, M., and Sutanto, A. Impact analysis of fintech on banking industry. In *Proceedings of 2019 International Conference on Information Management and Technology (ICIMTech)* (Jakarta/Bali, Indonesia, 2019), IEEE, pp. 356–361.

[34] Thakor, A. V. Fintech and banking: What do we know? *Journal of Financial Intermediation 41* (2020), 100833.

[35] Tut, D. FinTech and the COVID-19 pandemic: Evidence from electronic payment systems. *Emerging Markets Review 54* (2023), 100999.

[36] Vasenska, I., Dimitrov, P., Koyundzhiyska-Davidkova, B., Krastev, V., Durana, P., and Poulaki, I. Financial transactions using FINTECH during the COVID-19 crisis in Bulgaria. *Risks 9*, 3 (2021), 48.

[37] Wang, Y., Xiuping, S., and Zhang, Q. Can fintech improve the efficiency of commercial banks? — An analysis based on big data. *Research in International Business and Finance 55* (2021), 101338.

[38] White, L., and Withers, I. (27 January 2022). Now or never? European banks eye comeback against wall street. (accessed on 14 September 2022).

[39] Yao, Y., Li, J., and Sun, X. Measuring the risk of Chinese Fintech industry: evidence from the stock index. *Finance Research Letters 39* (2021), 101564.

[40] Ziegler T., Zhang B. Z., Carvajal A, Barton M. E., Smit H., Wenzlaff K., Natarajan H., et al. *Global COVID-19 FinTech market rapid assessment study*. CCAF, University of Cambridge, World Bank Group and the World Economic Forum, 2020.