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Financial contagion during COVID–19 crisis

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Financial contagion during COVID–19 crisis

Abstract

This study examines how financial contagion occurs through financial and nonfinancial firms between China and G7 countries during the COVID–19 period. The empirical results show that listed firms across these countries, financial and non-financial firms alike, experience significant increase in conditional correlations between their stock returns. However, the magnitude of increase in these correlations is considerably higher for financial firms during the COVID-19 outbreak, indicating the importance of their role in financial contagion transmission. They also show that optimal hedge ratios increase significantly in most cases, implying higher hedging costs during the COVID-19 period.

Keywords: COVID–19; financial contagion; spillover index; financial firms; nonfinancial firms; hedge ratio

JEL classification: G15; G20; G21; G22; G23

1. Introduction

The outbreak of COVID-19 has been declared as a global pandemic on March 11, 2020 by the World Health Organisation. As of April 21, 2020, there are 2,397,216 confirmed cases and 162,956 deaths across the world (WHO, 2020a). China and G7 countries account for the majority of COVID-19 confirmed cases and deaths (WHO, 2020a). The outbreak of COVID-19 has shaken the global financial markets. Level 1 market-wide circuit-breakers based on drops of 7% from the previous close were triggered four times on 9, 12, 16 and 18 March 2020 in the US stock market to prevent larger crashes (World Economic Forum, 2020).¹ This mechanism has been triggered only once in 1997 since its implementation in 1988. Dow Jones Industrial Average (DJIA) and S&P500 indices dropped by 33% and 29%, respectively on March 20, 2020 from December 31, 2019, when the first confirmed case is reported by the World Health Organisation (World Economic Forum, 2020). Also, 16 March (12.93% drop) and 12 March (9.99% drop) were recorded third and sixth largest daily drops, respectively in DJIA (World Economic Forum, 2020). FTSE100, the UK main index suffered the worst quarter since 1987, recording a drop of 24.80% (The Guardian, 2020). Japan experienced more than 20% drop from December 2019 high (Bloomberg, 2020).

Central banks, government agencies, and multilateral organisations have engaged in an ongoing series of interventions in the financial market to stimulate economies. The International Monetary Fund (IMF) estimated that government stimulus packages adopted during the COVID-19 pandemic amounted to USD3.3 trillion, and that additional loans, equity injections and guarantees amounted to USD4.5 trillion (Congressional Research Service, 2020). The Federal Reserve has taken exceptional steps to address the economic effects of COVID-19 and announced a zero-percent interest rate policy on March 15, 2020 and declared a USD700 billion Quantitative Easing (QE) program. Central banks in other

¹ Level 1 circuit breaker is triggered when the market index falls by 7% in a day (World Economic Forum, 2020).

countries have reduced policy interest rates and reserve requirements and announced additional financing facilities. Also, some of the central banks have relaxed capital and countercyclical buffers for financial institutions (Congressional Research Service, 2020). IMF predicted that “the increase in borrowing by governments globally will rise from 3.7% of global gross domestic product (GDP) in 2019 to 9.9% in 2020” (Congressional Research Service, 2020, p. 1).

Following such a huge worldwide impact, the literature on the economic effects of COVID–19 has started to grow rapidly (Baker et al., 2020; Conlon & McGee, 2020; Corbet et al., 2020; Kristoufek, 2020; McKibbin & Fernando, 2020; Ramelli & Wagner, 2020; Zhang et al., 2020). Baker et al. (2020) and Zhang et al. (2020) investigate the effects of COVID–19 on the aggregate markets. Conlon and McGee (2020) explore whether Bitcoin is a safe haven during the COVID–19 bear market. McKibbin and Fernando (2020) show how the outbreak of COVID–19 is impacting the global economy. Sharif et al. (2020) find that the effect of COVID-19 on the US economic uncertainty is much lower than that on the geopolitical risk. Yarovaya et al. (2020) do not detect any herding behavior in cryptocurrency markets during the COVID-19 pandemic.

However, to the best of our knowledge, none of these studies has attempted to examine the effects of COVID–19 on financial firms compared to nonfinancial firms, financial contagion originated by them, and its implications on the portfolio design. Our study fills this void in the literature by investigating whether the financial contagion occurs across Chinese and G7 listed firms, financial and nonfinancial alike, and how the optimal portfolio design changes during the COVID–19 pandemic era.

The empirical results show that dynamic conditional correlations (DCCs) between Chinese and G7 stock returns, financial and nonfinancial alike, increased significantly during the COVID–19 period. However, the magnitude of the increase in DCCs is higher for financial firms, implying that they play a more important role in transmitting financial contagion than nonfinancial firms do. During the outbreak, China and Japan appear to be net transmitters of spillovers, suggesting that financial contagion follows a similar pattern to that of the virus contagion. Finally, optimal hedge ratios increase significantly in most cases during the COVID–19 period, implying higher hedging costs during this period of extreme turbulence. These results provide guidance to policymakers, regulators, practitioners, and other market participants to devise strategies to cope with financial contagion.

The rest of the paper is organized as follows. Section 2 presents the empirical strategy. Section 3 explains the data. Section 4 presents the results, while Section 5 conducts robustness checks. Section 6 concludes.

2. Empirical strategy

2.1 VARMA (1,1) DCC-GARCH model

This study employs alternative specifications of GARCH models to choose the best fit GARCH model and then estimates a VARMA (1,1) DCC-GARCH model based on information criteria.²

$$r_t = \alpha + \varphi r_{t-1} + \omega \varepsilon_{t-1} + \varepsilon_t \quad (1)$$

$$\varepsilon_t = H_t^{1/2} \eta_t \quad (2)$$

where α is the vector of constants. r_t refers to a $n \times 1$ vector of returns on Chinese, G7 and World financial and nonfinancial returns φ and ω refer to a $n \times 1$ vector of co-efficients for

² Alternative specifications of GARCH models include GARCH, GJR-GARCH, EGARCH, PARCH and APARCH. VARMA (1,1) DCC-GARCH model is the best-fit model based on both information criteria (Akaike and Schwarz).

AR (1) and MA (1), respectively. ε_t is the vector of residuals. η_t refers to independently and identically distributed (i.i.d) random errors. H_t is the conditional variance-covariance matrix estimated by the DCC methodology of Engle (2002).

2.2 Optimal portfolio design and hedging ratios

In the second step of our analysis, we investigate how the optimal portfolio design changes during COVID-19 pandemic. Following Kroner and Ng (1998), we estimate the optimal weight of Chinese financial/nonfinancial sector in a one-dollar portfolio of G7 countries (or world). The optimal weight at time t is denoted by $w_t^{i/China}$:

$$w_t^{i/China} = \frac{h_t^i - h_t^{i/China}}{h_t^i - 2h_t^{i/China} + h_t^{China}} \quad (3)$$

where h_t^i , and h_t^{China} are the conditional volatility of G7 countries (or world) financial/nonfinancial firm returns and China financial/non-financial firm returns, respectively, and $h_t^{i/China}$ is the covariance between China and G7 countries (or world) financial/nonfinancial firm returns at day t . The conditional variances and covariances at day t are estimated using the benchmark model, VARMA (1,1) DCC GRACH, as explained above. However, the portfolio optimization process imposes the following constraints to assume no short-selling

$$w_t^{i/China} = \begin{cases} 0 & \text{if } w_t^{i/China} < 0 \\ w_t^{i/China} & \text{if } 0 \leq w_t^{i/China} \leq 1 \\ 1 & \text{if } w_t^{i/China} > 1 \end{cases} \quad (4)$$

A long position of one-dollar in China financial/non-financial sector must be hedged by shorting $\beta_t^{i/China}$ dollars in the G7 countries (or world) financial/nonfinancial sector, to minimise the portfolio risk where $\beta_t^{i/China}$ is the optimal hedge ratio (see Kroner & Sultan, 1993) calculated as:

$$\beta_t^{i/China} = \frac{h_t^{i/China}}{h_t^i} \quad (5)$$

2.3 Directional spillover model

We use Diebold and Yilmaz's (2012) model (hereafter, DY model) to examine the return and volatility spillovers across financial and nonfinancial firms of China and G7 countries. The DY model measures the spillovers in a “generalised vector autoregression (VAR)” framework that removes the order-dependent results using “Cholesky factor orthogonalization” (see Diebold & Yilmaz, 2009).

Assuming an N-variable VAR(p), $y_t = \sum_{i=1}^p \varphi_{y_{t-i}} + \varepsilon_t$, where $\varepsilon \sim (0, \Sigma)$ is a vector of i.i.d disturbances. The moving average (MA) is

$$y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$$

where A_i is an $N \times N$ matrix of a recursive pattern:

$$A_i = \omega_1 A_{i-1} + \omega_2 A_{i-2} + \dots + \omega_p A_{i-p} \text{ with } A_{i-p} = 0 \text{ for } i < 0.$$

The DY model calculates the H-step-ahead “Forecast Error Variance Decompositions” (FEVD) as

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} ((e_i' A_h \Sigma e_j))^2}{\sum_{h=0}^{H-1} ((e_i' A_h \Sigma A_h' e_i))^2} \quad (6)$$

where σ_{jj} is the standard deviation of the residuals, e_i is a selection vector, with 1 as the i^{th} element and 0 otherwise. $\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$. The row sum normalises each element:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)} \quad (7)$$

with $\sum_{j=1}^N \theta_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$

Following the DY model, the spillover index is estimated in Equation (8):

$$S^g(H) = \frac{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{i \neq j} \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \quad (8)$$

The directional spillover to market i from all other markets j is measured in Equation (9):

$$S_{i \cdot}^g = \frac{\sum_{j=1}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{j \neq i} \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \quad (9)$$

Similarly, the directional spillover to all other markets j from market i is measured in Equation (10)

$$S_{\cdot i}^g = \frac{\sum_{j=1}^N \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ji}^g(H)} \cdot 100 = \frac{\sum_{j=1}^N \tilde{\theta}_{ji}^g(H)}{N} \cdot 100 \quad (10)$$

The net spillover to all markets j from market i is measured by subtracting Equation (10) from Equation (9)

$$S_i^g = S_{\cdot i}^g - S_i^g \quad (11)$$

3. Data and descriptive statistics

3.1 Data

Our sample period covers both pre-COVID–19 period (January 1, 2013– December 30, 2019) and COVID–19 period (December 31, 2019–March 20, 2020). We take the starting date of COVID–19 period as December 31, 2019, the date when the first case of COVID–19 was reported to the World Health Organisation (WHO) by China (WHO, 2020b). On the other hand, we choose the first date of pre-COVID–19 period as January 1, 2013, to not overlap with the global financial crisis (2007–2009) and European sovereign debt crisis (2010–2012). To investigate the financial contagion due to COVID–19 outbreak, we have chosen China and G7 countries in our sample for the following reasons. First, China is a source of COVID–19. Second, China and G7 countries are among the most affected countries as they account for 68.19% of total confirmed cases as of 20 March 2020 (WHO, 2020c). Third, China and G7 countries account for 61.11% of global GDP as of 2018 (World Bank, 2020). For robustness, we also use the world financial and nonfinancial stock returns to compare our results with those obtained from G7 countries.

Data on the return indices of financial and nonfinancial sectors from China, G7 countries, and the world are obtained from DataStream. Financial sector and non-financial sector have been categorised following DataStream Level 2.³ We have used USD

³ DataStream industry levels follow the Industry Classification Benchmark (ICB) (<https://www.ftserussell.com/data/industry-classification-benchmark-icb>). DataStream Global Equity Indices

denominated return series to calculate daily returns.⁴ Daily returns were computed from the return index: $r_t = \ln(RI_t/RI_{t-1})$, where r_t is return and RI_t is the Return Index obtained from DataStream.⁵ Data on confirmed cases are obtained from the World Health Organisation and European Centre for Disease Prevention and Control.

3.2 Descriptive statistics

The mean financial and nonfinancial stock returns of China, G7 countries, and world indices during COVID–19 period are negative while the pre-COVID–19 period has positive daily returns. Italian financial firms experienced the highest negative return during COVID–19 period, while the UK had the highest negative return for its nonfinancial firms during the same period. Negative returns are associated with the number of confirmed cases in China and G7 countries (see, Figure 1). The UK market return dropped by 40% during the period (December 31, 2019–March 20, 2020). Similarly, market indices in other G7 countries experienced a significant drop during the COVID–19 period (see, Figure 1).

The volatility of financial and nonfinancial stock returns is higher during COVID–19 period compared to those during the pre-COVID–19 period as evidenced by increased standard deviations. The skewness of all returns is far from zero and the kurtosis is well over 3 in all cases, indicating the non-normality of return series. This is formally confirmed by the Jarque-Bera test. All portfolio return series appear not to have unit roots. The Box–Pierce–Ljung portmanteau test shows that most returns have autocorrelation. Both financial and nonfinancial stock returns do not have unit roots during the pre-COVID–19 period.

break down to six levels. Level 1 is the market index. Level 2 divides the market to industry sectors. Levels 3 to 6 further break down to industry sub-sectors. Nonfinancial sector includes all industry sectors except the financial sector.

⁴ Mink (2015) argues for using local currency-denominated returns than common currency returns. Studies such as Akhtaruzzaman et al. (2019), Akhtaruzzaman and Shamsuddin (2016) and Forbes and Rigobon (2002) find similar results irrespective whether examining financial contagion using local currency returns or USD returns.

⁵ Return Index (RI) from Datastream is a price index adjusted by the dividend yield.

However, most of them have unit roots during the COVID–19 period because stock indices experienced a trend of negative returns during the same period. Pearson correlations between Chinese and G7 (or world) financial and nonfinancial stock returns appear to be much higher during the COVID–19 period as compared to those during the pre-COVID–19 period, suggesting some preliminary results on financial contagion.

“Insert Table 1 about here”

“Insert figures 1 & 2 about here”

4. Empirical results

4.1 Dynamic Conditional Correlations (DCCs)

DCCs between Chinese and G7 (world) financial and nonfinancial stock returns are higher during the COVID–19 period as compared to those during the pre-COVID–19 period. The difference in DCCs between crisis period and non-crisis period varies across countries. The UK exhibits the highest difference (0.1101) for financial firms, whereas Germany has the highest difference (0.0776) for nonfinancial firms. Empirical results pass diagnostic tests. The Lagrange multiplier test of Tse (2000) rejects constant correlations. Hosking (1980) test presents no evidence of serial correlation, and Li and McLeod (1981) test provides no evidence of misspecification in the model. Also, t-test shows that there is a significant difference between DCCs in the pre-COVID–19 period and DCCs in the COVID–19 period. The results of higher DCCs during this crisis period are consistent with those studies on the global financial crisis (Akhtaruzzaman et al., 2014; Dimitriou et al., 2013; Kim et al., 2015). Except for Germany and the US, the increase in dynamic correlations is much higher for the financial compared to non-financial firms. The results not only confirm the existence of financial contagion between China and G7 countries, but also show that the degree of contagion is much higher for financial compared to non-financial companies. Evidence points

out to the fact that investors and policymakers should be particularly cautious with regards to the price behaviour of financial firm stocks.

“Insert Table 3 about here”

“Insert Figure 3 about here”

4.2 Optimal portfolio design and hedging ratios

The optimal weights have been estimated using Equation (3). The results show that the optimal weights in the Chinese financial and nonfinancial sectors are less than 0.50 except for the Italian financial sector in both periods. The results imply that investors should allocate less than half of a one-dollar portfolio in the Chinese financial (nonfinancial) sector to reduce the portfolio’s risk without decreasing its return. Interestingly, the optimal weights appear to be time-varying (see, Figure 4) and change during the COVID–19 period. For instance, the optimal weight of the Chinese financial sector in the portfolio of Chinese and US financial sector increased from 0.2949 in the pre-COVID–19 period to 0.4199 during the COVID–19 period. This might be due to the fact that towards the end of our sample, Chinese markets start to recover whereas western markets continue to experience big drops. In this case, adding Chinese securities to such portfolios can balance the outcomes and improve the overall performance.

The optimal hedge ratios are estimated using Equation (5) with a VARMA (1,1) DCC GARCH model. Figure 5 shows that these optimal ratios are time-varying. The results provide interesting insights for portfolio design. First, it seems that most of the optimal hedge ratios for financial and nonfinancial sectors have significantly changed during the COVID–19 period. Some of them have increased while others have decreased. For example, the hedge ratio for China-Japan financial (nonfinancial) firms increased from 0.2645 (0.2788) in the pre-COVID–19 period to 0.4252 (0.4240) in the COVID–19 period. The increase in hedging

ratios suggests higher hedging costs during the COVID–19 period due to the larger number of contracts required to short Chinese financial and non-financial sectors. The results are consistent with the literature that shows higher hedge ratios during crisis periods (Antonakakis et al., 2018; Batten et al., 2019). Also, Chow breakpoint test indicates that there is a structural break in hedge ratios on December 31, 2019, when the first confirmed case of COVID–19 is reported by the WHO. Second, the hedge ratios for China-World financial and nonfinancial sectors appear to be higher than those of developed countries (G7). This implies that compared to G7 countries, the hedging cost is higher for the global financial and nonfinancial sectors when shorting Chinese financial and nonfinancial sectors. These results suggest the increased challenges for financial risk management during COVID19 period and show that the situation is more challenging when hedging financial firm stocks (see, Figure 5).

“Insert tables 3 & 4 about here”

“Insert figures 4 & 5 about here”

4.3 Return and volatility spillovers

This section examines spillovers within a DY framework. The empirical results show that financial (nonfinancial) return and volatility spillovers amount, on average, to 61.99% (64.09%) and 60.13% (65.51%), respectively.⁶ According to Figure 6, both return and the volatility spillover indices are high, indicating that shock transmission between Chinese and G7 financial and nonfinancial firms is high. These results also indicate that shock transmission between Chinese and G7 financial and nonfinancial firms is high.

Following the DY model, we measure the return and volatility spillover using a 200-day rolling window to examine the magnitude and type of spillovers during the pre-COVID–19 and COVID–19 periods. The spillover plots demonstrate that both return and volatility

⁶ Spillover tables are not provided here for sake of brevity. The results are available from the authors upon request.

spillovers increased significantly during the COVID–19 period. These results corroborate previous studies (Elsayed & Yarovaya, 2019; Lau et al., 2017; Zhang & Broadstock, 2018). Moreover, Figure 7 demonstrates the net spillover measured by S_i^g in Equation (11). Figure 7 shows that Chinese and Japanese financial and nonfinancial firms are net transmitters of spillover to other G7 countries during the COVID–19 period, indicating that financial contagion trails the same path to that of COVID-19.⁷ Thus, policymakers in G7 countries should pay special attention to the market movements in these countries.

“Insert Figures 6&7 about here”

5. Robustness checks

We consider several alternative specifications to check the robustness of our results. In particular, we investigate whether the results from local currency returns differ from those obtained from USD returns. The results demonstrate that findings from local currency returns appear to be similar to those from USD return (See, Figure A1). Also, we generate the spillover indices for a forecast horizon of 5, 10, and 15 days with a VAR lag structure of 5, 10, and 15 days, and rolling windows of 200 days. We find that spillover indices from alternative specifications appear to be similar in magnitude and trend to those from the baseline specification (see, figures A2 to A7), suggesting that our findings are robust to alternative specifications.

“Insert figures A1–A7 about here”

6. Conclusion

This paper analyses how financial contagion occurs through financial and nonfinancial firms between China and G7 countries. The empirical results show that dynamic conditional correlations (DCCs) between Chinese and G7 financial and nonfinancial stock

⁷ In the initial phase of the COVID-19, Japan had higher number of confirmed cases of COVID-19 as compared to other G7 countries.

returns increased significantly during the COVID–19 period. However, the magnitude of the increase in DCCs was higher for financial firms, implying that they play a more important role in financial contagion transmission than nonfinancial firms do. The results also show that China and Japan appear to be net transmitters of spillovers during the COVID–19 period. Hence, the role of Chinese and Japanese financial and nonfinancial firms in the cross-market transmission of shocks to G7 countries may be of interest to policymakers, regulators, practitioners, and other market participants. Optimal hedge ratios have increased significantly in most cases during the COVID–19 period, implying larger hedging costs during the crisis. These results provide a snapshot of what has happened in the past few weeks following the COVID19 pandemic outbreak.

Our findings offer many suggestions to investors in optimising their portfolios and provide guidance to policymakers and regulators. During this COVID19 phase, not only international stock markets but also foreign exchange markets had extremely volatile days. More important hedging costs in equity markets combined with currency mismatches in portfolios have increased both market and credit risk for international investors. These developments force market participants (in particular banks) to reduce their risk-taking capacity and dampen the growth in both financial markets and global economies. In order to prevent these actions, policymakers should keep providing liquidity to international markets as illustrated by the recent global swap arrangements made by the Federal Reserve. Research on the effects of COVID–19 is still in a very nascent stage. Further future research is warranted on the topic, particularly with the availability of longer time periods under the COVID–19.

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Table 1: Descriptive statistics

Panel A: Financial firm return: Pre-COVID–19 period (January 1, 2013–December 30, 2019)

	China	Canada	France	Germany	Italy	Japan	UK	US	World
Mean	0.0003	0.0003	0.0003	0.0003	0.0002	0.0001	0.0001	0.0005	0.0003
Std.Dev	0.0152	0.0082	0.0124	0.0097	0.0175	0.0123	0.0118	0.0089	0.0069
Skewness	-0.3822	-0.0973	-1.0666	-0.6513	-1.1087	-0.0391	-2.5147	-0.4952	-0.9315
Kurtosis	9.4909	5.8654	17.4658	8.7996	16.9558	6.6088	44.9585	6.1164	9.2479
Jarque-Bera ($\times 10^3$)	3.2***	0.63***	16.3***	2.7***	15.2***	0.99***	135.7***	0.81***	3.2***
Observations	1825	1825	1825	1825	1825	1825	1825	1825	1825
Q (10)	30.40***	46.07***	22.23**	24.22**	16.49*	36.05***	60.42***	15.51*	96.96***
ADF	-41.4***	-38.7***	-40.0***	-41.8***	-42.5***	-48.2***	-22.4***	-43.6***	-34.6***
Pearson Correlation with China	1.0000	0.1391	0.1289	0.1366	0.0912	0.1562	0.1615	0.1269	0.2870

Panel B: Financial firm return: COVID–19 period (December 31, 2019–March 20, 2020)

	China	Canada	France	Germany	Italy	Japan	UK	US	World
Mean	-0.0027	-0.0077	-0.0100	-0.0082	-0.0088	-0.0060	-0.0085	-0.0081	-0.0076
Std.Dev	0.0186	0.0362	0.0340	0.0321	0.0345	0.0155	0.0256	0.0391	0.0258
Skewness	-1.6583	-1.1801	-2.7389	-2.3737	-2.8101	-2.2496	-2.6733	-0.8660	-2.0971
Kurtosis	8.8833	9.6082	12.5255	10.4504	14.7099	9.0253	12.3601	6.6663	8.5486
Jarque-Bera	112***	121***	297***	192***	415***	139***	286***	40***	119***
Observations	59	59	59	59	59	59	59	59	59
Q (10)	8.26	27.31***	19.40***	16.74*	16.11*	15.65	13.61	45.72***	23.32***
ADF	-9.1***	0.5	0.5	1.32	-0.05	-2.27	0.67	-0.42	0.80
Pearson Correlation with China	1.0000	0.2646	0.3349	0.3208	0.1978	0.2875	0.3836	0.2863	0.3840

Panel C: Nonfinancial firm return: Pre-COVID–19 period (January 1, 2013–December 30, 2019)

	China	Canada	France	Germany	Italy	Japan	UK	US	World
Mean	0.0002	0.0003	0.0004	0.0002	0.0003	0.0004	0.0002	0.0005	0.0003
Std.Dev	0.0147	0.0082	0.0097	0.0098	0.0110	0.0107	0.0094	0.0080	0.0063
Skewness	-1.0272	-0.0973	-0.4944	-0.5115	-0.6667	-0.3174	-0.8187	-0.4980	-0.6763
Kurtosis	9.5130	5.8654	7.4409	6.4318	8.1531	6.6691	14.3710	6.6057	6.8862
Jarque-Bera	3547***	627***	1574***	975***	2154***	1054***	10036***	1064***	1288***
Observations	1825	1825	1825	1825	1825	1825	1825	1825	1825
Q (10)	39.18***	19.67**	23.72***	18.65***	23.01**	99.65***	46.19***	13.03	95.13***
ADF	-8.12***	39.48***	21.89***	20.75***	18.00***	23.62***	22.18***	31.56***	21.70***
Pearson Correlation with China	1.0000	0.1441	0.1601	0.1697	0.1280	0.2034	0.1819	0.1486	0.2752

Panel D: Nonfinancial firm return: COVID–19 period (December 31, 2019–March 20, 2020)

	China	Canada	France	Germany	Italy	Japan	UK	US	World
Mean	-0.0012	-0.0077	-0.0064	-0.0071	-0.0066	-0.0048	-0.0084	-0.0053	-0.0056
Std.Dev	0.0204	0.0328	0.0254	0.0247	0.0324	0.0138	0.0251	0.0321	0.0235
Skewness	-1.7575	-2.1937	-2.6429	-2.2157	-3.5850	-1.7165	-3.0288	-1.0107	-1.8450
Kurtosis	8.9188	9.2108	13.5835	8.5982	21.0208	7.9480	14.5055	6.6343	7.9011
Jarque-Bera	116***	142***	344***	125***	925***	89***	416***	43***	93***
Observations	59	59	59	59	59	59	59	59	59
Q (10)	6.74	22.73***	11.09	16.04*	8.31	8.83	13.25	44.38***	25.73***
ADF	8.51***	-0.16	0.28	-0.34	1.25	-5.47***	1.28	0.07	0.34
Pearson Correlation with China	1.0000	0.3462	0.3905	0.4390	0.2723	0.4064	0.4539	0.3273	0.4267

Notes: The Jarque–Bera test is used to check whether the return distribution is normal. The Box–Pierce–Ljung statistic, Q (10) statistic is distributed as a χ^2 with 10 degrees of freedom. The augmented Dickey–Fuller (ADF) is used to check the unit root of return series. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 2: DCCs between China and G7 countries and theWorld**Panel A: Between financial firms**

	Canada	France	Germany	Italy	Japan	UK	US	World
Pre-COVID19 Mean DCC	0.1420	0.1512	0.1502	0.1146	0.1951	0.1956	0.0758	0.2686
Covid19 Period Mean DCC	0.2134	0.2309	0.1988	0.1476	0.2719	0.3066	0.0939	0.3459
Difference in DCC	0.0714	0.0797	0.0486	0.0330	0.0768	0.1110	0.0181	0.0773
t-stat difference	-30.25***	-49.12***	-31.80***	-24.98***	-60.60***	-80.00***	-6.55***	-32.93**
Diagnostic Tests:								
Tse (2000) test	2.26**	2.27**	2.66***	2.87***	2.99***	4.60***	5.02***	3.12***
Hosking (1980) test	40.42	34.98	47.78	40.59	40.03	44.60	35.96	43.20
Li and McLeod (1981) test	40.43	34.97	47.73	40.57	40.04	44.58	35.97	43.19

Panel B: Between nonfinancial firms

	Canada	France	Germany	Italy	Japan	UK	US	World
Pre-COVID19 Mean DCC	0.1480	0.1589	0.1713	0.1576	0.1812	0.1959	0.1199	0.2253
Covid19 Period Mean DCC	0.1737	0.1783	0.2489	0.1532	0.2314	0.2602	0.1506	0.2511
Difference in DCC	0.0257	0.0194	0.0776	-0.0044	0.0502	0.0643	0.0307	0.0258
t-stat difference	-8.61***	-3.81***	-14.80**	0.88	-19.77***	-24.64***	-11.42***	-5.12***
Diagnostic Tests:								
Tse (2000) test	3.58***	5.33***	5.50***	6.47***	5.62***	5.59***	3.75***	4.45***
Hosking (1980) test	45.65	19.35	34.25	34.34	30.09	23.88	50.01	43.57
Li and McLeod (1981) test	46.30	21.39	34.11	35.21	31.61	25.56	49.64	43.43

[^]Difference is calculated from COVID19 mean minus pre-COVID19 mean.

Notes:

1. Tse (2000) tests the null hypothesis of constant correlation: $H_0: \delta_{ij} = 0$ for the equation: $\rho_{ij,t} = \rho_{ij} + \delta_{ij}\varepsilon_{i,t-1}\varepsilon_{j,t-1}$, where $\varepsilon_{i,t-1}$ and $\varepsilon_{j,t-1}$ are the standard residuals in Chinese (i), G7 and World (j) financial stock returns, respectively from the best fit GARCH (1,1) process.
2. Hosking (1980) test checks the null hypothesis of no serial correlation.
3. Li and McLeod (1981) test checks the null hypothesis of no misspecification in the model.
4. t-test for the difference in mean DCC is conducted.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Optimal weights and hedge ratios**Panel A: Optimal weights-Financial firms**

	Canada	France	Germany	Italy	Japan	UK	US	World
Pre-COVID19 Mean Optimal Weights	0.2460	0.4432	0.3389	0.6001	0.4229	0.3629	0.2949	0.1399
COVID19 Period Mean Optimal Weights	0.2561	0.3922	0.3669	0.5088	0.2621	0.3969	0.4199	0.2569
Difference in Optimal weights [^]	0.0102	-0.0510	0.0279	-0.0913	-0.1608	0.0344	0.1250	0.1171
t-stat difference	-0.23	1.46	-0.80	3.17***	6.00***	-0.99	-3.08***	-2.76***

Panel B: Optimal weights-Nonfinancial firms

	Canada	France	Germany	Italy	Japan	UK	US	World
Pre-COVID19 Mean Optimal Weights	0.3114	0.3533	0.3693	0.4278	0.3741	0.3138	0.2563	0.1436
COVID19 Period Mean Optimal Weights	0.2579	0.3557	0.3578	0.4049	0.2716	0.3481	0.3819	0.2719
Difference in Optimal weights [^]	-0.0535	0.0024	-0.0115	-0.0228	-0.1026	0.0342	0.1255	0.1283
t-stat difference	1.32	-0.07	0.38	0.69	4.25***	-0.99	-3.17***	-3.23***

Panel C: Optimal hedge ratios-Financial firms

	Canada	France	Germany	Italy	Japan	UK	US	World
Pre-COVID19 Mean Optimal hedge ratios	0.2736	0.2003	0.2431	0.1151	0.2645	0.3213	0.1825	0.6380
COVID19 Period Mean Optimal hedge ratios	0.4048	0.2803	0.2334	0.1355	0.4252	0.3056	0.1536	0.5441
Difference in Optimal hedge ratios [^]	0.1312	0.0800	-0.0097	-0.0204	0.1608	-0.0148	-0.0289	-0.0939
t-stat difference	-5.19***	-4.87***	0.94	-2.96***	6.54***	0.80	2.72***	2.95***

Panel D: Optimal hedge ratios-Nonfinancial firms

	Canada	France	Germany	Italy	Japan	UK	US	World
Pre-COVID19 Mean Optimal hedge ratios	0.2244	0.2214	0.2293	0.1916	0.2788	0.3044	0.1976	0.5024
Covid19 Period Mean Optimal Weights Optimal hedge ratios	0.3337	0.2504	0.2646	0.1992	0.4240	0.3200	0.1578	0.4155
Difference in Optimal hedge ratios [^]	0.1093	0.0287	0.0353	0.0076	0.1452	0.0156	-0.0398	-0.0869
t-stat difference	-5.47***	-1.88*	-3.24***	-0.67	-6.53***	-0.70	2.83***	3.06**

Notes:

1) Optimal weights and optimal hedge ratios are computed using Equation (4) and Equation (5), respectively.

2) t-test for the difference in mean optimal weights and hedge ratios is conducted.

[^]Difference is calculated from COVID19 mean minus pre-COVID19 mean.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

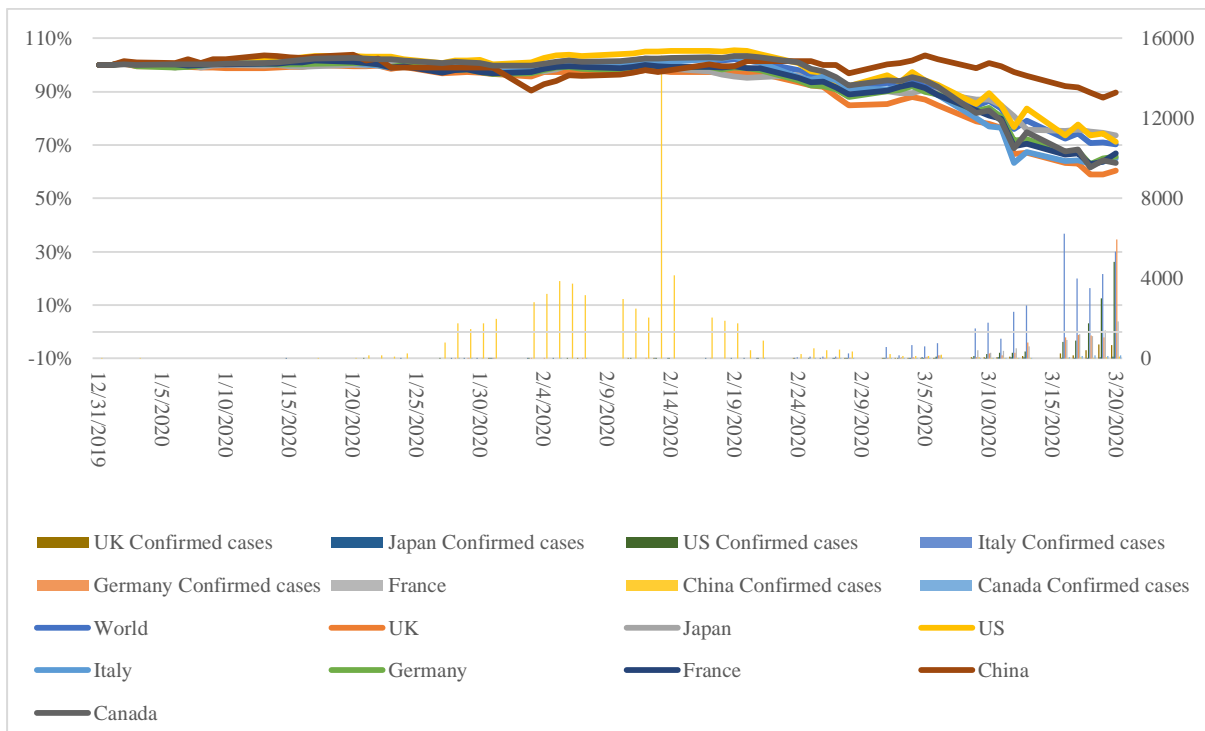
Table 4: Structural breaks in hedge ratios

	Canada	France	Germany	Italy	Japan	UK	US	World
Date	31 Dec 2019	31 Dec 2019	31 Dec 2019	31 Dec 2019	31 Dec 2019	31 Dec 2019	31 Dec 2019	31 Dec 2019
Financial firms								
F (1,1882)	41.39***	36.84***	0.44	9.51***	88.52***	0.62	4.07**	7.08***
Nonfinancial firms								
F (1,1882)	39.22***	2.77*	3.07*	0.43	42.74***	0.88	4.68**	6.62***

Notes: Chow Breakpoint test is conducted with a null hypothesis that there is no structural break on December 31, 2019 when the first confirmed case is reported by the WHO, with only regressor, constant allowed to vary across breakpoints.

*, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Figure 1: Return indices and daily changes in confirmed cases of COVID-19

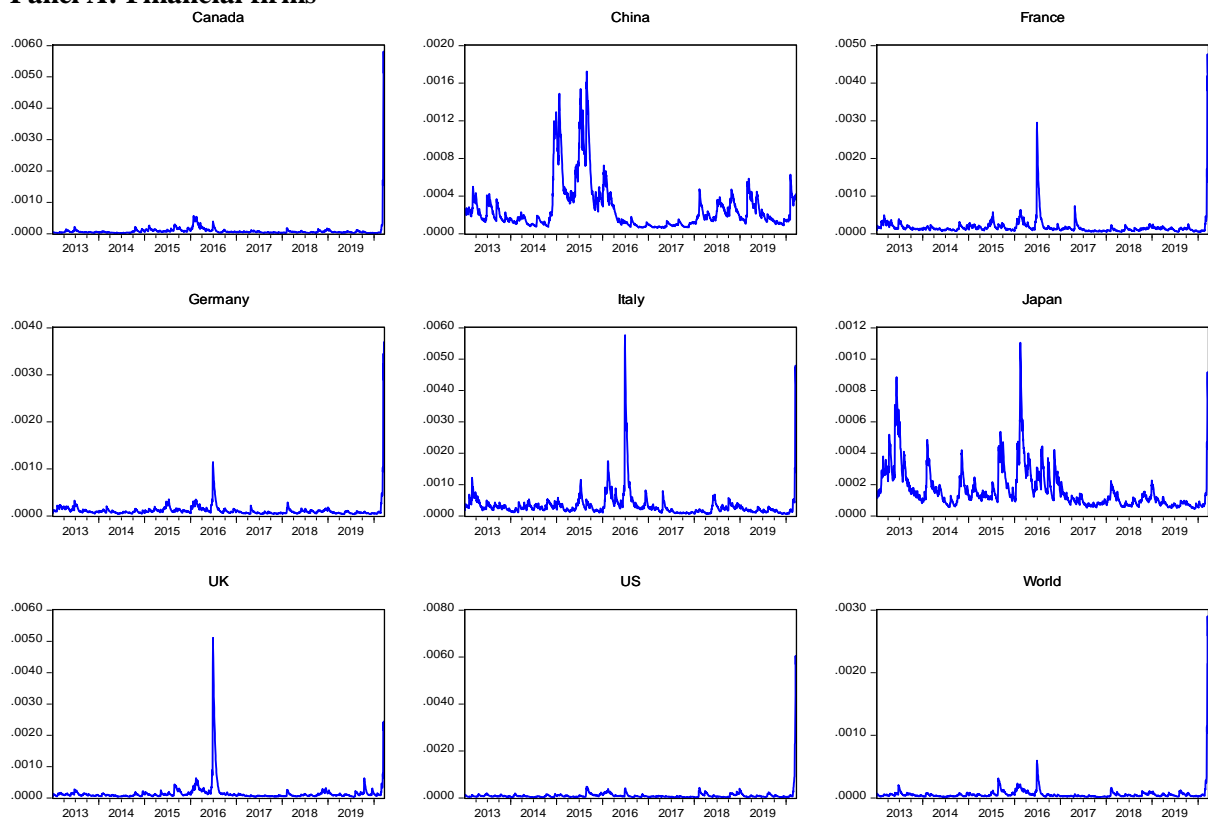


Notes:

USD return indices are created for World, China, and G7 countries with a base of 100 on December 31, 2019 when the first confirmed case of COVID-19 is reported. The right axis represents daily changes in confirmed cases of COVID-19, and the left axis represent the base percentage of return indices.

Source: Datastream and <https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide>

Figure 2: Return volatility
Panel A: Financial firms



Panel B: Nonfinancial firms

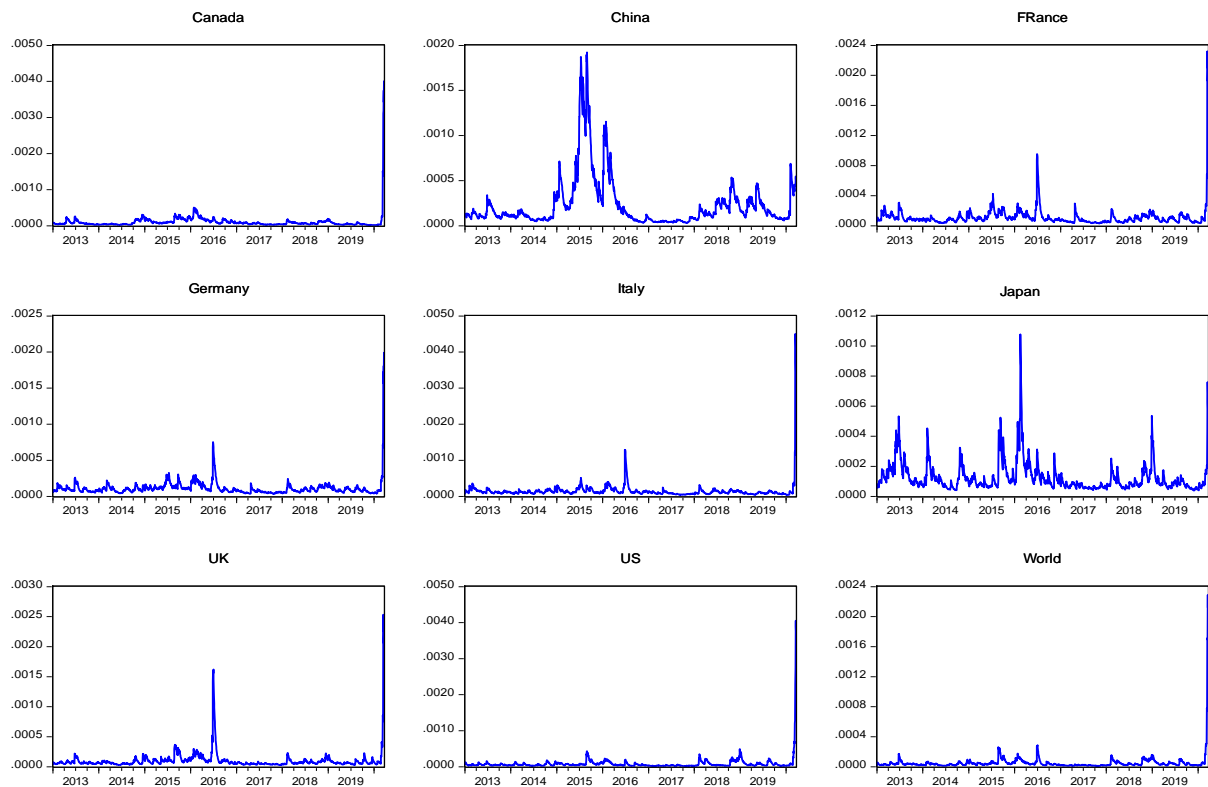
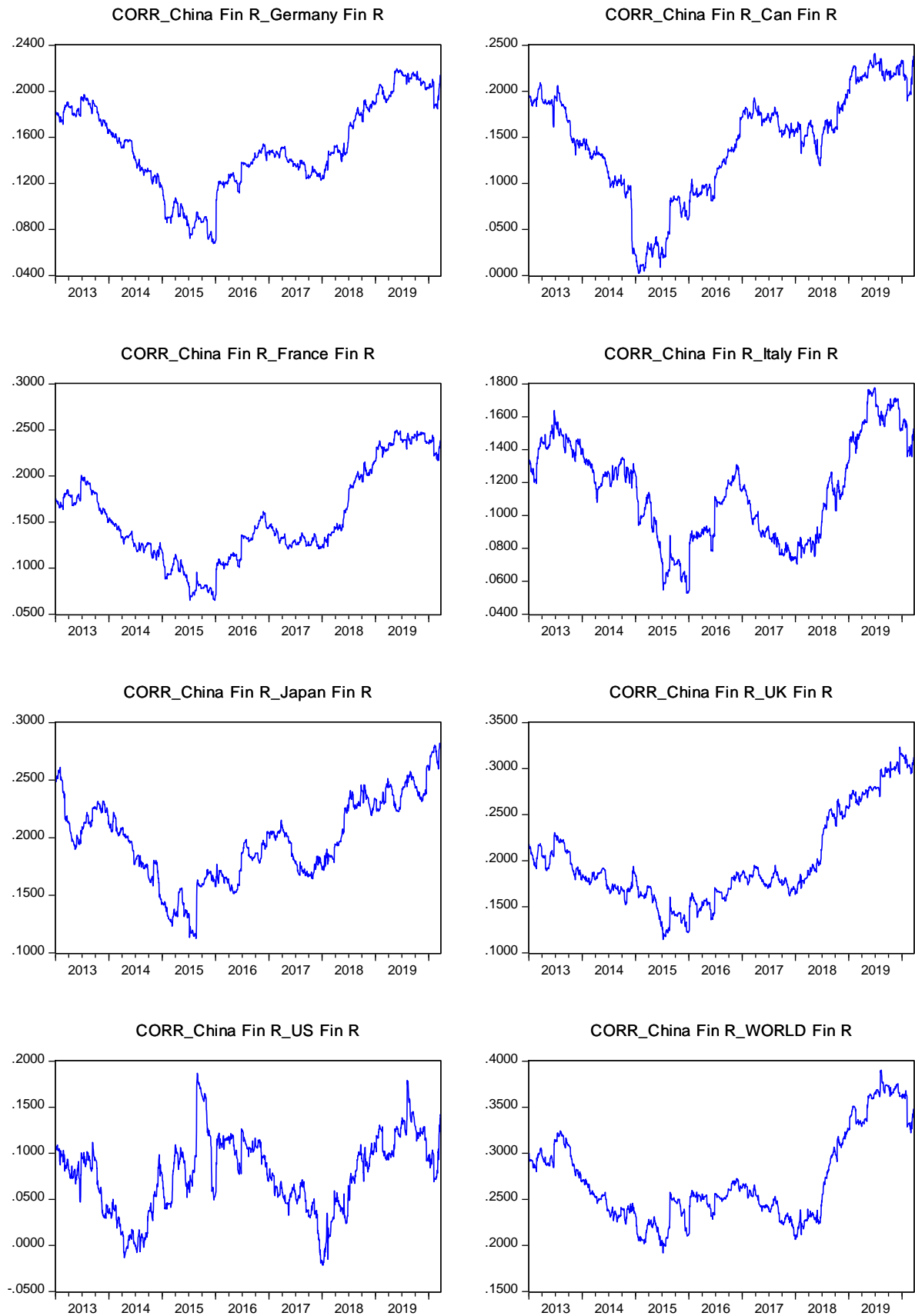
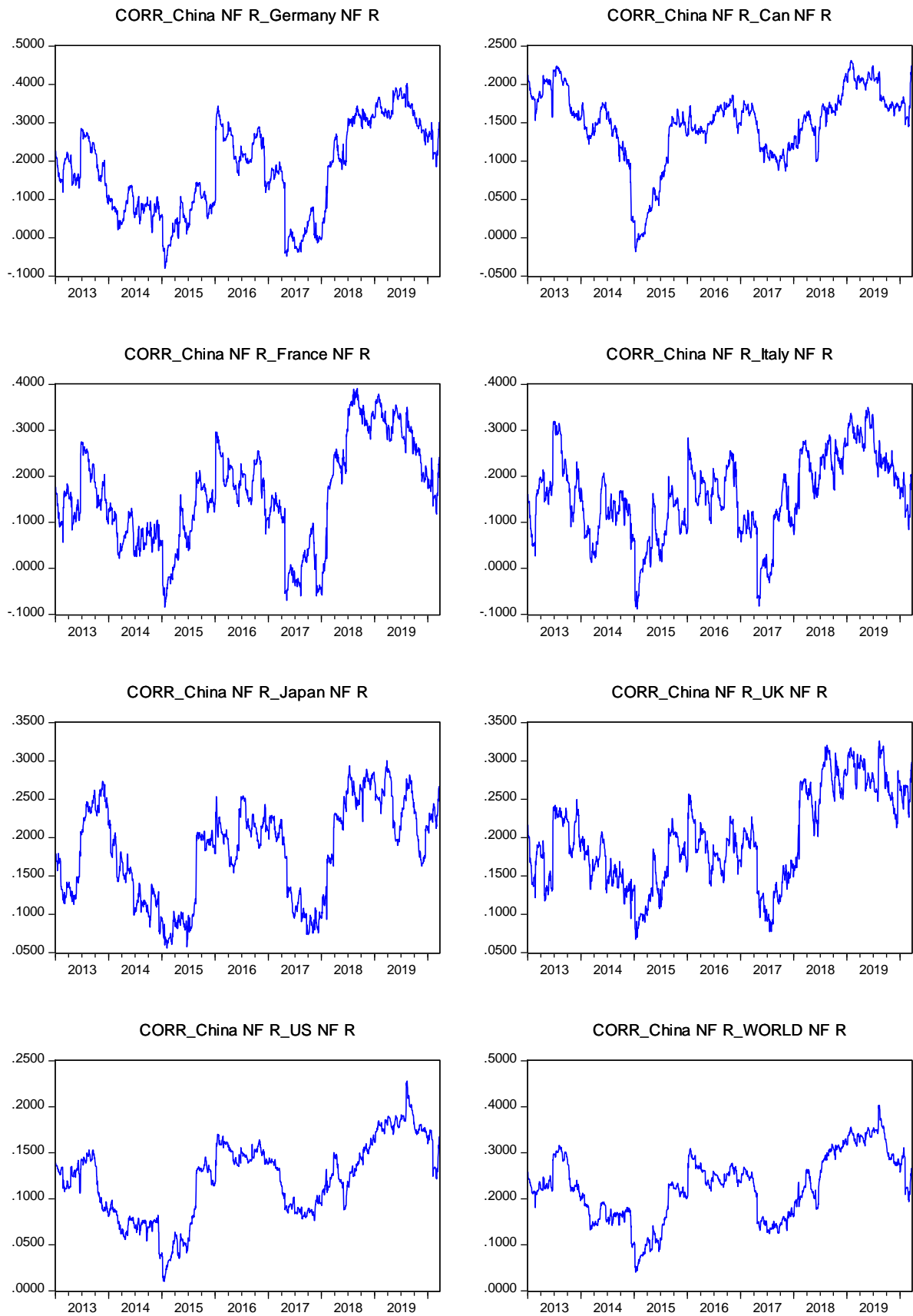


Figure 3: DCCs between China and G7 countries and World

Panel A: Between financial firms



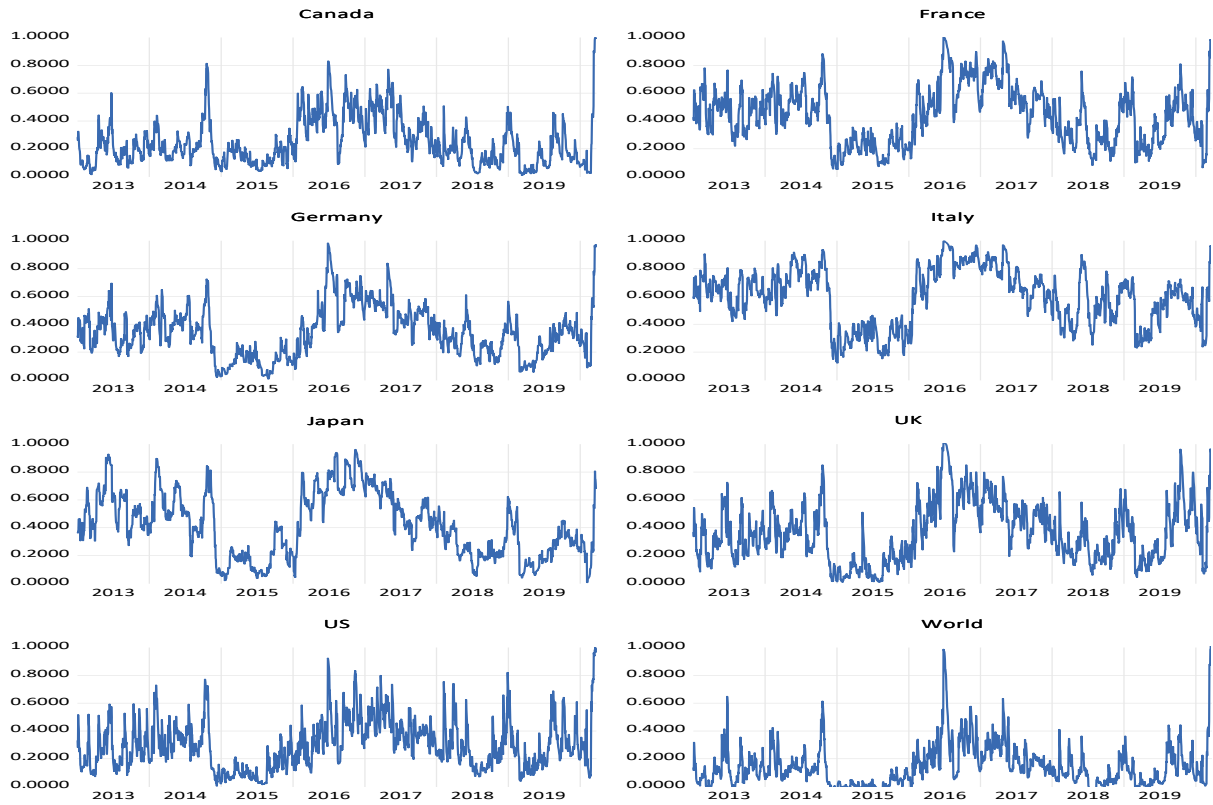
Panel B: Between nonfinancial firms



Note: CORR_China_Fin_R_Germany and CORR_China_NF_R_Germany mean DCCs between Chinese and German financial and nonfinancial stock returns, respectively and likewise.

Figure 4: Optimal weights

Panel A: Optimal weights for financial firms



Panel B: Optimal weights for nonfinancial firms

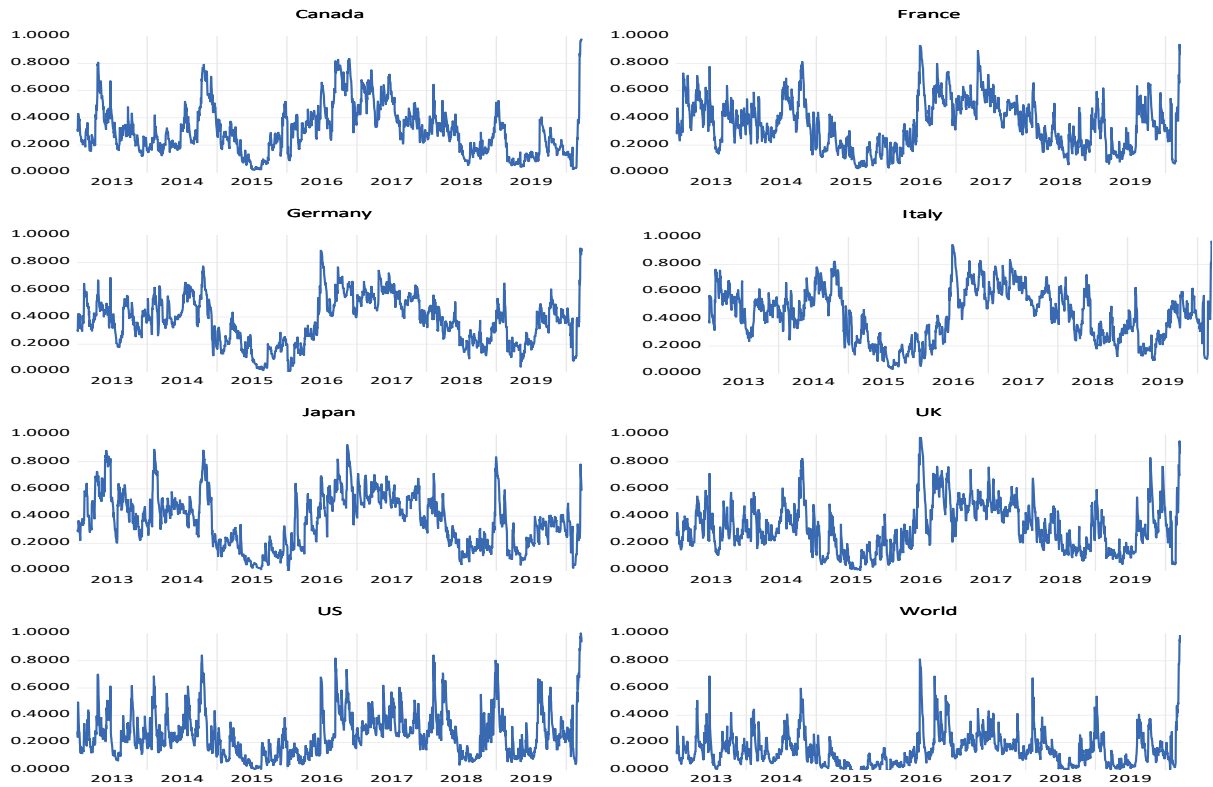
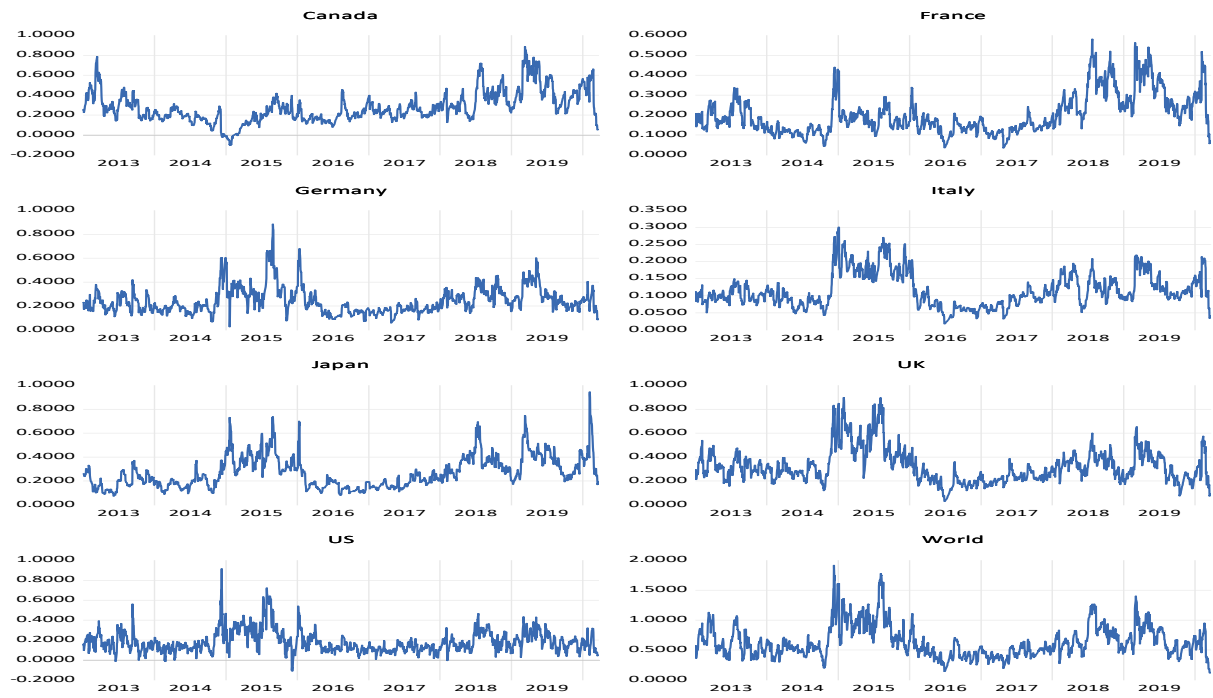


Figure 5: Optimal hedge ratios

Panel A: Optimal hedge ratios for financial firms



Panel B: Optimal hedge ratios for nonfinancial firms

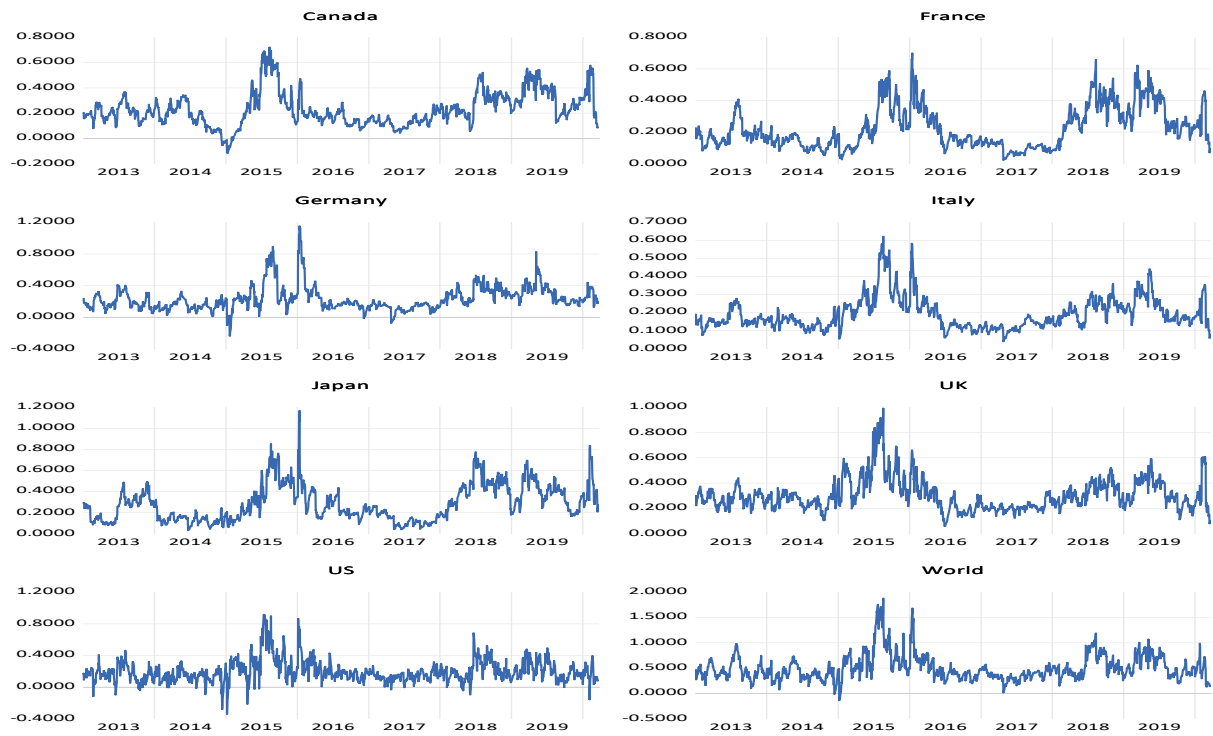
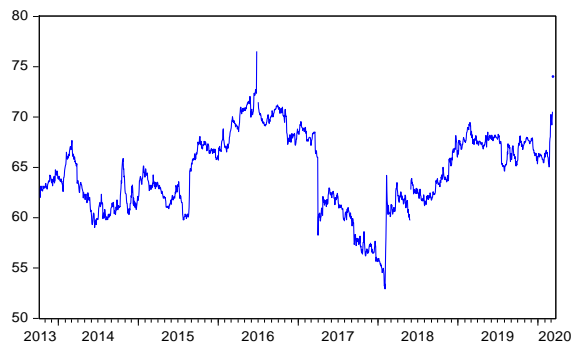
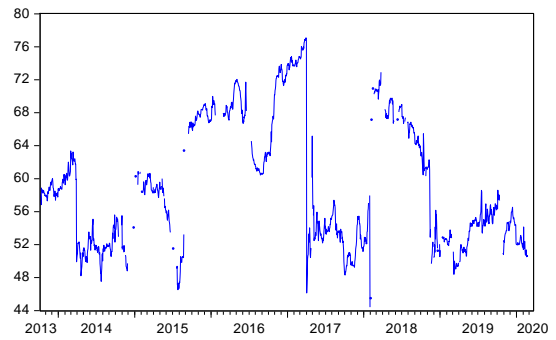


Figure 6: Total spillover plots

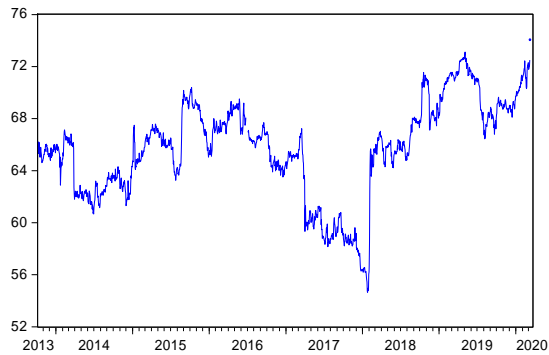
Panel A: Financial return



Panel B: Financial return volatility



Panel C: Nonfinancial return



Panel D: Nonfinancial return volatility

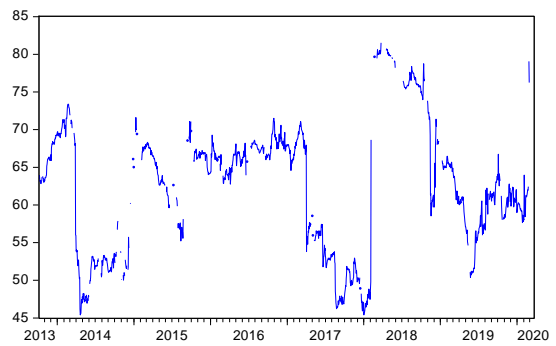
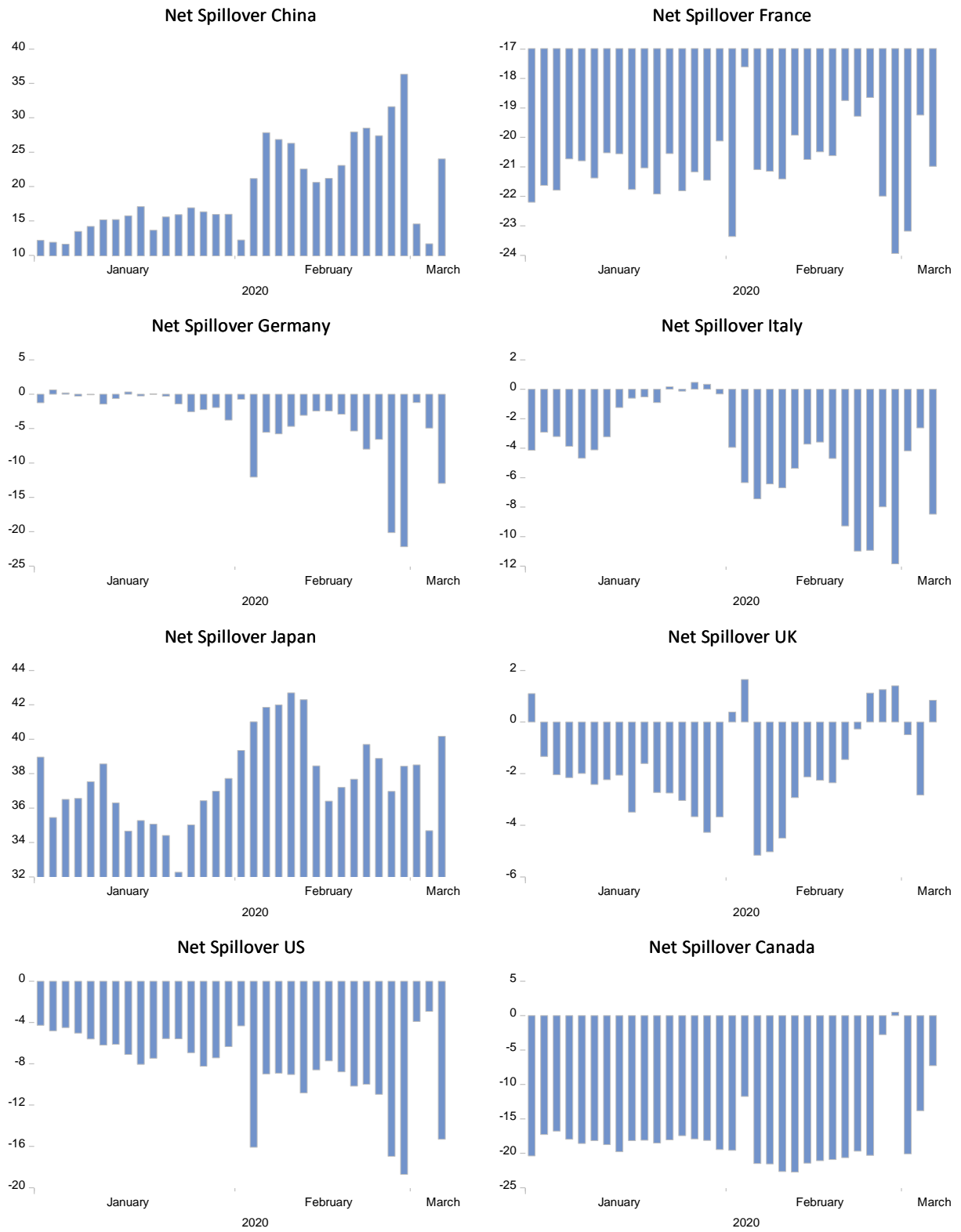
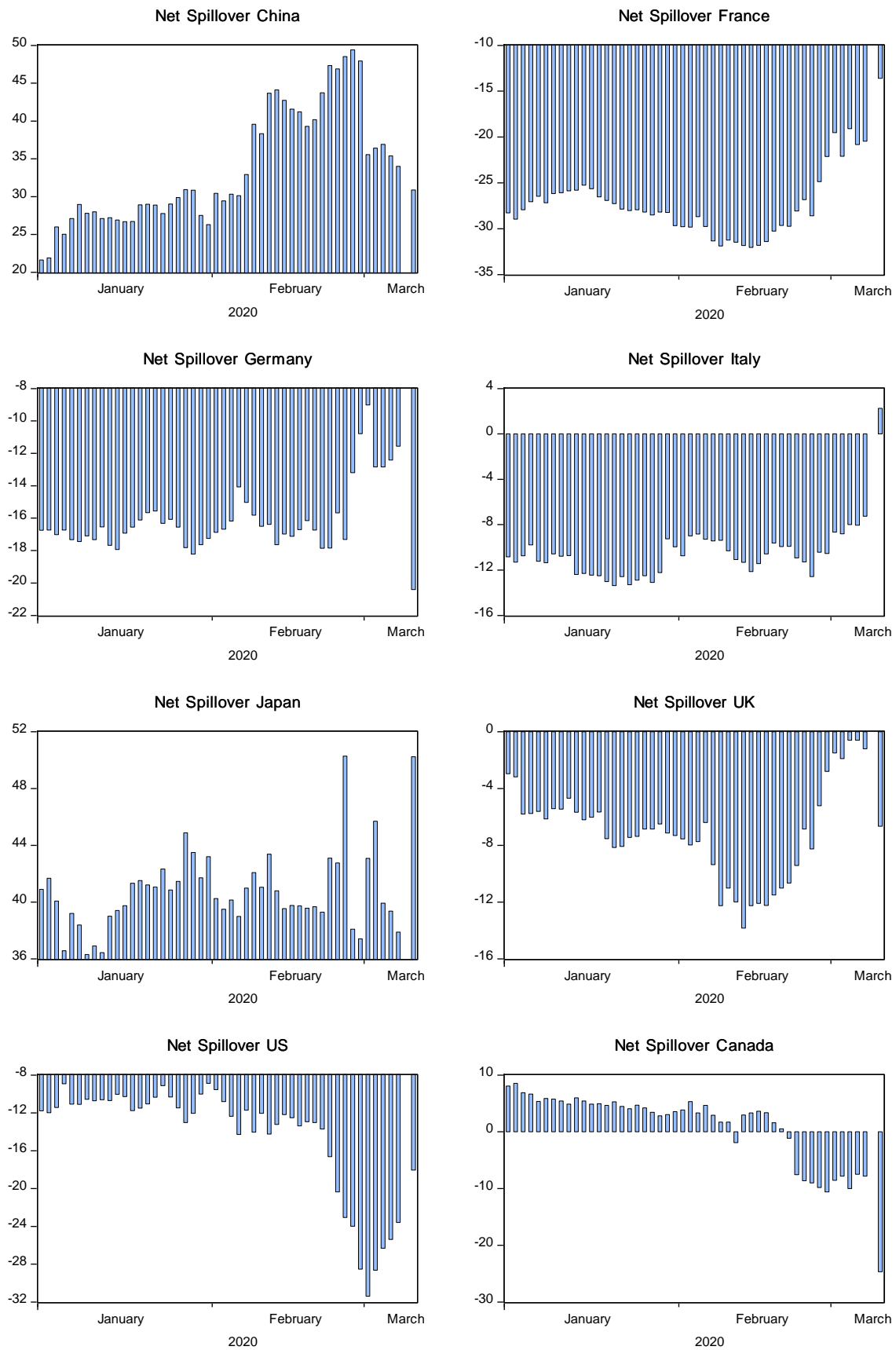


Figure 7: Net spillover plots

Panel A: Financial firms



Panel B: Nonfinancial firms

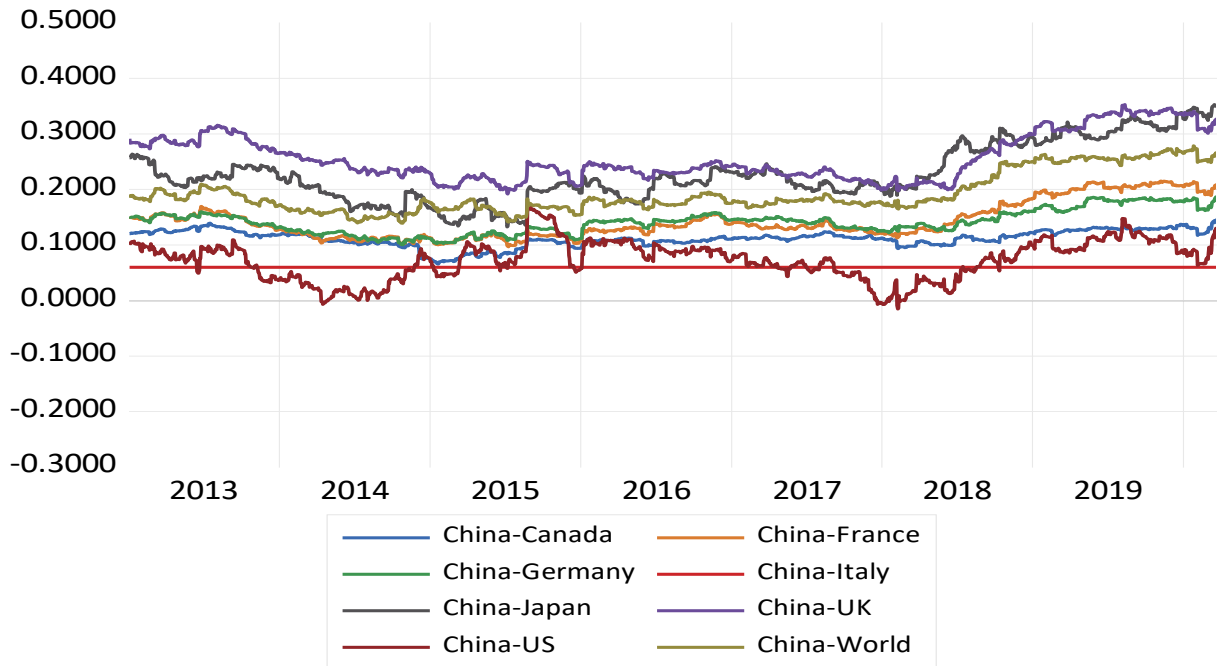


Notes: Net spillover plots have been created using Diebold and Yilmaz (2012) model

Appendix

Figure A1: DCCs from local currency return

Panel A: Between financial firms



Panel B: Between nonfinancial firms

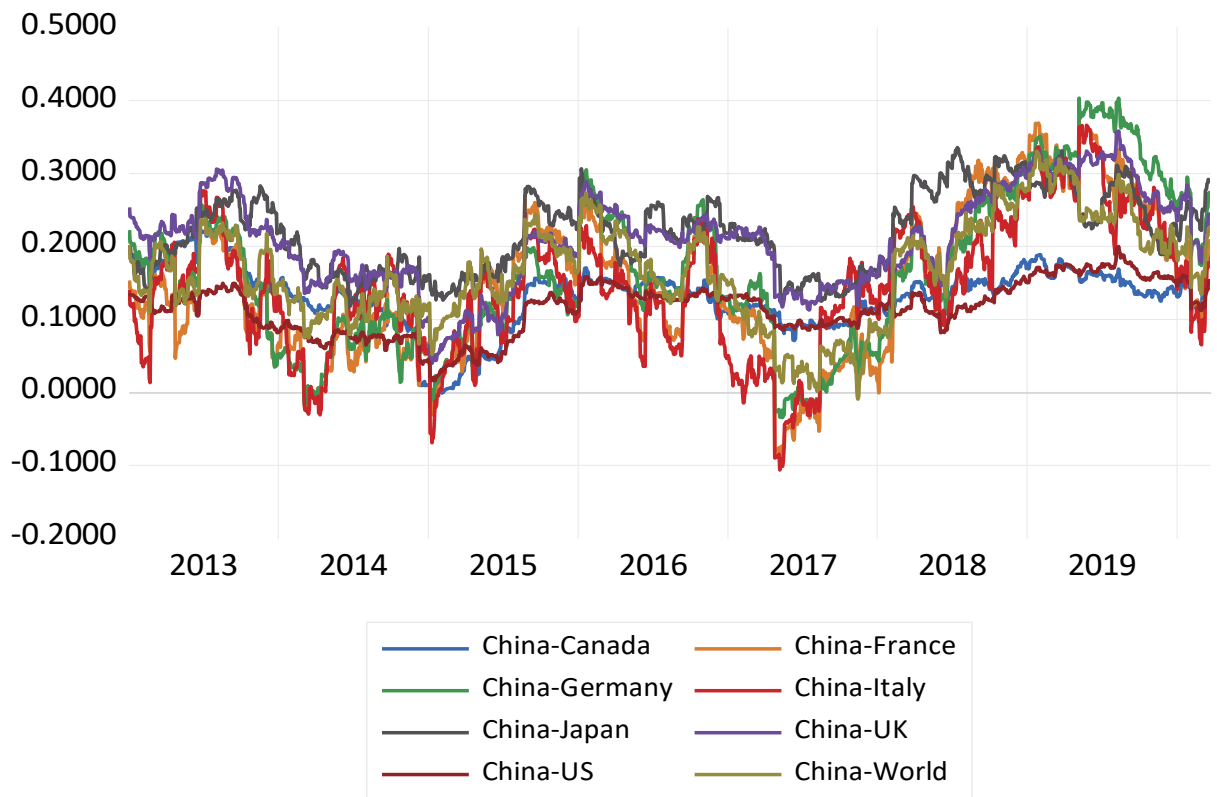


Figure A2–A7: Sensitivity of return spillover and volatility spillover to varying VAR lag structure and forecast horizon.

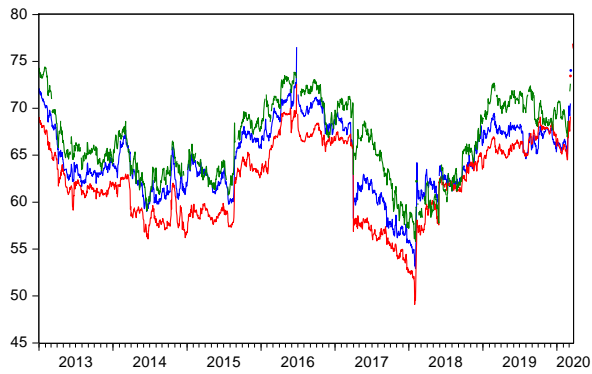


Figure A2: Sensitivity of the return spillover index (financial firms) to the VAR lag structure (orders of 5, 10 and 15)

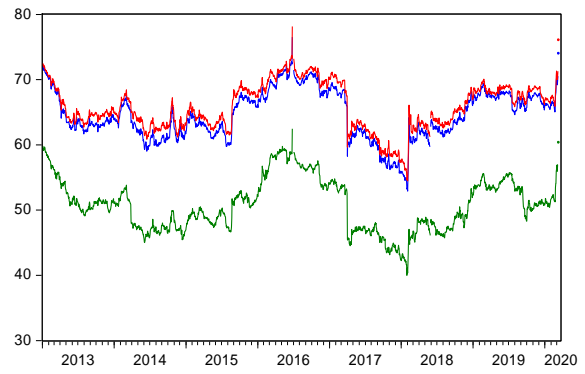


Figure A3: Sensitivity of the return spillover index (financial firms) to the forecast horizon (5, 10 and 15 days)

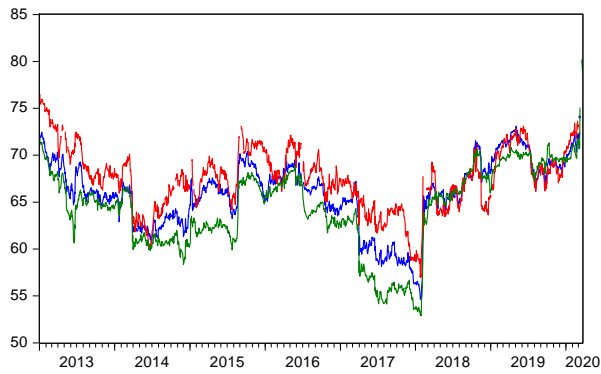


Figure A4: Sensitivity of the return spillover index (nonfinancial firms) to the VAR lag structure (orders of 5, 10 and 15)

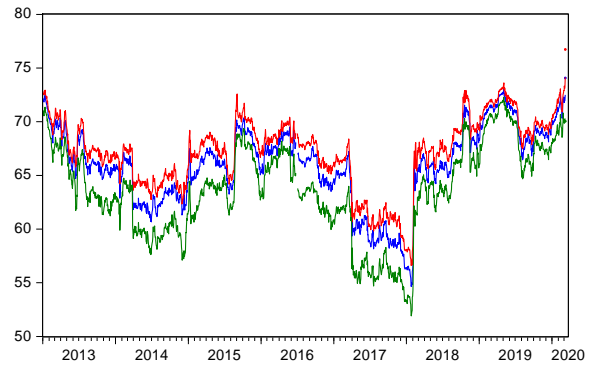


Figure A5: Sensitivity of the return spillover index (nonfinancial firms) to the forecast horizon (5, 10 and 15 days)

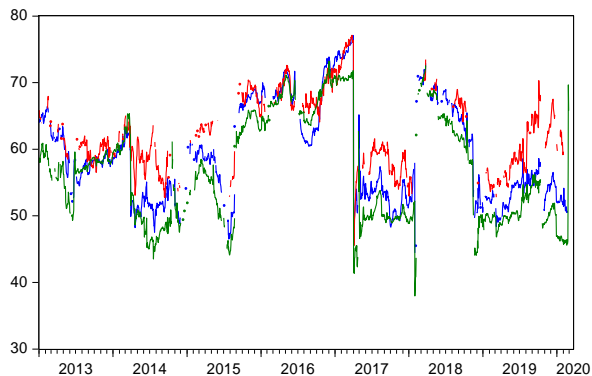


Figure A6: Sensitivity of the volatility spillover index (financial firms) to the VAR lag structure (orders of 5, 10 and 15)

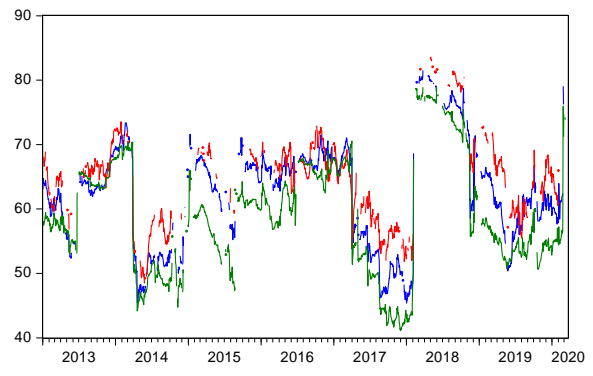


Figure A7: Sensitivity of the volatility spillover index (nonfinancial firms) to the VAR lag structure (orders of 5, 10 and 15)