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Determinants of connectedness in financial institutions: Evidence from Taiwan☆

Yi-Pei Chen [a], Yu-Lun Chen [b], Shu-Hen Chiang [b], Wan-Shin Mo [b,*]

[a] Department of Finance, College of Business, National Pingtung University, Taiwan
[b] Department of Finance, College of Business, Chung Yuan Christian University, Taiwan

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A B S T R A C T

This study estimates the interconnectedness among financial holding companies (FHCs) in Taiwan to identify its determinants. Using the Diebold and Yilmaz's (2012) measure, we find that larger directional connectedness stems from state-owned FHCs, indicating their dominant role in transmitting systemic risk. In addition, we find that bank performance and monetary policy both play an important role in financial connectedness. Finally, we show that syndicated loans may affect interconnectedness because the arranger bank transmits systemic risk to other participating banks.

1. Introduction

The 2007–2009 global financial crisis left researchers concerned about the vulnerability of the financial system, which in turn increased their investigation into the interconnectedness among financial institutions (Billio et al., 2012; Volcker, 2012; Diebold and Yilmaz, 2014; Gofman, 2017; Demirer et al., 2018). Volcker (2012), former chairman of the Federal Reserve, suggests that "the risk of failure of 'large, interconnected firms' must be reduced, whether by reducing their size, curtailing their interconnections or limiting their activities." Gofman (2017) finds that restricting the interconnectedness of banks can improve market stability. Systemic risk can arise from the interconnectedness between an individual financial company and other peers, and hence the individual financial company's failure, such as the collapse of Lehman Brothers, may diffuse to the entire financial system.

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* Corresponding author at: 200 Chung Pei Rd., Jhongli, Taoyuan 32023, Taiwan.
E-mail addresses: epchen@mail.nptu.edu.tw (Y.-P. Chen), yoloom@cycu.edu.tw (Y.-L. Chen), shchiang@cycu.edu.tw (S.-H. Chiang), cmo@cycu.edu.tw (W.-S. Mo).

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Compared with a large number of studies, which explore the interconnectedness among financial institutions in the United States and Europe, few studies focus on the interconnectedness of financial institutions in emerging markets (see Silva et al., 2017).[1] Emerging economies rely more on indirect finance via banks, and they are often classified as bank-based economies (i.e., banks are the dominant financial institutions). Authorities in emerging economies often adopt credit controls and directed credit programs at concessional prices and relax the constraints on financing to guide the direction of economic development. Although emerging economies continue to undergo financial reforms and liberalization (i.e., as government-owned banks become privatized), consolidate financial institutions, and globalize financial institutions, bank-based financial systems are still dominated by the government rather than the capital market. In particular, the Taiwanese economic structure primarily comprises small and medium-sized enterprises, which predominantly rely on bank financing (Berger and Udell, 2006), making Taiwan the most notable example of a bank-based system. In fact, the percentages of indirect and direct finance are 82.61% and 17.39%, respectively, according the 2019 statistics of the Central Bank of Taiwan.[2] For the reasons mentioned previously, we decide to evaluate Taiwanese financial institutions' interconnectedness.

Our primary aim in this study is to identify the determinants of interconnectedness in Taiwan's financial institutions. Using the return and return volatility data of financial holding companies (FHCs) in Taiwan, we employ the connectedness measure of Diebold and Yilmaz (2012) based on forecast error variance decompositions from vector autoregressions (VARs).[3] We further adopt the rolling-window estimation of Diebold and Yilmaz's (2012) measure to explore determinants of the total and directional connectedness of the financial system, as well as the pairwise directional connectedness from one FHC to another.

Diebold and Yilmaz (2014) point out that there is no single definition of systemic risk and Billio et al. (2012) also suggest that there is currently no widely accepted definition in systemic risk.[4] Systemic risk can be defined and investigated from two strands. First, previous studies define systemic risk with a focus on the extreme losses of financial institutions as financial distress occurs, for example, Adrian and Brunnermeier's (2016) conditional value-at-risk (CoVaR) based on VaR, Acharya et al.'s (2017) marginal expected shortfall (MES) and a revised version of MES, namely, long-run MES (LRMES) or SRISK based on expected capital shortfall (Engle et al., 2015). The common theme among these closely related measures is the magnitude of losses during periods when many institutions are simultaneously distressed.

Second, according to Billio et al. (2012), systemic risk involves the financial system, a collection of interconnected institutions that have mutually beneficial business relationships through which illiquidity, insolvency, and losses can quickly propagate during periods of financial distress. They emphasize that the measure of systemic risk must capture the degree of connectivity of financial institutions to some extent. Diebold and Yilmaz (2014) argue that their connectedness method can measure systemic risk and point out that their connectedness measures are related to CoVaR and MES. Our study belongs to the second strand of the literature regarding systemic risk and we gauge the degree of connectedness of the financial system to explore systemic risk not just during financial extreme distressed times but also during normal times.

We find that the greatest directional connectedness stems from partially government-owned FHCs, which are transmitters of systemic risk in Taiwan's financial system. Diebold and Yilmaz (2014) find that U.S. commercial banks with the largest market capitalization, such as Citigroup, Bank of America, and American Express, are net transmitters of systemic risk to other commercial banks. To sum up, in Taiwan, the major transmitter of systemic risk is not the FHC with the largest market capitalization, rather than partially government-owned FHCs.

In addition, we find that microfinance (i.e., bank performance of FHCs) and macroeconomic (i.e., monetary policy) factors both play an important role in determining total and directional connectedness in Taiwan. It is very reasonable to find that a lower capital

[1] With regard to a developed country, Furfine (2003) measures U.S. interbank contagion risk and shows that illiquidity of the borrower of federal funds escalates the interbank contagion risk to a level greater than the federal funds' exposure. Liu et al. (2020) show that U.S. interbank contagions and weak lending market liquidity both lead to bank failures during the global financial crisis. Upper and Worms (2004) find that contagions arise from interbank credit exposures in Germany's banking industry. Paltalidis et al. (2015) investigate systemic risk in Europe's banking system and show that losses arising from a sovereign credit risk channel are the primary source of systemic risk. Calabrese et al. (2017) estimate interdependence in the Eurozone's banking system and document a high level of contagion during the European debt and banking crisis. Aldasoro and Alves (2018) examine systemic risk among 53 large European banks and find that an institution's role in interbank systemic contagion risk at the national level also determines its role at the international level. With regard to emerging markets, Wang et al. (2018a) and Fang et al. (2018) find that the total connectedness of China's financial institutions reaches a peak when the market is under stress, such as during the Chinese stock market crash in June 2015. Wang et al. (2018b) show that city commercial banks are the largest contributors to the interbank volatility connectedness, rather than state-owned and joint-stock commercial banks in China. Huynh et al. (2020) document stock return contagion in Vietnam's banking system.

[2] If the investment of financial institutions is classified into indirect finance, the percentages of indirect and direct finance are 82.61% and 17.39%. By contrast, if the investment of financial institutions is classified into direct finance, the percentages of indirect and direct finance fall to 62% and 38%.

[3] We refer to FHCs established after the Gramm-Leach-Bliley Act in 1999 in accordance with the Taiwan Financial Holding Company Act in 2001 by means of controlling interest in a bank, insurance company, and/or securities firm.

[4] We thank an anonymous reviewer and editor for suggesting the discussion in systemic risk and Diebold and Yilmaz's connectedness measure.

adequacy ratio, a higher nonperforming loan ratio, a lower return on equity, a lower liquidity reserve ratio, higher interest rate sensitivity assets/interest rate sensitivity liabilities, and a lower deposit growth rate in banks are all associated with a higher level of FHC connectedness. With regard to monetary policy, a lower bank discount rate and higher M2 growth rate[5] (intermediate target) are positively related to a higher level of connectedness among FHCs. Therefore, we confirm that underperformance of the bank system and expansionary monetary policy increase the interconnectedness of FHCs.

Finally, we find that bank syndicated loans also affect FHCs' interconnectedness. The arranger bank in a syndicated loan transmits systemic risk to the other involved banks. Syndicated loan fraud can also increase the interconnectedness of FHCs.

We contribute to the literature in several ways. First, this study focuses on the determinants of connectedness among financial institutions, whereas previous studies only analyze the interconnectedness among financial institutions. For example, Billio et al. (2012) explore the return connectedness among the 100 largest financial institutions, including banks, brokers, hedge funds, and insurers, and find that connectedness can correctly capture financial crises and that banks play a more important role in transmitting shocks than other financial institutions. Diebold and Yilmaz (2014) find that the greatest connectedness comes from U.S. commercial banks with the largest market capitalization, such as Citigroup, Bank of America, and American Express. Demirer et al. (2018) find that banks located in North America and Europe generate the greatest net volatility connectedness to banks located in the rest of the world.

Second, to the best of our knowledge, our study is the first to consider the joint effects of bank performance and monetary policy on financial system interconnectedness. Zhang et al. (2016) suggest that an increase in the nonperforming loan ratio leads to riskier lending, potentially causing further deterioration of loan quality and financial system instability. Van Oordt and Zhou (2019) find that banks with lower capital ratios are associated with a significantly higher level of systemic risk, and Beltrame et al. (2018) find a combined effect of leverage and asset quality on systemic risk. However, these studies neither consider the role of bank performance in return and volatility interconnectedness in financial institutions nor account for monetary policy.

Third, we find that a seasonal pattern, which is analogous to the January effect, exists in FHCs' return and volatility connectedness. This issue has rarely been addressed. In Taiwan, corporate announcements occur frequently in the first quarter of the year. For example, the deadline for disclosure in an annual financial report of a firm is March 31st of the next year. We find that a higher level of FHC connectedness occurs in February and March. This finding fills a research gap and contributes to extant literature by providing new evidence for the seasonal pattern of FHCs' interconnectedness.

Finally, considering the specific financial structure, regulation, and industry in Taiwan, we find that partially government-owned FHCs play a leading role in interconnectedness, especially following syndicated loan fraud. This finding not only contributes to extant literature but also is crucial for policy makers and regulators. In Taiwan, government-owned banks are often the arranger bank in syndicated loans that support important public policies to stimulate the economy, such as offshore wind power or green energy. Evaluating and monitoring the connectedness contribution of these government-owned banks is important and useful to maintain financial system stability and stimulate economic growth.

Our study of Taiwan may serve as a reference for other emerging markets. We expect the dominance of government-owned banks in syndicated loans and the key role of government-owned banks to also exist in other emerging markets. Our findings may also be useful for central banks or regulators to supervise and stabilize financial systems in other emerging markets.

The rest of this paper proceeds as follows: Section 2 provides background information on the banking system and reform measures in Taiwan. Section 3 discusses the data and research methodology. Section 4 analyzes the empirical results and Section 5 shows the comparison of connectedness measures. Section 6 concludes.

2. Overview of Taiwan's banking system

Taiwan's banking system has experienced fundamental structural changes and reforms, including the First Financial Restructuring (FFR) from 2002 to 2003, the Second Financial Restructuring (SFR) from 2004 to 2008, and preparation for the implementation of Basel Accords II and III in 2001 and 2010, respectively. According to Hsiao et al. (2010), FFR required the nonperforming loan ratio of financial institutions to be below 5% and the capital adequacy ratio to be at least 8% by 2003. Nonperforming loan and capital adequacy ratio regulations encourage bank managers to adopt better banking and risk management practices to avoid bankruptcy. Hsiao et al. (2010) find that while banks decreased operating efficiency on average during the reform period (2002−2003) in comparison with the pre-reform period (2000−2001), the post-reform period reflects improvement in operating efficiency (2004–2005).

However, Hwang and Wu (2007) argue that by the end of 2004, there were still too many banks (50 banks) in Taiwan, and the market concentration of banks is relatively lower than that in other emerging markets.[6] The state-owned banks in Taiwan hold the major market share (approximately 60%), and thus the Taiwan government adopted the SFR to encourage mergers and acquisitions to enhance the degree of bank competition. The four goals of the SFR are that (1) the market shares of at least three FHCs reach more than 10% by the end of 2005, (2) the number of state-owned banks be reduced from 12 to six by the end of 2005, (3) the number of FHCs be reduced from 14 to seven, and (4) financial institutions be operated by foreign counterparts or listed overseas.

[5] In Taiwan, M2 monetary aggregates include all physical currency circulating in the economy (banknotes and coins), operational deposits in central bank, money in current accounts, saving accounts, money market deposits and small certificates of deposit.

[6] The market shares of the top five banks by asset size in 2004 were 89% in South Korea, 73% in Singapore, 76% in Hong Kong, and 37% in Taiwan.

Most of the important banks in Taiwan are owned by FHCs, which are all supervised by Taiwan's Central Bank and Financial Supervisory Commission. Taiwan's FHCs include four control types: dual-executive,[7] single-family-controlled,[8] state-controlled,[9] and management-controlled. Eight of 14 FHCs in Taiwan are family-controlled, including Cathay, China Development, CTBC, Fu Bon, Shin Kong, SinoPac, Tai Shih, and Yuanta. In addition, First, Mega, and Taiwan Cooperative are government-controlled FHCs. E. SUN and Hua Nan are dual-executive FHCs. The majority shareholders of International Bills Finance (IBF) FHC do not directly participate in operations or the decision-making process, and therefore IBF is mainly managed by professionals.

It is worth noting that in Hua Nan, the control rights held by ultimate shareholders is 5.81%, and the government ownership is as much as 21.43%. The government serves multiple identities as the largest, second-largest, and seventh-largest shareholder. The government also assigns the chairman of the board, CEO, and more than 50% of the director seats. The government has the dominant influence over the decision-making process in Hua Nan under the dual-executive system.

In 2019, the ratios of indirect and direct finance accounted for 82.61% and 17.39%, respectively, indicating that bank loans are the most important sources of external financing for firms in Taiwan. Domestic banks, especially state-owned banks, are largely controlled by the government. Officials can use their political power to influence the selection of bank managers and further disturb bank-lending practices (Lu et al., 2012). Government-owned banks include the Bank of Taiwan, First, Mega, and Taiwan Cooperative, which were the top four providers of syndicated loans in 2020, according to REFINITIV statistics. These banks often serve as the arranger bank for syndicated loans that support important government policies to stimulate the economy, such as offshore wind power or green energy. Therefore, we expect that government-owned banks play a vital role in transmitting systemic risk to other FHCs.

3. Data and methodology

In this section, we discuss the content of our related data, including stock prices and FHCs' operating performance in Taiwan. Next, we propose the connectedness (i.e., spillover) method of Diebold and Yilmaz (2012) to evaluate the FHCs' interconnectedness.

3.1. Data

We obtained the daily closing prices of the FHCs from the Taiwan Economic Journal database. The sample period covers January 1, 2003 to November 23, 2020. We include 13 FHCs in the following connectedness analysis and show their operating performance in Table 1.[10] In Taiwan, the central bank generally evaluates and supervises all bank performance by using the CAELSG method, which includes the bank's capital adequacy (C), asset quality (A), earnings (E), liquidity (L), interest rates sensitivity (S), and growth rates in major businesses (G).[11] In this study, we employ the capital adequacy ratio (CAR) for C, the nonperforming loan ratio (NPLR) for A, the return on equity (ROE) for E, liquidity reserve ratio (LRR) for L, interest rate sensitivity assets/interest rate sensitivity liabilities (AL) for S, and deposit growth rate (DGR) for G, which are all reported on the official website of the central bank of Taiwan.[12]

Table 1 shows the shareholding ratio for FHCs of the Ministry of Finance, R.O.C., in Taiwan, and it divides the FHCs in our sample into two groups: private and partially government-owned. The partially government-owned FHCs include dual-executive and state-controlled FHCs. In First, Mega, Taiwan Cooperative, and Hua Nan FHCs, the Ministry of Finance appointed the chairman of the board. Thus, government policy and guidance play an important role in the business performance of partially government-owned FHCs. However, we find a relatively lower CAR, ROE, and LRR for First, Hua Nan, Mega, and Taiwan Cooperative FHCs than those for Cathay FHC. The NPLRs for First, Hua Nan, Mega, and Taiwan Cooperative FHCs are relatively higher than those for Cathay and Fu Bon FHCs. These results suggest underperformance of government-owned FHCs compared with private FHCs, which have higher market capital, such as Cathay, CTBC, and Fu Bon FHCs.

We also examine the daily returns and return volatilities for the 13 FHCs. Daily returns are calculated as the log difference in closing prices, and we plot these companies' returns from January 2003 to November 2020 in Fig. 1. We observe that these financial companies' returns are heavily affected by the 2008 U.S. subprime mortgage crisis and the 2020 COVID-19 pandemic. The volatility

[7] The ultimate controlling shareholders include at least two groups, which may include families or the government. The individual group cannot unilaterally participate in the operations and the decision-making process without cooperating with the other group(s).

[8] According to Claessens et al. (2000), the summation of direct and indirect ownership measures this control right. Indirect ownership represents the minimum ownership in the controlling chain. Family-controlled businesses are defined by the following conditions: (1) the family control right is greater than the required control right; (2) the chairman and CEO are family members; and (3) family members hold at least 50% of the seats on the board of directors, and the seats held by related parties and outsiders are less than 33%. Alternatively, family members may hold at least 33% seats on the board of directors, and at least three family members may serve as directors, supervisors, and managers.

[9] The ultimate controlling shareholder is the government.

[10] Because Taiwan Cooperative FHC was established on December 1, 2011, we exclude it in our analysis because of the longer sample period. We also examine the return and volatility interconnectedness and consider Taiwan Cooperative FHC in the shorter sample period from December 1, 2011 to November 23, 2020 and find similar results. Given space constraints, we do not provide the estimation results of the inclusion of the Taiwan Cooperative FHC in our sample. They are available on request.

[11] The CAMELS model is another popular way to evaluate banks and financial institutions' performance. CAMELS represents capital adequacy (C), asset quality (A), management (M), earnings (E), liquidity (L), and sensitivity (S).

[12] The CAR is calculated by dividing a bank's capital by its risk-weighted assets on the basis of Basel III. The NPLR is calculated by dividing a bank's nonperforming loan by the total amount of outstanding loans. The ROE is calculated by dividing a bank's net income by the value of its total shareholders' equity. The LRR is calculated by dividing a bank's required liquid reserves by its total reservable liabilities.

Table 1
Variable Definitions and Description of Financial Holding Co., Ltd. in Taiwan.

Panel A. Variable definitions and sources

Variable	Data description	Measurement	Data source
CAR	Capital adequacy ratio	Capital adequacy	Official website of the central bank of Taiwan
NPLR	Nonperforming loan ratio	Asset quality	Official website of the central bank of Taiwan
ROE	Return on equity	Earning quality	Official website of the central bank of Taiwan
LRR	Liquidity reserve ratio	Liquidity quality	Official website of the central bank of Taiwan
AL	Ratio of interest rate sensitivity assets to interest rate sensitivity liabilities	Interest rates sensitivity	Official website of the central bank of Taiwan
DGR	Deposit growth rate	Growth rates in major businesses	Official website of the central bank of Taiwan
NII	Non-interest income	Control variable	Official website of the central bank of Taiwan
R^D	Discount rate	Monetary policy	Official website of the central bank of Taiwan
R^I	3-month Taipei interbank offered rate (TAIBOR)	Monetary policy	Official website of the central bank of Taiwan
R^{M2}	M2 growth rate	Monetary policy	Official website of the central bank of Taiwan
Size	Total assets	Control variable	Official website of the central bank of Taiwan

Panel B. Description of Financial Holding Co., Ltd. in Taiwan

Full Name	Abb.[1]	MC[2]	SMF[3]	CAR	NPLR	ROE	LRR	AL	DGR
Cathay Financial Holding Co.	C	551,131	0% (5.71%)	15.30%	0.13%	13.40	37.96%	109.82	7.52%
China Development Financial Holding Co.	CD	141,626	0% (0%)	14.29%	0.16%	6.59	41.44%	116.93	9.75%
CTBC Financial Holding Co.	CT	396,763	0% (0%)	13.31%	0.24%	10.06	28.36%	104.76	7.23%
E.SUN Financial Holding Co.	ES	323,022	0% (0.23%)	14.12%	0.19%	12.34	33.72%	121.45	12.42%
First Financial Holding Co.	F	282,262	11.49% (14.53%)	13.43%	0.29%	9.62	36.28%	110.65	12.73%
Fu Bon Financial Holding Co.	FB	449,255	0% (19.42%)	13.73%	0.19%	11.21	30.11%	111.05	8.75%
Hua Nan Financial Holding Co.	HN	243,454	1.70% (27.63%)	13.77%	0.19%	7.34	26.51%	98.42	10.58%
IBF Financial Holdings Co.[4]	IBF	33,464	0% (0%)						
Mega Financial Holdings Co.	M	420,234	8.40% (19.42%)	13.45%	0.27%	7.42	38.37%	124.57	2.89%
Shin Kong Financial Holding Co.	SK	111,975	0% (0.14%)	14.18%	0.19%	10.23	25.84%	85.76	12.15%
SinoPac Financial Holdings Co.	SP	122,290	0% (0.62%)	13.91%	0.16%	8.10	30.59%	113.51	14.07%
Taiwan Cooperative Financial Holding Co.[5]	TC	268,626	26.06% (26.98%)	13.86%	0.38%	7.31	30.05%	99.76	8.82%
Tai Shin Financial Holding Co.	TS	142,312	0% (0.87%)	14.47%	0.18%	9.52	24.86%	173.75	10.10%
Yuanta Financial Holding Co.	Y	203,652	0% (1.97%)	15.20%	0.14%	8.38	35.76%	84.03	7.89%

[1] Abbreviation: Abb.
[2] Market Capitalization: MC (in millions of NTD).
[3] Shareholding ratio for Ministry of Finance, R.O.C., Taiwan (SMF). Shareholding ratio for all governmental organizations in parentheses.
[4] The bank's performance data for IBF Financial Holdings Co. is not available because it has not held a bank during our sample period.
[5] Taiwan Cooperative Financial Holding Co. was established on December 1, 2011. Finally, all the statistics data are shown as of June 2020.

clustering is apparent in Fig. 1. Thus, we employ the univariate generalized autoregressive conditional heteroscedasticity, namely, GARCH(1,1) model with AR(1) for the returns equation to capture volatility clustering to examine each FHC's return volatility. The in-sample predicted values of volatility based on the GARCH(1,1) model for the period from January 2003 to November 2020 enable us to construct daily volatility, which we plot in Fig. 2. We observe similar volatility patterns for these financial companies and higher volatility during the 2008 U.S. subprime mortgage crisis and 2020 COVID-19 pandemic periods in Fig. 2. The co-movement of returns and return volatilities in Taiwanese financial companies show that their high level of connectedness and values of connectedness may be related to market risk and market condition.

3.2. Methodology

Using the framework of Diebold and Yilmaz (2012), we first consider a VAR (p) model of variable (X) with N-variables and p lags, as in Eq. (1)[13]:

$$\mathrm{X}_t = \sum_{k=1}^{p} \mathrm{A}_k X_{t-k} + \varepsilon_t, \varepsilon_t \sim (0, \Sigma) \tag{1}$$

where ε is a random error with a zero mean and covariance matrix, Σ, and A_i is the impact of the lagged variable (X_{t-k}). X may be returns (R) or return volatilities (V). This equation can be rewritten by a moving average representation ($R_t = \sum_{k=0}^{\infty} A_k \varepsilon_{t-k}$) and adjustment coefficient matrix A_k, which is equal to $\Phi_1 A_{l-1} + \ldots + \Phi_p A_{l-p}$.

Diebold and Yilmaz (2012) rely on variance decompositions, which allow us to parse the forecast error variances of each variable

[13] VAR and generalized VAR methods both assume that all variables are stationary. To meet this requirement, we use stock returns and volatility to calculate the connectedness index.

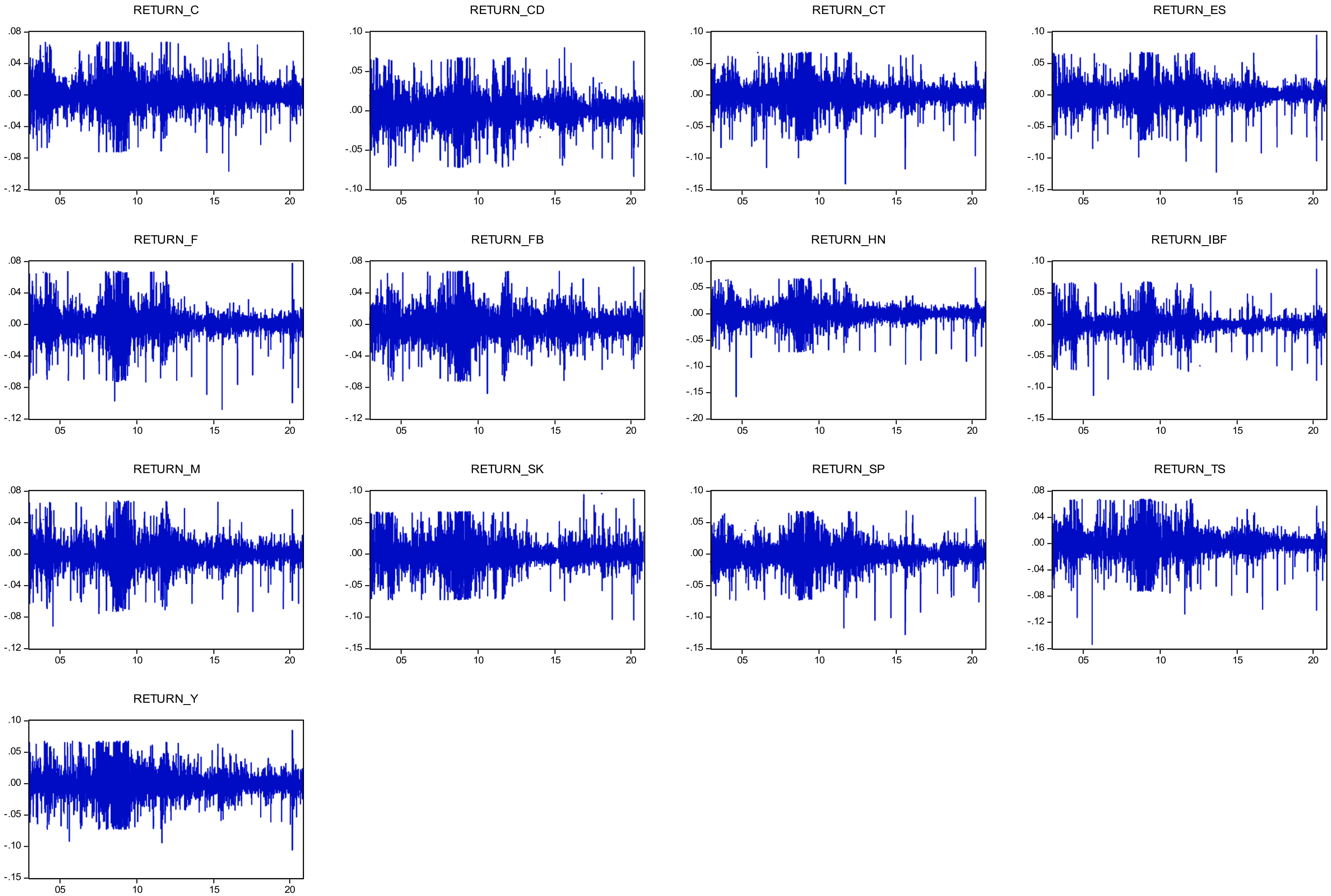

Fig. 1. Daily Stock Return of Financial Holding Co.

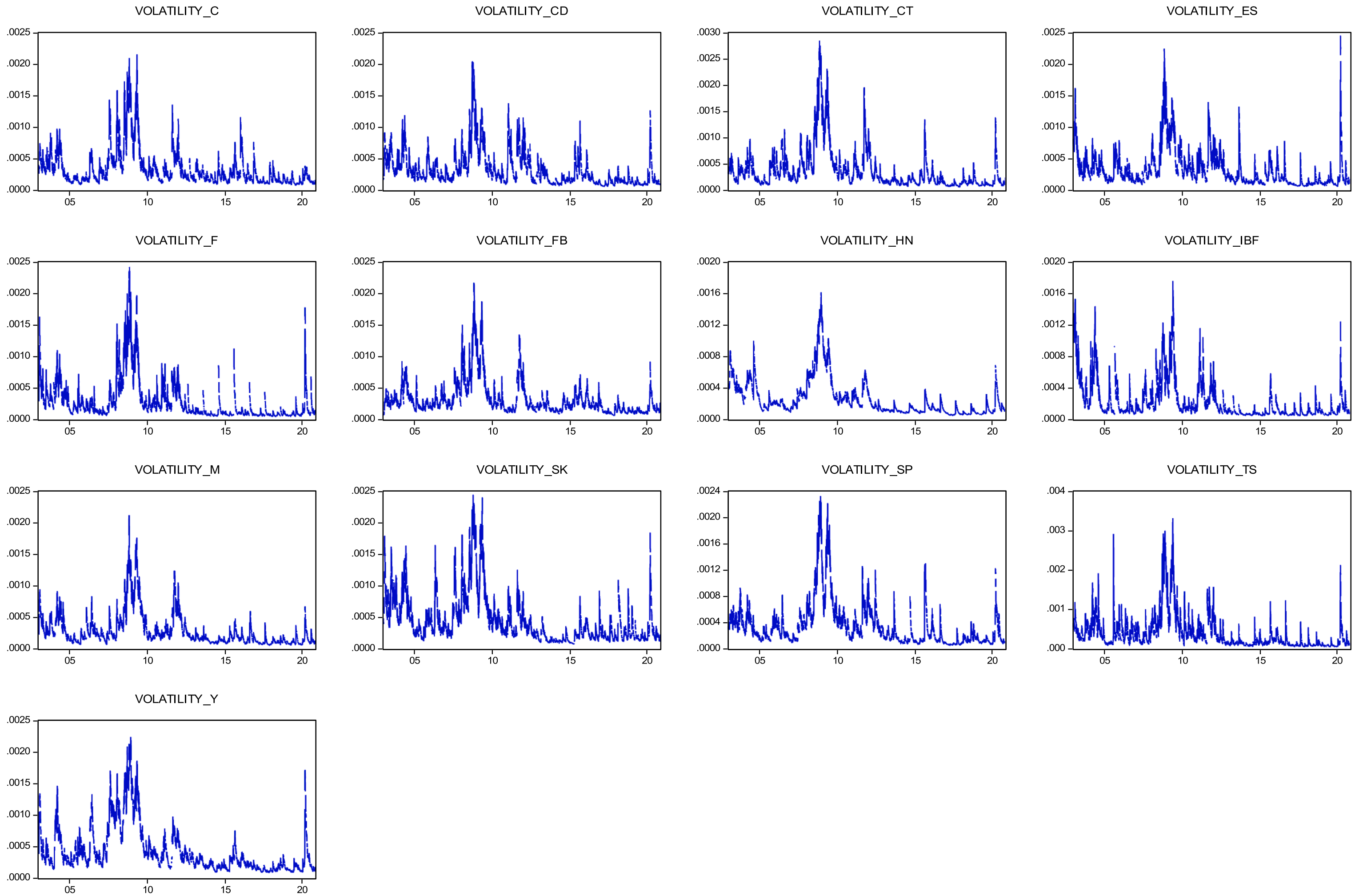

Fig. 2. Daily Stock Return Volatility of Financial Holding Co.

into parts that are attributable to the various system shocks by means of the fraction of the h-step-ahead error variance in forecasting X_i that is due to shocks to X_j, $\forall j \neq i$, for each i. Moreover, Diebold and Yilmaz (2012) adopt the generalized VAR (GVAR) methodology, which produces variance decompositions that are invariant to the ordering.[14] Finally, we compute the extent of the connectedness among all FHCs using h-step-ahead cross-variance shares, namely, $\varphi_{ij}^{g}(H)$, where the superscript (g) stands for the estimation results based on the GVAR:

$$\varphi_{ij}^{g}(\mathrm{H}) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \sum A_h' e_i\right)} \tag{2}$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation, and e_i is the selection vector, with one as the ith element and zeros otherwise. Finally, the cross-variance shares can be normalized, as in Eq. (3):

$$\widetilde{\varphi}_{ij}^{g}(H) = \frac{\varphi_{ij}^{g}(H)}{\sum_{j=1}^{N}\varphi_{ij}^{g}(H)} \tag{3}$$

According to Diebold and Yilmaz (2012), we can construct the total connectedness (TC) index of return and volatility as follows:

$$TC_t(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N}\widetilde{\varphi}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\varphi}_{ij}^{g}(H)}, \text{ where } \sum_{i,j=1}^{N}\widetilde{\varphi}_{ij}^{g}(H) = N. \tag{4}$$

The total connectedness index is calculated by the average value of the aggregation of the connectedness, regardless of whether from or to other FHCs (minus itself), namely, $\widetilde{\varphi}_{ii}^{g}$. Thus, the value of the total connectedness between zero and unity can show the overall connectedness across all FHCs. A higher total connectedness index reflects a more active connectedness across FHCs and, thus, higher systemic risk (Diebold and Yilmaz, 2014).

Furthermore, we can learn more about the directions of the connectedness—that is, a directional connectedness index by FHC i "from" other FHCs as $DC_{i.}$ in Eq. (5) and a directional connectedness index by FHC i "to" other FHCs as $DC_{.i}$ in Eq. (6):

$$DC_{i.}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\widetilde{\varphi}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\varphi}_{ij}^{g}(H)} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\widetilde{\varphi}_{ij}^{g}(H)}{N} \tag{5}$$

$$DC_{.i}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\widetilde{\varphi}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\widetilde{\varphi}_{ji}^{g}(H)} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N}\widetilde{\varphi}_{ji}^{g}(H)}{N} \tag{6}$$

We can obtain a net directional connectedness, referred to as the net connectedness index (NC_i), as in Eq. (7), through the application of the connectedness to other FHCs in Eq. (6) minus the connectedness from other FHCs in Eq. (5). Compared with other FHCs, a positive net directional connectedness indicates that an FHC is a provider or transmitter of systemic risk, whereas a negative value of this index indicates that an FHC is a receiver:

$$NC_i(H) = DC_{.i}^{g}(H) - DC_{i.}^{g}(H) \tag{7}$$

In addition, another index can examine the net pairwise connectedness between two specific FHCs by a net pairwise connectedness index (NPC_{ij}), as in Eq. (8). A positive NPC implies that FHC i has the connectedness to FHC j. This index provides insight into the net connectedness of an FHC "to" or "from" another FHC, rather than other all FHCs:

[14] According to the Cholesky decomposition in the ordinary VAR model, changing the order of variables in the VAR system may change the estimation results; moreover, a variable with a more preceding order can obtain a higher explainable ability.

$$NPC_{ij}(H) = \left[\frac{\widetilde{\varphi}_{ji}^{g}(H)}{\sum_{i,k=1}^{N} \widetilde{\varphi}_{ik}^{g}(H)} - \frac{\widetilde{\varphi}_{ij}^{g}(H)}{\sum_{i,k=1}^{N} \widetilde{\varphi}_{ik}^{g}(H)} \right] = \left[\frac{\widetilde{\varphi}_{ji}^{g}(H) - \widetilde{\varphi}_{ij}^{g}(H)}{N} \right] \tag{8}$$

More important, we introduce the rolling-window calculation into the total connectedness and net direction connectedness of return and volatility to examine the dynamic evolution of connectedness and spillover. Considering the time-varying total connectedness and net direction connectedness, we further explore the determinants of total connectedness and net direction connectedness of return and volatility.

4. Empirical results

4.1. Static estimation results: return and volatility connectedness

We study the return and return volatility connectedness in Taiwan's FHCs and report the full-sample static connectedness in Tables 2 and 3. In the "directional connectedness to others (TO)" row in Table 2, we show that the gross directional return connectedness to others is relatively greater for First (93%), Hua Nan (92.3%), Cathay (91.6%), and Mega (82.4%). In the "directional connectedness from others (FROM)" column, the gross directional return connectedness from other companies to the FHCs is at a similar level (71.5%–82.8%). For the net directional return connectedness, the greatest levels of connectedness stem from First (93–82.8 = 10.2%), Hua Nan (92.3–82.7 = 9.6%), and Cathay (91.6–82.7 = 8.9%).

In the "directional connectedness to others (TO)" row of Table 3, we show that the gross directional return volatility connectedness from each individual FHC to other companies is relatively greater for First (97.8%), China Development (91.5%), and Hua Nan (85.7%). In the "directional connectedness from others (FROM)" column, we find that the gross directional return volatility connectedness from other companies to individual FHCs is similar. The greatest net directional return volatility connectedness are from First (97.8–74.6 = 23.2%), China Development (91.5–74.3 = 17.2%), and Hua Nan (85.7–72.2 = 13.5%). These connectedness results may be best explained by the partial government ownership of the First, Hua Nan, and Mega FHCs, which also act as government agents in the financial sector and play a dominant role in syndicated loans. These FHCs serve as the major transmitters of systemic risk to other private FHCs.

4.2. Dynamic estimation results: total connectedness for return and volatility

The previous analysis illustrates the average return and volatility connectedness among FHCs. The average value of return and volatility connectedness among Taiwan's FHCs are 80.60% and 71.60%, respectively. We provide a dynamic analysis for the 13 FHCs by using rolling-window estimations to further explore the evolution of return and volatility connectedness over time. The width of a rolling window is 100 days, and the predictive horizon for the underlying variance decomposition is 10 days. We plot the dynamic total connectedness of returns and volatility in Figs. 3 and 4. The total connectedness of returns among these 13 FHCs jumps to 85% in 2007–2008, and the highest level of connectedness is achieved in the spring of 2020 in Fig. 3. The total connectedness of return volatility also jumps to the highest level in the spring of 2020 in Fig. 4. In other words, the peaks of total connectedness among Taiwan's FHCs directly correspond to the global financial crisis and COVID-19 pandemic. This also fully proves that total connectedness can be

Table 2
Full-Sample Return Connectedness.

	C	CD	CT	ES	F	FB	HN	IBF	M	SK	SP	TS	Y	FROM
C	17.3	7.2	7	5.7	7.5	8.7	7.2	3.7	6.7	8.3	6.8	6.7	7.1	82.7
CD	7.5	18	6.5	6.1	7.6	6.3	8.1	4.4	7.3	6.9	7.2	6.9	7.1	82
CT	7.8	7	19.2	6.3	7.9	7.4	7.2	3.2	7.3	6	6.9	6.8	6.9	80.8
ES	6.8	7	6.8	20.8	7.5	6.2	8.1	3.7	7.2	5.9	6.6	7.1	6.2	79.2
F	7.4	7.3	7	6.3	17.2	6.6	9.5	4.1	7.5	6.6	6.8	6.9	7	82.8
FB	9.6	6.8	7.4	5.8	7.4	19.3	6.9	2.9	7	6.6	6.9	6.2	7.1	80.7
HN	7.1	7.7	6.4	6.8	9.5	6.2	17.3	4.5	7.7	6.6	6.7	6.5	6.9	82.7
IBF	6.1	6.9	4.8	5.2	6.7	4.3	7.3	28.5	5.8	6.6	5.8	6.1	6	71.5
M	7.2	7.7	7.1	6.5	8.3	6.8	8.4	3.8	18.8	6	6.7	6.4	6.3	81.2
SK	9.2	7.4	6	5.5	7.4	6.6	7.3	4.5	6.1	19.1	6.8	7.4	6.9	80.9
SP	7.5	7.6	6.8	6.1	7.6	6.9	7.4	3.8	6.8	6.8	19.1	7	6.8	80.9
TS	7.4	7.4	6.8	6.5	7.8	6.1	7.2	4.2	6.6	7.4	7.2	19.2	6.2	80.8
Y	7.9	7.5	6.9	5.7	7.8	7.1	7.7	4	6.4	6.9	6.8	6.2	19.1	80.9
TO	91.6	87.5	79.6	72.5	93	79.2	92.3	46.9	82.4	80.4	81.2	80.1	80.4	**80.60%**
NET	8.9	5.5	−1.2	−6.7	10.2	−1.5	9.6	−24.6	1.2	−0.5	0.3	−0.7	−0.5	

Note: The *ij*-th entry of the upper-left 13 × 13 firm submatrix gives the *ij*-th pairwise directional connectedness (i.e., the percentage of 10-day-ahead forecast error variance of firm *i* due to shocks from firm *j*). The rightmost (FROM) column gives total directional connectedness (from) (i.e., row sums [from all others to *i*]). The bottom (TO) row gives total directional connectedness (i.e., column sums [to all others from *j*]). The bottommost (NET) row gives the difference in total directional connectedness (to–from). The bottom-right element (in boldface) is total connectedness.

Table 3
Full-Sample Return Volatility Connectedness.

	C	CD	CT	ES	F	FB	HN	IBF	M	SK	SP	TS	Y	**FROM**
C	25.2	8.5	5.6	3	7.4	9.9	9	3	7.7	4.3	6.3	3.7	6.4	74.8
CD	8.1	25.7	5.4	4.8	7.6	5.8	8.2	4	7.1	4.6	5.8	6.1	6.7	74.3
CT	6.9	7.1	26.6	5.6	8.4	7.7	6.3	2.7	6.6	3.6	5.7	5	7.7	73.4
ES	4.3	7.5	4.8	31	7.7	4.9	5.9	3.9	6.3	5.4	6	6.2	6	69
F	6.8	7.6	5.9	6.1	25.4	6.5	7	3.8	7.3	7.1	3.7	5.1	7.7	74.6
FB	11.2	7.2	7.5	4.2	7.9	24.7	7	2.1	6.9	4.3	5.1	4.4	7.8	75.3
HN	9.2	8.4	5.3	4.1	7.6	5.4	27.8	4.8	8	4.4	5	4.8	5.2	72.2
IBF	4.3	7.1	2.8	4.1	6.6	2.5	6.6	46.2	5.4	4.2	2.3	3.7	4.2	53.8
M	7.4	7.3	7	5.5	7.9	6	7.7	3.4	29.3	5	4.2	3.8	5.6	70.7
SK	5.9	7	4.9	5.3	12	5.6	6.4	3.8	6.2	26.4	4.9	5	6.5	73.6
SP	7.3	7.6	6.6	4.7	7.5	6.4	6.7	2.7	6.2	4.1	27.8	5.7	6.7	72.2
TS	5.8	7.8	5.9	4.9	8.7	5.8	8.2	3.8	4.6	3.6	5.8	28.6	6.6	71.4
Y	6.9	8.4	8.6	5.1	8.5	7.9	6.8	3.2	5.3	4.5	5.6	4.2	24.9	75.1
TO	84	91.5	70.2	57.3	97.8	74.5	85.7	41.2	77.7	55.1	60.4	57.6	77.3	**71.60%**
NET	9.2	17.2	−3.2	−11.7	23.2	−0.8	13.5	−12.6	7	−18.5	−11.8	−13.8	2.2	

Note: The *ij*-th entry of the upper-left 13 × 13 firm submatrix gives the *ij*-th pairwise directional connectedness (i.e., the percentage of 10-day-ahead forecast error variance of firm *i* due to shocks from firm *j*). The rightmost (FROM) column gives total directional connectedness (i.e., row sums [from all others to *i*]). The bottom (TO) row gives total directional connectedness (i.e., column sums [to all others from *j*]). The bottom (NET) row gives the difference in total directional connectedness (to–from). The bottom-right element (in boldface) is total connectedness.

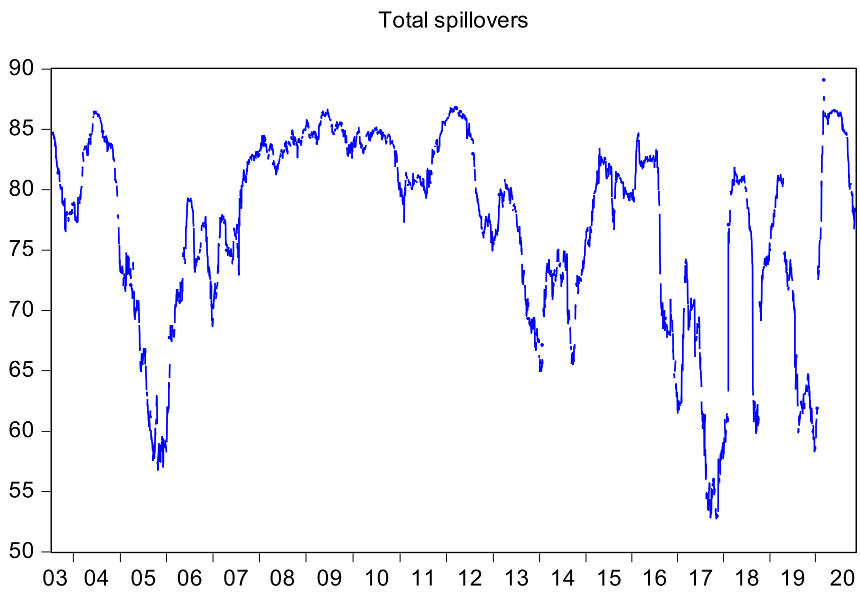

Fig. 3. Total Connectedness for Stock Return of Financial Holding Co.

used to monitor systemic risk.

4.3. Determinants of total connectedness for return and volatility

In this subsection, we not only examine the total connectedness of return and return volatility patterns but also identify the potential determinants of total connectedness. Both microfinance (i.e., CAELSG indicators) and macroeconomic (i.e., monetary policy) factors may play important roles in total connectedness. Klomp and De Haan (2012) note that there is the common agreement in the empirical literature that the CAMEL indicators (i.e., capital adequacy, asset quality, management, earnings, liquidity) are useful in assessing the financial vulnerability of banks. In addition, supervisors also use these indicators to assess a bank's soundness. Van Oordt and Zhou (2019) find that banks with lower capital ratios are associated with a significantly higher level of systemic risk, and Beltrame et al. (2018) find a combined effect of leverage and asset quality on systemic risk. Furthermore, Brunnermeier et al. (2020) find that non-interest income is positively correlated with the systemic risk for U.S. banks. Therefore, we expect that the aggregate level of all banks' CAELSG indicators and non-interest income, which are supervised by the central bank of Taiwan, is a crucial determinant of systemic risk and FHC connectedness.

To maintain macroeconomic and financial stability, central banks can adjust the level of short-term interest rates to influence

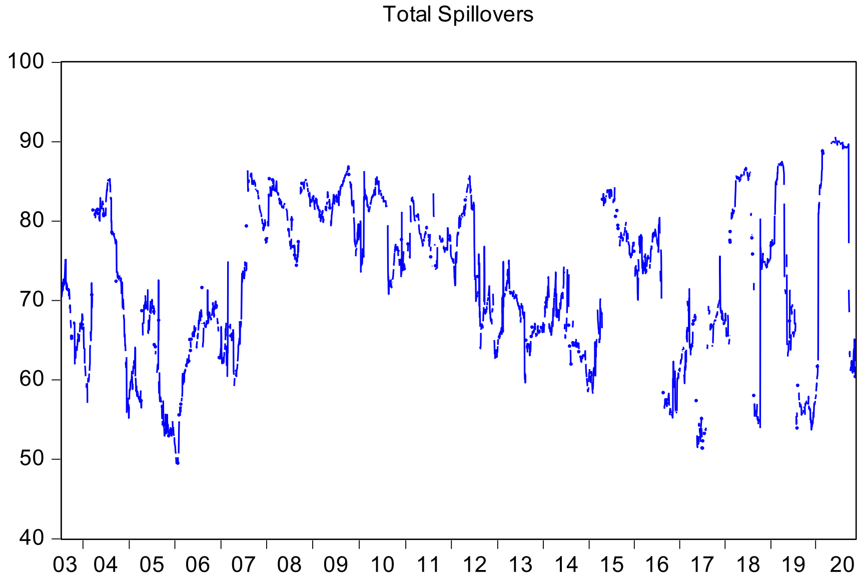

Fig. 4. Total Connectedness for Stock Return Volatility of Financial Holding Co.

spending, production, employment, and inflation or provide liquidity (short-term loans) for financial institutions. The balance sheets of financial institutions can be an important link in the monetary policy transmission mechanism (Hosono, 2006; Igan et al., 2017). According to the hypothesis advanced by Samuelson (1945), changes in interest rates affect bank performance. Mamatzakis and Bermpei (2016) find that an unconventional monetary policy has a negative relationship to bank performance. Thus, monetary policy may affect bank performance and systemic risk.

To further investigate the determinants of total connectedness of return and volatility, we estimate the linear model for total connectedness (TC_t^i) on return ($i = R$) and return volatility ($i = V$),[15] respectively as follows:

$$TC_t^i = \alpha_1 + \sum_{k=2}^{12} \alpha_k D_{k,t}^{Month} + \sum_{h=4}^{20} \beta_h D_{h,t}^{Year} + \gamma_1 CAR_{t-1} + \gamma_2 NPLR_{t-1} + \gamma_3 ROE_{t-1} + \gamma_4 LRR_{t-1} + \gamma_5 AL_{t-1} + \gamma_6 DGR_{t-1}$$

$$+\gamma_7 NII_{t-1} + \varnothing_1 R_{t-1}^D + \varnothing_2 R_{t-1}^I + \varnothing_3 R_{t-1}^{M2} + e_{i,t} \tag{9}$$

where $D_{k,\,t}^{Month}$ is a monthly dummy equal to one if the total connectedness occurs in February ($k = 2$; $k = 3$ for March, etc.) and zero otherwise, and $D_{h,\,t}^{Year}$ is a yearly dummy equal to one if the total connectedness occurs in 2004 ($h = 04$; $h = 05$ for 2005, etc.) and zero otherwise. We consider the six CAELSG indicators for all banks (i.e., the average value of all banks CAELSG indicators): *CAR* represents the capital adequacy ratio, *NPLR* represents the nonperforming loan ratio, *ROE* represents return on equity, *LRR* represents liquidity reserve ratio, *AL* represents interest rate sensitivity assets/interest rate sensitivity liabilities, and *DGR* represents the deposit growth rate. *NII* represents the total non-interest income of all FHCs (divided by 10^4). To consider the monetary policy impact, we adopt the R^D, R^I, and R^{M2} variables, which denote the discount rate, 3-month Taipei interbank offered rate (TAIBOR), and M2 growth rate, respectively. We employ the Newey–West robust heteroskedasticity autocorrelation-consistent standard errors to adjust for the presence of heteroskedasticity and autocorrelation in the regression errors (Newey and West, 1987).

To our knowledge, our study is the first attempt to identify the role of the CAELSG indicators and monetary policy in FHC connectedness. Table 4 provides the results for the total connectedness on return and return volatility. The higher values of return and volatility connectedness occur in February and March. This phenomenon may be explained by the high market uncertainty and business risk at the beginning of the year so that it induces higher systemic risk of the financial system. For example, the Chinese New Year festival usually falls during the months of January and February (and even extends into March), and many firms' new financial forecasts are provided from January to March.

Table 4 also shows that a higher total connectedness on return and volatility occurs in 2003–2004, in 2008, and in 2020 by a higher total connectedness occurred during the first and second financial reforms, the 2008 U.S. subprime mortgage crisis, and the 2020 COVID-19 pandemic periods. In addition, the results of the microfinance variables show that all banks with a lower capital adequacy

[15] We thank an anonymous reviewer for noting an endogeneity concern in Eq. (9). In line with Boehmer and Kelley (2009), we conducted regressions of Eqs. (9)–(11) using explanatory variables lagged by one period to reduce the potential endogeneity problem. The lagged explanatory variables can be interpreted as instruments for the corresponding current values. The results of lagged explanatory variables remain qualitatively and quantitatively similar to the current explanatory variables, checking the robustness of the results.

Table 4
Determinants of Total Connectedness for Return and Volatility.

	TC_t^R	TC_t^V
Monthly effect variables		
$D_{2,\ t}^{Month}$	5.82***	5.47***
	(0.31)	(0.49)
$D_{3,\ t}^{Month}$	5.29***	5.77***
	(0.28)	(0.45)
$D_{4,\ t}^{Month}$	4.51***	8.40***
	(0.31)	(0.50)
$D_{5,\ t}^{Month}$	4.25***	8.85***
	(0.30)	(0.49)
$D_{6,\ t}^{Month}$	4.30***	8.38***
	(0.30)	(0.48)
$D_{7,\ t}^{Month}$	2.33***	5.26***
	(0.30)	(0.48)
$D_{8,\ t}^{Month}$	−0.29	2.38***
	(0.31)	(0.51)
$D_{9,\ t}^{Month}$	−2.00***	−0.17
	(0.31)	(0.48)
$D_{10,\ t}^{Month}$	−4.19***	−5.51***
	(0.34)	(0.54)
$D_{11,\ t}^{Month}$	−4.67***	−5.49***
	(0.36)	(0.56)
$D_{12,\ t}^{Month}$	−5.56***	−6.73***
	(0.37)	(0.58)
Yearly effect variables		
$D_{04,\ t}^{Year}$	−7.17***	−7.38***
	(0.67)	(1.07)
$D_{05,\ t}^{Year}$	−32.43***	−25.47***
	(1.13)	(1.78)
$D_{06,\ t}^{Year}$	−30.97***	−30.95***
	(1.33)	(2.09)
$D_{07,\ t}^{Year}$	−20.66***	−6.64***
	(1.41)	(2.22)
$D_{08,\ t}^{Year}$	−28.59***	−23.85***
	(1.70)	(2.65)
$D_{09,\ t}^{Year}$	−38.54***	−40.15***
	(1.95)	(3.05)
$D_{10,\ t}^{Year}$	−41.70***	−43.17***
	(2.25)	(3.52)
$D_{11,\ t}^{Year}$	−45.96***	−43.42***
	(2.48)	(3.87)
$D_{12,\ t}^{Year}$	−47.51***	−51.60***
	(2.55)	(3.98)
$D_{13,\ t}^{Year}$	−59.34***	−54.30***
	(2.96)	(4.63)
$D_{14,\ t}^{Year}$	−61.98***	−52.90***
	(3.02)	(4.72)
$D_{15,\ t}^{Year}$	−61.55***	−58.26***
	(3.24)	(5.05)
$D_{16,\ t}^{Year}$	−68.09***	−72.03***
	(3.30)	(5.16)
$D_{17,\ t}^{Year}$	−86.24***	−84.67***
	(3.44)	(5.38)
$D_{18,\ t}^{Year}$	−76.01***	−73.25***
	(3.54)	(5.53)
$D_{19,\ t}^{Year}$	−79.94***	−81.57***
	(3.58)	(5.61)
$D_{20,\ t}^{Year}$	−70.81***	−73.07***
	(3.70)	(5.78)
CAELSG variables (Average value of all banks)		
CAR_{t-1}	−1.35**	−7.57***
	(0.55)	(0.71)
$NPLR_{t-1}$	1.70***	4.42***
	(0.43)	(0.87)
ROE_{t-1}	−0.82***	−1.85***
	(0.05)	(0.08)

(*continued on next page*)

Table 4 (*continued*)

	TC_t^R	TC_t^V
LRR_{t-1}	−1.42***	−3.17***
	(0.11)	(0.18)
AL_{t-1}	1.09***	1.33***
	(0.06)	(0.10)
DGR_{t-1}	−0.20***	−0.15
	(0.07)	(0.12)
NII_{t-1}	0.27***	0.12***
	(0.02)	(0.03)
Monetary policy variables		
R_{t-1}^D	−1.61***	−0.20
	(0.47)	(0.74)
R_{t-1}^I	−11.81**	−38.11***
	(5.92)	(9.41)
R_{t-1}^{M2}	3.05***	1.55**
	(0.43)	(0.67)
Constant	−12.62	219.41***
	(11.45)	(18.25)
A. R^2	0.78	0.65

Note: This table reports the estimation of linear models for total connectedness (TC_t^i) on return ($i = R$) and return volatility ($i = V$):

$$TC_t^i = \alpha_1 + \sum_{k=2}^{12} \alpha_k D_{k,t}^{Month} + \sum_{h=4}^{20} \beta_h D_{h,t}^{Year} + \gamma_1 CAR_{t-1} + \gamma_2 NPLR_{t-1} + \gamma_3 ROE_{t-1} + \gamma_4 LRR_{t-1} + \gamma_5 AL_{t-1} + \gamma_6 DGR_{t-1}$$

$$+\gamma_7 NII_{t-1} + \varnothing_1 R_{t-1}^D + \varnothing_2 R_{t-1}^I + \varnothing_3 R_{t-1}^{M2} + e_{i,t},$$

where $D_{k,\,t}^{Month}$ is a monthly dummy equal to one if the total connectedness occurs in February ($k = 2$; $k = 3$ for March, etc) and zero otherwise. $D_{h,\,t}^{Year}$ is a yearly dummy equal to one if the total connectedness occurs in 2004 ($h = 04$; $h = 05$ for 2005, etc.) and zero otherwise. *CAR* represents the capital adequacy ratio, *NPLR* represents the nonperforming loan ratio, *ROE* represents the return on equity, *LRR* represents the liquidity reserve ratio, *AL* represents interest rate sensitivity assets/interest rate sensitivity liabilities, and *DGR* represents the deposit growth rate. *NII* represents the total non-interest income of all FHCs (divided by 10^4). R^D, R^I, and R^{M2} denote the discount rate, 3-month Taipei interbank offered rate (TAIBOR), and M2 growth rate, respectively. Robust standard errors (Newey and West, 1987) are in parentheses. ***,**, and * indicate significance at the 1%, 5%, and 10% levels.

ratio (CAR), a higher nonperforming loan ratio (NPLR), a lower return on equity (ROE), a lower liquidity reserve ratio (LRR), higher interest rate sensitivity assets/interest rate sensitivity liabilities (AL), and a lower deposit growth rate (DGR) are associated with a significantly higher level of FHC total connectedness.

Finally, Table 4 shows that monetary policy factors significantly affect the FHCs' total connectedness. A lower bank discount rate (R^D), lower Taipei interbank offered rate (R^I), and higher M2 growth rate (R^{M2}) are associated with a significantly higher level of FHC total connectedness.

4.4. Determinants of net connectedness for return and volatility

In this subsection, we analyze the dynamic net connectedness for each FHC in Fig. 5. We present the net return connectedness from each FHC to other companies, which corresponds to the "NET" row in Table 2. We focus on the net return connectedness from First (F) FHC to other companies because its contribution to other companies is dominant in comparison with other FHCs. We find that from 2016 to 2017 (gray area), the net connectedness from First (F) increases to almost 80% in contrast with levels below 40% in a normal period. This peak is the largest net return connectedness in Fig. 5. In Fig. 6, we present the directional net volatility connectedness from each FHC to other companies, which corresponds to the "NET" row in Table 3. We still find that the largest net return volatility connectedness occurs from 2016 to 2017 (gray area) from First (F) to other companies. We find that the major impact of First FHC is due to the syndicated loan fraud scandal of Ching Fu Shipbuilding Co. Many banks were involved in this loan fraud, and we discuss this case in our pairwise net connectedness analysis in the next section.

Following the previous analysis of the determinants of total connectedness, we estimate the panel regression model for net connectedness on return ($NC_{i,\,t}^R$) and on return volatility ($NC_{i,\,t}^V$) to investigate the determinants of net connectedness of return and volatility form each i company, as follows:

$$NC^R_{i,t} = \alpha_0 + \alpha_1 CAR_{i,t-1} + \alpha_2 NPLR_{i,t-1} + \alpha_3 ROE_{i,t-1} + \alpha_4 LRR_{i,t-1} + \alpha_5 AL_{i,t-1} + \alpha_6 DGR_{i,t-1} + \alpha_7 NII_{i,t-1} + \alpha_8 R^D_{t-1}$$
$$+\alpha_9 R^I_{t-1} + \alpha_{10} R^{M2}_{t-1} + \alpha_{11} D^{L1}_{i,t} + \alpha_{12} D^{L2}_{i,t} + \alpha_{13} D^G_{i,t} + \alpha_{14} Size_{i,t} + e_{i,t}, \tag{10}$$

$$NC^V_{i,t} = \alpha_0 + \alpha_1 CAR_{i,t-1} + \alpha_2 NPLR_{i,t-1} + \alpha_3 ROE_{i,t-1} + \alpha_4 LRR_{i,t-1} + \alpha_5 AL_{i,t-1} + \alpha_6 DGR_{i,t-1} + \alpha_7 NII_{i,t-1}$$
$$+\alpha_8 R^D_{t-1} + \alpha_9 R^I_{t-1} + \alpha_{10} R^{M2}_{t-1} + \alpha_{11} D^{L1}_{i,t} + \alpha_{12} D^{L2}_{i,t} + \alpha_{13} D^G_{i,t} + \alpha_{14} Size_{i,t} + e_{i,t} \tag{11}$$

where *CAR* represents a capital adequacy ratio of *i* FHC, *NPLR* represents a nonperforming loan ratio of *i* FHC, *ROE* represents the return on equity of *i* FHC, *LRR* represents a liquidity reserve ratio of *i* FHC, *AL* represents interest rate sensitivity assets/interest rate sensitivity liabilities of *i* FHC, and *DGR* represents deposit growth rate of *i* FHC. *NII* represents the non-interest income for *i* FHC (divided by 10^4). In addition, R^D, R^I, and R^{M2} denote the discount rate, 3-month Taipei interbank offered rate (TAIBOR), and M2 growth rate, respectively, and $D^{L1}_{i,t}$ is a dummy equal to one if the net return connectedness occurs in the period of the syndicated loan fraud of Ching Fu before government investigation (February 1, 2016–July 31, 2017) and zero otherwise. Finally, $D^{L2}_{i,t}$ is a dummy equal to one if the net return connectedness occurs in the period of the Ching Fu syndicated loan fraud during government investigation (August 1, 2017 to December 29, 2017) and zero otherwise, and $D^G_{i,t}$ is a dummy equal to one if the net return connectedness belongs to government-owned banks (e.g., First, Hua Nan, and Mega) and zero otherwise. $Size_i$ represents the log of asset size of *i* FHC.

Table 5 provides the results for the determinants of the net return connectedness from each FHC to other companies. Yearly effects also exist in net return connectedness, as well as in the total return connectedness.[16] In addition, Table 5 shows that in terms of the microfinance variables, banks with a lower capital adequacy ratio (CAR), a higher nonperforming loan ratio (NPLR), a lower return on equity (ROE), a lower liquidity reserve ratio (LRR), higher interest rate sensitivity assets/interest rate sensitivity liabilities (AL), and a lower deposit growth rate (DGR) are associated with a significantly higher net return connectedness.

Table 5 also shows that for the monetary policy variables, only lower bank discount rates (R^D_t) are significantly associated with a higher level of net return connectedness. More importantly, we find the period before and during the government investigation of the Ching Fu loan fraud to be significantly associated with a higher level of net return connectedness. These higher values of net return connectedness could be due to the partially government-owned companies, such as First, Hua Nan, and Mega. These results confirm that these FHCs are the major contributors to connectedness. In addition, we use size, the asset size of each FHC in logarithm term, as a control variable. This variable has a positive and significant impact on the net return connectedness, further strengthening that these partially government-owned FHCs' role of transmitting systemic risks. Finally, Table 6 provides the results for the determinants of the net return volatility connectedness from each FHC to other companies and shows simillar results to those of net return connectedness in Table 5.

4.5. Pairwise net connectedness analysis: a case of syndicated loan fraud

We previously discussed the net return and volatility connectedness from each individual FHC to other companies and found that the greatest directional net return and volatility connectedness stems from First FHC, especially during 2016–2017. To further investigate the role of First FHC in connectedness and systemic risk, we execute a pairwise net connectedness analysis. We calculate the net pairwise connectedness between two FHCs by estimating the previously mentioned pairwise return and volatility connectedness between two specific FHCs in Tables 2 and 3 over time (i.e., rolling approach). As space is limited, we focus only on the connectedness of all participating banks, including First, Hua Nan, Mega, Shin Kong, and Yuanta in Figs. 7 and 8.[17]

We utilize the dataset from *Taiwan* News (2018) reports that, in August 2017, an anonymous whistleblower alerted the navy that the Ching Fu Shipbuilding Co. was falsifying its progress reports for a NT$35.8 billion (US$1.18 billion) project, which was contracted by the Ministry of National Defense, Taiwan, to construct six minesweeper ships.[18] The company defaulted on a NT$20.5 billion (US $679 million) syndicated loan from banks and incurred NT$14.897 billion (US$496 million) in losses. Banks in our sample data that were involved in the Ching Fu syndicated loan include the First Commercial Bank (Arranger), Hua Nan Commercial Bank, Mega International Commercial Bank, Shin Kong Commercial Bank, and Yuanta Commercial Bank. This syndicated loan began in February 2016, and the governemnt investigated the case from August 1, 2017 to December 29, 2017. The First Commercial Bank may incur approximately NT$6.6 billion in losses.

Fig. 7 shows that the net return connectedness from First to Hua Nan (partially government-owned) stayed around zero throughout several stages and reached higher than 6% during the investigation of the Ching Fu loan fraud (i.e., the red area). The net return connectedness from First to Mega (partially government-owned) also reached about 30% during the investigation into the loan fraud of Ching Fu and reached its first high of about 25% before the government investigation (in the gray area). Fig. 7 also shows that the net return connectedness from First to Shin Kong and Yuanta increased significantly during the investigation into the loan fraud of Ching

[16] Given space constraints, we do not provide the estimation results of the coefficients of yearly variables in Tables 5 and 6. They are available on request.

[17] All results of the pairwise net connectedness are available from the authors upon request.

[18] Ching Fu Shipbuilding Co. Chairman Ching-Nan Chen was sentenced to 25 years in prison by the Kaohsiung District Court for loan fraud offenses related to a navy contract. The Financial Supervisory Commission in Taiwan censured the related banks for their failure to notice the financial conditions of Ching Fu and to ensure the shipbuilder had the manufacturing and financial capability to deliver on its tender.

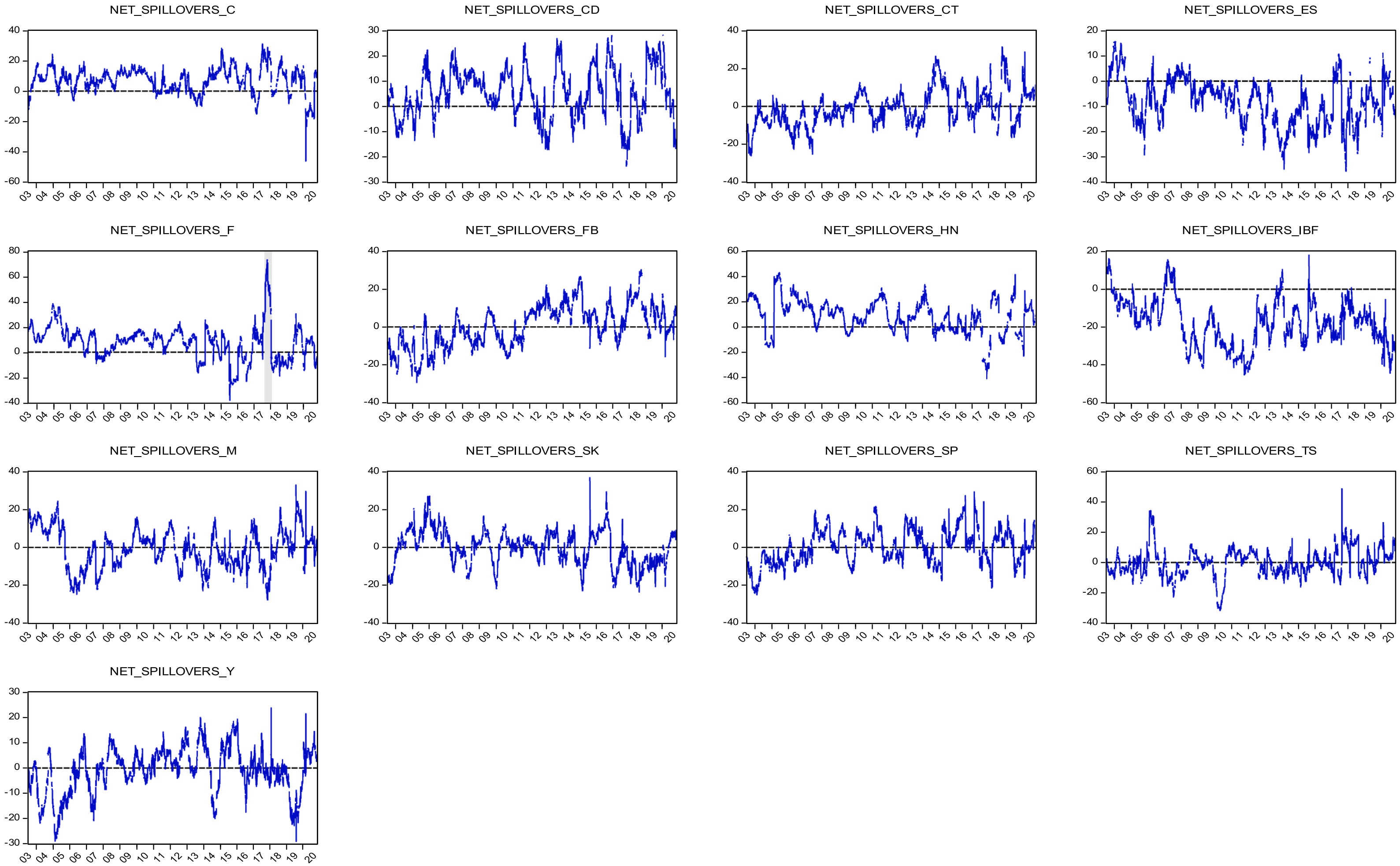

Fig. 5. Directional Net Connectedness for Stock Return of Financial Holding Co.
Note: The gray area depicts the syndicated loan fraud scandal of ChingFu Shipbuilding Co. over 2016–2017.

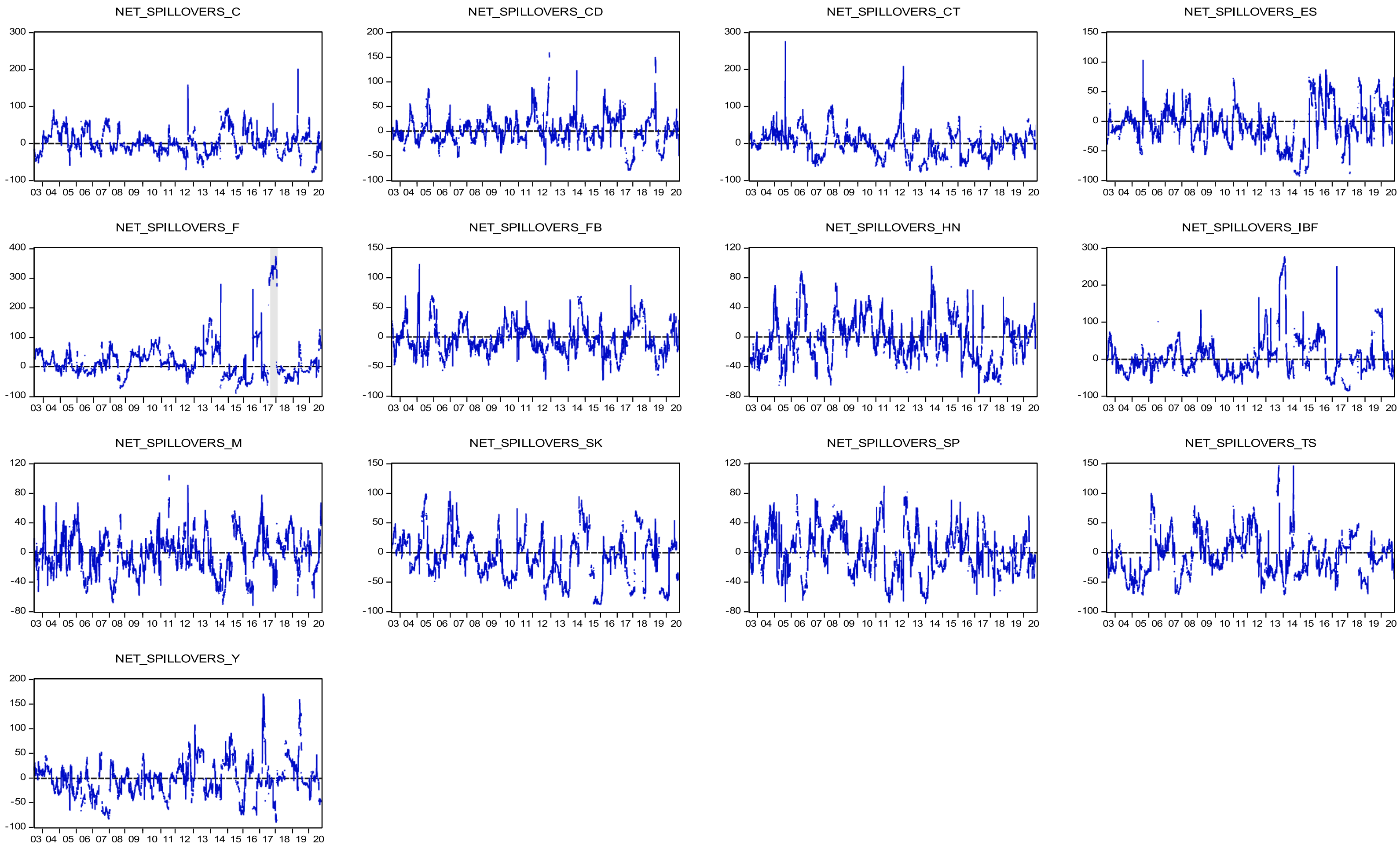

Fig. 6. Directional Net Connectedness for Stock Return Volatility of Financial Holding Co.
Note: The gray area depicts the syndicated loan fraud scandal of ChingFu Shipbuilding Co. over 2016–2017.

Table 5
Determinants of Net Directional Connectedness for Return.

	(1)	(2)	(3)	(4)	(5)
Constant	9.07***	3.73	8.54	−9.39	−39.63***
	(0.77)	(5.62)	(9.49)	(5.74)	(6.28)
CAELSG variables					
$CAR_{i,\ t-1}$	−0.88***		−0.87***	−0.89***	−0.48***
	(0.05)		(0.17)	(0.05)	(0.05)
$NPLR_{i,\ t-1}$	1.50***		1.50**	1.52**	2.47***
	(0.14)		(0.15)	(0.14)	(0.14)
$ROE_{i,\ t-1}$	−0.05***		−0.05	−0.05***	−0.08***
	(0.00)		(0.03)	(0.01)	(0.01)
$LRR_{i,\ t-1}$	−0.02**		−0.02*	−0.03***	−0.13***
	(0.01)		(0.01)	(0.01)	(0.01)
$AL_{i,\ t-1}$	0.09***		0.09***	0.09***	0.07***
	(0.01)		(0.01)	(0.01)	(0.01)
$DGR_{i,\ t-1}$	−0.05***		−0.06***	−0.06***	−0.07***
	(0.01)		(0.01)	(0.01)	(0.01)
$NII_{i,\ t-1}$					0.26***
					(0.02)
Monetary policy variables					
R^D_{t-1}		−0.27	−1.55*	−1.66***	−1.10***
		(0.32)	(0.86)	(0.32)	(0.34)
R^I_{t-1}		−0.38	−0.15	−14.90***	−18.31***
		(0.30)	(1.19)	(4.12)	(4.33)
R^{M2}_{t-1}		2.40	1.04	0.53*	0.47
		(4.10)	(3.72)	(0.30)	(0.31)
Dummy variables					
$D^{L1}_{i,\ t}$				1.44**	1.53**
				(0.59)	(0.62)
$D^{L2}_{i,\ t}$				2.48***	2.26***
				(0.45)	(0.47)
$D^{G}_{i,\ t}$					5.21***
					(0.12)
$Size_{i,\ t}$					3.54***
					(0.10)
Fixed year effects	Yes	Yes	Yes	Yes	Yes
Fixed firm effects	Yes	Yes	Yes	Yes	No
A. R^2	0.20	0.18	0.21	0.21	0.12

Note: This table reports the estimation of five linear models for net return directional connectedness ($NC^R_{i,\ t}$):

$$NC^R_{i,t} = \alpha_0 + \alpha_1 CAR_{i,t-1} + \alpha_2 NPLR_{i,t-1} + \alpha_3 ROE_{i,t-1} + \alpha_4 LRR_{i,t-1} + \alpha_5 AL_{i,t-1} + \alpha_6 DGR_{i,t-1} + \alpha_7 NII_{i,t-1}$$

$$+\alpha_8 R^D_{t-1} + \alpha_9 R^I_{t-1} + \alpha_{10} R^{M2}_{t-1} + \alpha_{11} D^{L1}_{i,t} + \alpha_{12} D^{L2}_{i,t} + \alpha_{13} D^G_{i,t} + \alpha_{14} Size_{i,t} + e_{i,t},$$

$$+ e_{i,t},$$

where *CAR* represents the capital adequacy ratio, *NPLR* represents the nonperforming loan ratio, *ROE* represents return on equity, *LRR* represents the liquidity reserve ratio, *AL* represents interest rate sensitivity assets/interest rate sensitivity liabilities, and *DGR* represents the deposit growth rate for *i* FHC. *NII* represents the non-interest income for *i* FHC (divided by 10^4). R^D, R^I, and R^{M2} denote the discount rate, 3-month Taipei interbank offered rate (TAIBOR), and M2 growth rate, respectively. $D^{L1}_{i,\ t}$ is a dummy equal to one if the net return connectedness occurs in the period of the Ching Fu Shipbuilding Co. loan fraud before the government investigation (February 1, 2016–July 31, 2017) and zero otherwise. $D^{L2}_{i,\ t}$ is a dummy equal to one if the net return connectedness occurs in the period of the Ching Fu loan fraud during the government investigation (August 1, 2017–December 29, 2017) and zero otherwise. $D^{G}_{i,\ t}$ is a dummy equal to one if the net return connectedness belongs to the government-controlled banks and zero otherwise. $Size_i$ represents the log of asset size of FHC *i*. Robust standard errors (Newey and West, 1987) are in parentheses. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level. Given space constraints, we do not provide estimation results of the coefficients of yearly variables in Table 5. They are available on request.

Table 6
Determinants of Net Directional Connectedness for Return Volatility.

	(1)	(2)	(3)	(4)	(5)
Constant	6.96**	−56.41	−36.93	−33.08	−61.99***
	(2.99)	(55.57)	(22.92)	(22.90)	(23.73)
CAELSG variables					
$CAR_{i,\ t-1}$	−0.62***		−0.61***	−0.70***	−0.60***
	(0.19)		(0.19)	(0.19)	(0.18)
$NPLR_{i,\ t-1}$	1.47***		1.48***	1.37**	1.15**
	(0.53)		(0.55)	(0.55)	(0.53)
$ROE_{i,\ t-1}$	−0.26***		−0.27***	−0.26***	−0.22***
	(0.03)		(0.03)	(0.03)	(0.03)
$LRR_{i,\ t-1}$	−0.05		−0.06*	−0.05*	−0.32***
	(0.03)		(0.03)	(0.03)	(0.03)
$AL_{i,\ t-1}$	0.07***		0.08***	0.07***	0.08***
	(0.02)		(0.02)	(0.02)	(0.01)
$DGR_{i,\ t-1}$	−0.14***		−0.15***	−0.15***	−0.18***
	(0.02)		(0.02)	(0.02)	(0.02)
$NII_{i,\ t-1}$					1.61***
					(0.10)
Monetary policy variables					
R^D_{t-1}		−2.93**	−2.73**	−2.77**	−2.65**
		(1.21)	(1.24)	(1.20)	(1.22)
R^I_{t-1}		−41.60***	−36.59**	−13.54***	−10.98**
		(16.11)	(16.67)	(3.55)	(4.91)
R^{M2}_{t-1}		0.90	0.20	1.84	2.82**
		(1.11)	(1.13)	(1.13)	(1.15)
Dummy variables					
$D^{L1}_{i,\ t}$				8.31***	8.63***
				(1.70)	(1.73)
$D^{L2}_{i,\ t}$				21.43***	21.81***
				(2.30)	(2.33)
$D^{G}_{i,\ t}$					5.39***
					(0.47)
$Size_{i,\ t}$					1.64***
					(0.38)
Fixed year effects	Yes	Yes	Yes	Yes	Yes
Fixed firm effects	Yes	Yes	Yes	Yes	No
A. R^2	0.05	0.05	0.05	0.06	0.03

Note: This table reports the estimation of five linear models for net directional connectedness of volatility ($NC^V_{i,\ t}$):

$$NC^V_{i,t} = \alpha_0 + \alpha_1 CAR_{i,t-1} + \alpha_2 NPLR_{i,t-1} + \alpha_3 ROE_{i,t-1} + \alpha_4 LRR_{i,t-1} + \alpha_5 AL_{i,t-1} + \alpha_6 DGR_{i,t-1} + \alpha_7 NII_{i,t-1}$$

$$+\alpha_8 R^D_{t-1} + \alpha_9 R^I_{t-1} + \alpha_{10} R^{M2}_{t-1} + \alpha_{11} D^{L1}_{i,t} + \alpha_{12} D^{L2}_{i,t} + \alpha_{13} D^G_{i,t} + \alpha_{14} Size_{i,t} + e_{i,t},$$

where *CAR* represents the capital adequacy ratio, *NPLR* represents a nonperforming loan ratio; *ROE* represents return on equity, *LRR* represents the liquidity reserve ratio, *AL* represents interest rate sensitivity assets/interest rate sensitivity liabilities, and *DGR* represents the deposit growth rate for *i* FHC. *NII* represents the non-interest income for *i* FHC (divided by 10^4). R^D, R^I, and R^{M2} denote the discount rate, 3-month Taipei interbank offered rate (TAIBOR), and M2 growth rate, respectively. $D^{L1}_{i,\ t}$ is a dummy equal to one if the net return connectedness occurs in the period of the Ching Fu Shipbuilding Co. loan fraud before the government investigation (February 1, 2016–July 31, 2017) and zero otherwise. $D^{L2}_{i,\ t}$ is a dummy equal to one if the net return connectedness occurs in the period of the Ching Fu loan fraud during the government investigation (August 1, 2017–December 29, 2017) and zero otherwise. $D^{G}_{i,\ t}$ is a dummy equal to one if the net return connectedness belongs to the government-controlled banks and zero otherwise. $Size_i$ represents the log of asset size of FHC *i*. Robust standard errors (Newey and West, 1987) are in parentheses. *** indicates significance at the 1% level; ** indicates significance at the 5% level; * indicates significance at the 10% level. Given space constraints, we do not provide the estimation results of the coefficients of yearly variables in Table 6. They are available on request.

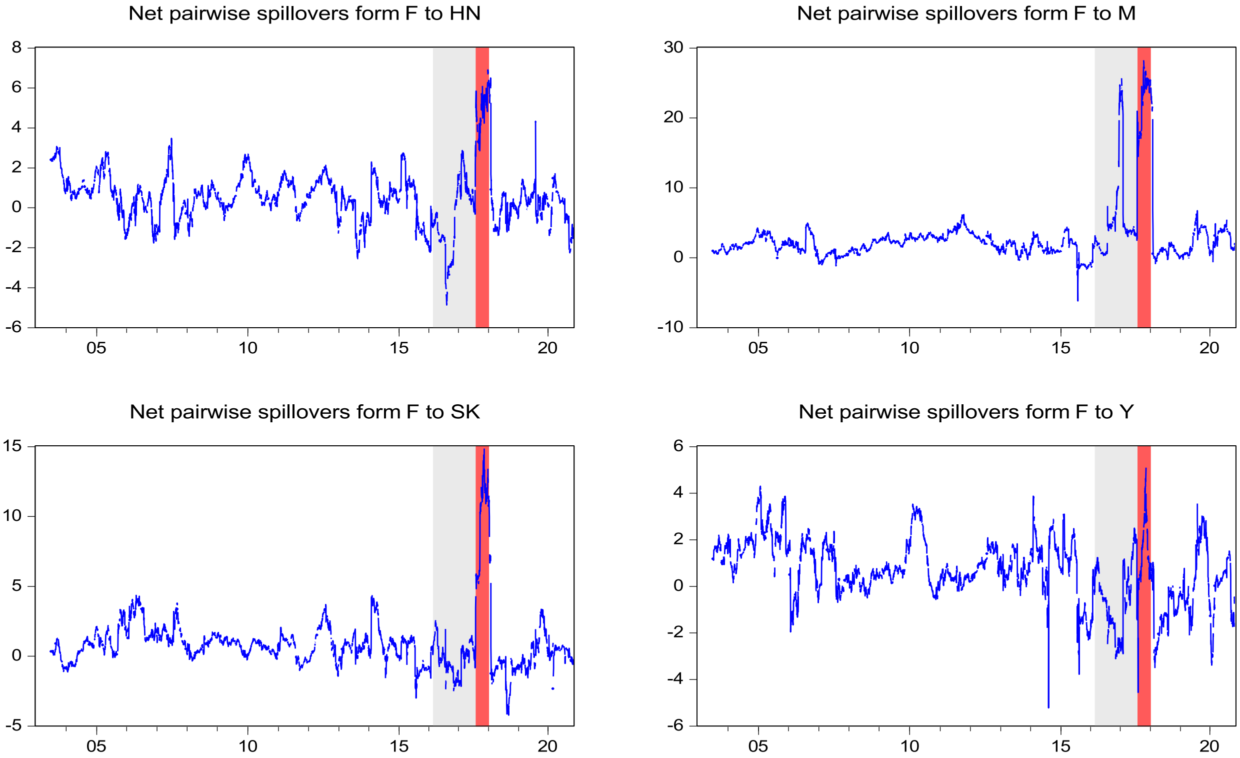

Fig. 7. Net Pairwise Return Connectedness from First (F) Financial Holding Co. to Hua Nan (HN), Mega (M), Shin Kong (SK), and Yuanta (Y) Financial Holding Co.
Note: Net pairwise rerun connectedness form F occur in the gray area (Ching Fu loan fraud before government investigation, 2016/02/01–2017/07/31). Net pairwise rerun connectedness form F occur in the red area (Ching Fu loan fraud during government investigation, 2017/08/01–2017/12/29). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fu.

Fig. 8 shows that the net return volatility connectedness from First to Hua Nan, Mega, Shin Kong, and Yuanta increased significantly during the investigation into the loan fraud of Ching Fu. These findings show that syndicated loan fraud affects connectedness and that an arranger bank in a syndicated loan will become a major contributor in retun and volatilty connectedness. In Taiwan, the government-owned FHCs, including the Bank of Taiwan, First, Mega, and Taiwan Cooperative, are the top four lenders of syndicated loans in 2020, according to REFINITIV statistics. These banks often act as arranger banks in syndicated loans. Therefore, the dominant role of government-owned banks in syndicated loans affects the return and volatility connectedness of the entire financial system.

5. Comparison of connectedness measures

There are various methods to measure connectedness.[19] Billio et al. (2012) propose Granger-causality method and principal components analysis (PCA) to measure connectedness by use of the monthly returns of the financial institutions. Diebold and Yilmaz (2014) point out that their connectedness measure and the Granger-causality method are complements: firstly, Diebold and Yilmaz's connectedness method based on a weighted network measures total, total directional, and pairwise directional connectedness among variables, whereas the Granger-causal approach measures directional relations among variables but provides pairwise and unweighted relations by testing whether the coefficients are different from zero with arbitrary significance levels yet tracking no magnitude of non-zero coefficients; secondly, one needs to determine the validity of assumptions when conducting variance decomposition and impulse response analyses with the Diebold and Yilmaz's connectedness approach, whereas this is unnecessary with the Granger-causal method.

In this study, we also consider the pairwise Granger-causality tests in the VAR models and PCA for FHCs returns and return volatilities to measure connectedness. We find similar results, supporting that the partial government-owned First and Hua Nan FHCs serve as the major return and volatility transmitters to other private FHCs. These results prove the robustness of Diebold and Yilmaz

[19] We thank an anonymous reviewer for suggesting the discussion and consideration of Diebold and Yilmaz's method with other connectedness method (i.e., Granger-causality method and PCA). Due to space constraints, the results of Granger-causality tests and PCA are not reported here and these results are available upon request

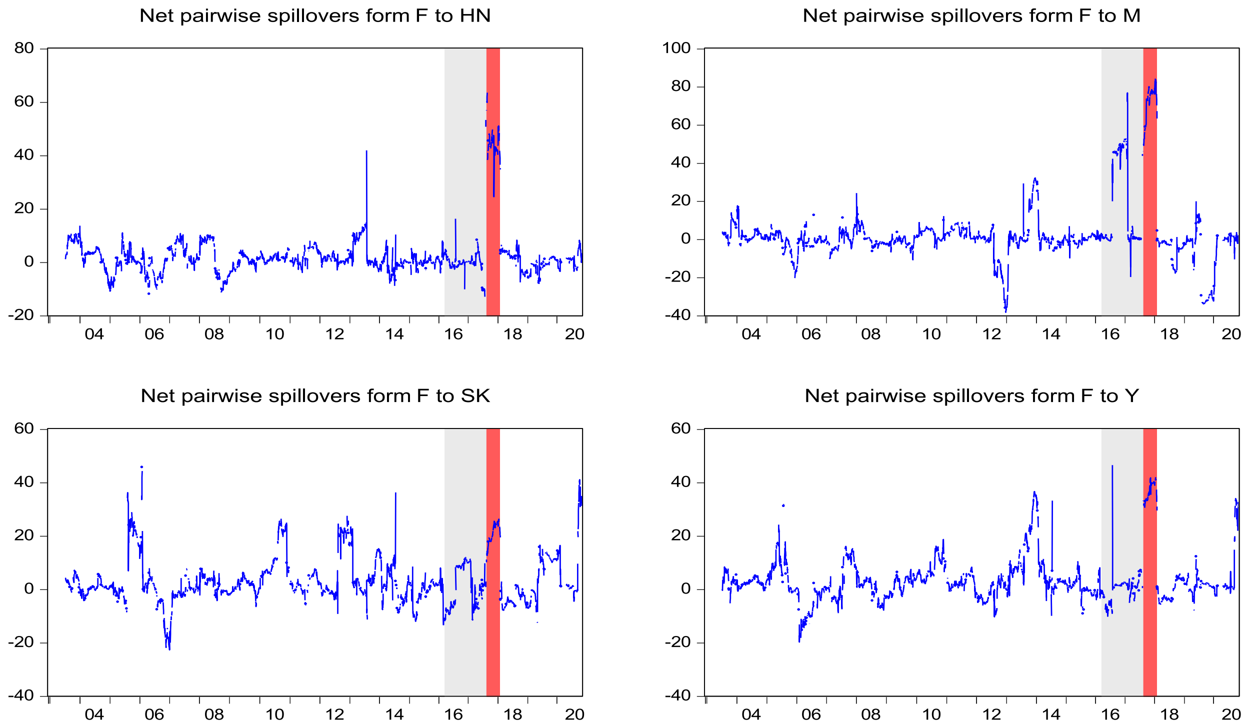

Fig. 8. Net Pairwise Return Volatility Connectedness from First (F) Financial Holding Co. to Hua Nan (HN), Mega (M), Shin Kong (SK), and Yuanta (Y) Financial Holding Co.

Note: Net pairwise volatility connectedness form F occur in the gray area (Ching Fu loan fraud before government investigation, 2016/02/01–2017/07/31). Net pairwise volatility connectedness form F occur in the red area (Ching Fu loan fraud during government investigation, 2017/08/01–2017/12/29. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

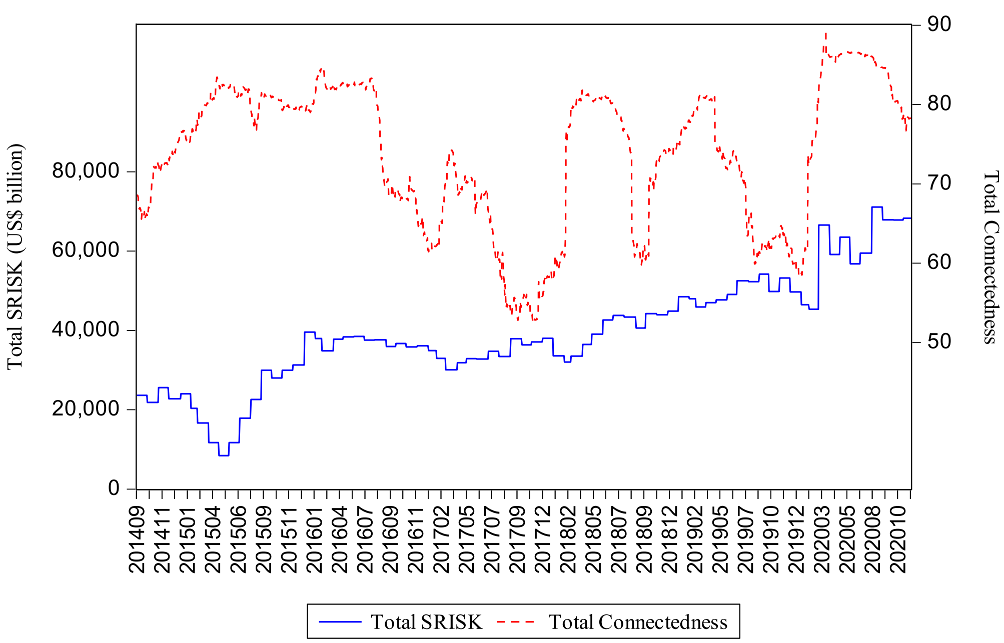

Fig. 9. Total SRISK and Total Connectedness for Stock Returns FHCs.

Note: The Systemic Risk Contribution, SRISK, is the FHC capital shortfall that would be experienced by a firm in the event of a crisis. Total SRISK is the sum of all the FHCs with positive values. To measure monthly SRISK, the capital requirement used in calculating capital shortfalls is set to be 8% and the six-month crisis threshold for the market index decline is 40%. Here we construct long-run marginal expected shortfall (LRMES) predictions using a GARCH DCC model to measure SRISK. Please see Engle et al. (2015) and Engle and Ruan (2018) about SRISK in detail.

connectedness measurement.

On the other side, we also provide an assessment of the robustness check of our results of Diebold and Yilmaz connectedness to the other systemic risk measure (i.e., the SRISK of Engle et al. (2015)). SRISK is the FHC capital shortfall that would be experienced by this FHC in the event of a crisis. Total SRISK is the sum of all FHCs SRISK (Engle et al., 2015; Engle and Ruan, 2018). We find that the correlation coefficient for total SRISK and Diebold and Yilmaz total connectedness is about 0.240 and is significantly different from zero. In addition, we plot the time series of Diebold and Yilmaz total connectedness measure and total SRISK in Fig. 9. Fig. 9 shows that the two series seem to follow similar patterns, supporting the positive relationship between total connectedness measure and total SRISK. To sum up, although these approaches capture different aspects of systemic risk, the positive correlation still exists.

6. Conclusions

This study investigates interconnectedness among Taiwan's FHCs and identifies the determinants of interconnectedness. We use the Diebold and Yilmaz's (2012) connectedness measure and adopt a rolling estimation to explore determinants of the total connectedness, the net connectedness between one FHC and other companies, and the pairwise net connectedness between one FHC and another.

We find that the greater directional connectedness from the partially government-owned FHCs, including First, Hua Nan, and Mega, supports the claim that these types of FHCs are the main transmitters of systemic risk. In addition, we find that microfinance (i.e., bank performance of FHCs) and macroeconomic (i.e., monetary policy) factors play an important role in determining total and directional connectedness in Taiwan. The underperformance of the bank system and expansionary monetary policy both increase the FHCs' interconnectedness. Finally, we find that bank-syndicated loans also affect the FHCs' interconnectedness. The arranger bank in a syndicated loane transmits systemic risk to other involved banks.

Our results are of interest to a variety of policy makers and regulators. Evaluating and monitoring the connectedness contribution from these government-owned banks is important and useful in maintaining financial system stability and stimulating economic growth in Taiwan. Our findings may also serve as a reference for other emerging markets to surpervise and stabilize their financial system.

CRediT authorship contribution statement

Yi-Pei Chen: Conceptualization, Data curation, Writing – original draft, Writing – review & editing, Investigation, Validation, Project administration. **Yu-Lun Chen:** Conceptualization, Methodology, Software, Data curation, Writing – original draft, Writing – review & editing, Investigation, Validation, Project administration. **Shu-Hen Chiang:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Investigation, Project administration. **Wan-Shin Mo:** Conceptualization, Writing – original draft, Writing – review & editing, Investigation, Validation, Project administration.

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References

Acharya, V.V., Pedersen, L.H., Philippon, T., Richardson, M., 2017. Measuring systemic risk. Rev. Financ. Stud. 30 (1), 2–47.
Adrian, T., Brunnermeier, M., 2016. CoVaR. Am. Econ. Rev. 106 (7), 1705–1741.
Aldasoro, I., Alves, I., 2018. Multiplex interbank networks and systemic importance: an application to European data. J. Financ. Stab. 35, 17–37.
Beltrame, F., Previtali, D., Sclip, A., 2018. Systemic risk and banks leverage: the role of asset quality. Financ. Res. Lett. 27, 113–117.
Berger, A.N., Udell, G.F., 2006. A more complete conceptual framework for SME finance. J. Banking Finance 30 (11), 2945–2966.
Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. J. Financ. Econ. 104 (3), 535–559.
Boehmer, E., Kelley, E.K., 2009. Institutional investors and the informational efficiency of prices. Rev. Financ. Stud. 22 (9), 3563–3594.
Brunnermeier, M.K., Dong, G.N., Palia, D., 2020. Banks' noninterest income and systemic risk. Rev. Corp. Financ. Stud. 9 (2), 229–255.
Calabrese, R., Elkink, J.A., Giudici, P.S., 2017. Measuring bank contagion in Europe using binary spatial regression models. J. Oper. Res. Soc. 68 (12), 1503–1511.
Claessens, S., Djankov, S., Lang, L.H.P., 2000. The separation of ownership and control in east Asian corporations. J. Financ. Econ. 58 (1–2), 81–112.
Demirer, M., Diebold, F.X., Liu, L., Yilmaz, K., 2018. Estimating global bank network connectedness. J. Appl. Econ. 33 (1), 1–15.
Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: predictive directional measurement of volatility spillovers. Int. J. Forecast. 28 (1), 57–66.
Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. J. Econ. 182 (1), 119–134.
Engle, R.F., Ruan, T., 2018. How much SRISK is too much? Available at SSRN 3108269.
Engle, R., Jondeau, E., Rockinger, M., 2015. Systemic risk in Europe. Rev. Financ. 19 (1), 145–190.
Fang, L., Sun, B., Li, H., Yu, H., 2018. Systemic risk network of Chinese financial institutions. Emerg. Mark. Rev. 35, 190–206.
Furfine, C.H., 2003. Interbank exposures: quantifying the risk of contagion. J. Money Credit Bank. 35 (1), 111–128.
Gofman, M., 2017. Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions. J. Financ. Econ. 124 (1), 113–146.
Hosono, K., 2006. The transmission mechanism of monetary policy in Japan: evidence from banks' balance sheets. J. Jpn. Int. Econ. 20 (3), 380–405.
Hsiao, H.C., Chang, H., Cianci, A.M., Huang, L.H., 2010. First financial restructuring and operating efficiency: evidence from Taiwanese commercial banks. J. Bank. Financ. 34 (7), 1461–1471.
Huynh, T.L.D., Nasir, M.A., Nguyen, S.P., Duong, D., 2020. An assessment of contagion risks in the banking system using non-parametric and Copula approaches. Econ. Anal. Policy 65, 105–116.
Hwang, D.Y., Wu, W.H., 2007. Financial system reform in Taiwan. J. Asian Econ. 18 (1), 21–41.
Igan, D., Kabundi, A., De Simone, F.N., Tamirisa, N., 2017. Monetary policy and balance sheets. J. Policy Model 39 (1), 169–184.
Klomp, J., De Haan, J., 2012. Banking risk and regulation: does one size fit all? J. Bank. Financ. 36 (12), 3197–3212.

Liu, A., Paddrik, M., Yang, S.Y., Zhang, X., 2020. Interbank contagion: an agent-based model approach to endogenously formed networks. J. Bank. Financ. 112, 105191.
Lu, Z., Zhu, J., Zhang, W., 2012. Bank discrimination, holding bank ownership, and economic consequences: evidence from China. J. Bank. Financ. 36 (2), 341–354.
Mamatzakis, E., Bermpei, T., 2016. What is the effect of unconventional monetary policy on bank performance? J. Int. Money Financ. 67, 239–263.
Newey, W.K., West, K.D., 1987. Hypothesis testing with efficient method of moments estimation. Int. Econ. Rev. 28 (3), 777–787.
Paltalidis, N., Gounopoulos, D., Kizys, R., Koutelidakis, Y., 2015. Transmission channels of systemic risk and contagion in the European financial network. J. Bank. Financ. 61 (1), S36–S52.
Samuelson, P.A., 1945. The effect of interest rate increases on the banking system. Am. Econ. Rev. 35 (1), 16–27.
Silva, W., Kimura, H., Sobreiro, V.A., 2017. An analysis of the literature on systemic financial risk: a survey. J. Financ. Stab. 28, 91–114.
Taiwan News, 2018. 54 managers of 7 Taiwanese banks punished for Ching-Fu loan scandal. https://www.taiwannews.com.tw/en/news/3402270.
Upper, C., Worms, A., 2004. Estimating bilateral exposures in the German interbank market: is there a danger of contagion? Eur. Econ. Rev. 48 (4), 827–849.
van Oordt, M., Zhou, C., 2019. Systemic risk and bank business models. J. Appl. Econ. 34 (3), 365–384.
Volcker, P., 2012. Unfinished business in financial reform. Int. Financ. 15 (1), 125–135.
Wang, G.J., Jiang, Z.Q., Lin, M., Xie, C., Stanley, H.E., 2018a. Interconnectedness and systemic risk of China's financial institutions. Emerg. Mark. Rev. 35, 1–18.
Wang, G.J., Xie, C., Zhao, L., Jiang, Z.Q., 2018b. Volatility connectedness in the Chinese banking system: do state-owned commercial banks contribute more? J. Int. Financ. Mark. Inst. Money 57, 205–230.
Zhang, D., Cai, J., Dickinson, D.G., Kutan, A.M., 2016. Non-performing loans, moral hazard and regulation of the Chinese commercial banking system. J. Bank. Financ. 63, 48–60.