Risk spillovers between FinTech and traditional financial institutions: Evidence from the U.S.

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Abstract:

In this paper, we propose a novel approach to examine the risk spillovers between FinTech firms and traditional financial institutions, during a time of fast technological advances. Based on the stock returns of U.S. financial and FinTech institutions, we estimate pairwise risk spillovers by using the Granger causality test across quantiles. We consider the whole distribution: the left tail (bearish case), the right tail (bullish case) and the center of the distribution and construct three types of spillover networks (downside-to-downside, upside-to-upside, and center-to-center) and obtain network-based spillover indicators. We find that linkages in the network are stronger in the bearish case when the risk of spillover is higher. FinTech institutions' risk spillover to financial institutions positively correlates with financial institutions' increase in systemic risk. These results have important policy implications, as they underscore the importance of enhancing the supervision and regulation of FinTech companies, to maintain financial stability.

Key words:

Financial technology (FinTech); Financial Risk; Risk spillover; Systemic risk; Financial stability

JEL classification: C32, D85, G20

1. Introduction

In recent years, financial technology (henceforth FinTech) has developed rapidly and innovative firms leveraging new technologies are playing an increasingly important role in the financial system. According to the Financial Stability Board (2017), FinTech can be defined as "*technologically-enabled financial innovation that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services*." The usage of technology in providing financial services is the key to FinTech (Thakor, 2019).

As new entrants, FinTech players are intrinsically linked to traditional financial institutions for the following three main reasons: (*i*) they compete in similar market segments and in similar businesses (Dorfleitner *et al*., 2017; Yao *et al*., 2018; Kommel *et al*., 2018); (*ii*) they cooperate closely (Romānova and Kudinska, 2017); and (*iii*) there is increasing investment from traditional financial institutions into FinTech companies (Lee and Shin, 2018). As a result of these multiple interconnections, the risks inherent to the FinTech institutions could spillover to traditional financial institutions, possibly causing systemic risk (Financial Stability Board, 2017; He *et al*., 2017).

In this paper, we propose a novel framework to examine the risk spillovers between FinTech firms and traditional financial institutions, during a time of fast technological advances and important changes in the business models of traditional financial institutions. The understanding of risk spillovers in the financial system is critical to the understanding of systemic risk and crucial to maintaining financial stability. While there is an extensive body of literature which has focused on the understanding of systemic risk and risk spillovers in the aftermath of the global financial crisis (see e.g. Billio *et al.*, 2012; Chau and Deesomsak, 2014; Choudhry and Jayasekera, 2014; Diebold and Yilmaz, 2014; Yao *et al*., 2017; Shahzad *et al*., 2017; Sun *et al*., 2019; Zhu *et al*., 2019), the extant literature related to FinTech is still at an early stage.

A number of studies investigate the relationship between FinTech, and traditional financial institutions based on qualitative analysis. Romānova and Kudinska (2017) identify the risks of banks facing the emergence of FinTech through analyzing recent development trends in banking and FinTech. Lee and Shin (2018) discuss the advantages of FinTech in providing financial services and the challenges for traditional financial institutions. In a qualitative setting, Ng and Kwok (2017), Drashch *et al*. (2018) and Anagnostopoulos (2018) acknowledge that the traditional financial sector faces new risks connected with the emergence of innovative FinTech startups. Further, the Financial Stability Board (2017) suggests that FinTech activities could intensify risk contagion and assets volatility in the financial system, thereby undermining financial stability. These studies acknowledge the potential risks faced by traditional financial institutions or even the financial system, connected with the development of FinTech institutions, but they lack empirical evidence to support their views.

There is also an emerging strand of the empirical literature that studies the relationship between FinTech firms and traditional financial institutions. Based on a Vector Auto-Regression (VAR) impulse response model, Yao *et al*. (2018) show a positive correlation between the innovation of third-party payments and the value creation capabilities of the traditional financial institutions in China. Zhang *et al*. (2017) utilize a bootstrap panel causality approach to demonstrate that causality between bank loans and Peer-to-Peer (P2P) loans varies across regions in China. Jagtiani and Lemieux (2018) provide evidence that FinTech lending penetrated areas that lack banking services in the U.S.

These studies, to some extent, demonstrate the close relations between the FinTech and traditional financial institutions based on empirical analysis. Nonetheless, there are gaps in the extant literature. First, most studies consider only the relationship between FinTech firms and a certain category of financial institutions offering similar products or services, with most studies focusing on banks. However, there are many other important categories of financial institutions, which have been mostly overlooked. Given the complex web of interconnections in the financial system, we argue that ignoring different types of financial institutions may lead to a biased understanding of risk spillovers. Although there is evidence in the literature that the relationship between different institutions vary in extreme cases compared to when they are experiencing normal trading patterns (see e.g. Balla *et al.*, 2014; Candelon and Tokpavi, 2016), only a handful of existing studies has considered these different interactions.

The contributions of this paper to the literature are manifold. First, we examine the risk spillovers between FinTech institutions and several major types of traditional financial institutions, including banks, diversified financials, insurers, and real estate lenders. This allows us to build a more complete picture of risk spillovers in the financial industry and complements the extant literature which has mainly focused on banks. Second, we develop a novel approach that constructs different types of spillover networks to estimate the risk spillovers in distinct cases. We build upon the work of Balla *et al*. (2014) and Candelon and Tokpavi (2016) and we consider both extreme and normal cases in this approach. Specifically, we consider three cases, i.e. the left tail (a downturn or crisis period), the right tail (an upswing period) and the center of the distributions of the institutions' stock returns. We define the left tail as the bearish case, the right tail as the bullish case and the center as the normal case (excluding the two extreme cases). We then construct three types of spillover networks (downside-to-downside, upside-to-upside, and center-to-center) and estimate pairwise risk spillovers by using the Granger causality test across quantiles (Candelon and Tokpavi, 2016). Next, we construct two network-based spillover indicators to estimate the risk spillovers within sectors, between sectors and within the whole system. Our empirical analysis is based on the stock returns of a sample of U.S financial institutions and Fintech firms from January 2011 to June 2018, a period of fast technological advances. We find that the risk spillovers between FinTech firms and traditional financial institutions vary in different cases and those in the bearish case are stronger.

We then consider time-varying risk spillover risk, with a 500-day rolling window, and our results confirm that during downturns the risk spillover between FinTech firms and traditional financial institutions in higher. Finally, we examine the correlation and causality between the risk spillover from FinTech firms to traditional financial institutions and the systemic risk of traditional financial institutions. By doing so, we aim to shed some light on whether the risk spillover from FinTech firms to financial institutions can be a potential cause of systemic risk, measured by SRISK (Brownlees and Engle, 2016). We find that the risk spillover from FinTech firms to traditional financial institutions is positively correlated with the systemic risk of these financial institutions. These results have important policy implications, as they underscore the importance of enhancing the supervision and regulation of FinTech companies, given their potential contribution to systemic risk.

The remainder of this paper is organized as follows. Section 2 introduces the proposed methodology. The data used in the empirical analysis are presented in Section 3, while the empirical results are discussed in Section 4. Finally, Section 5 concludes.

2. Methodology

In this section, we present our proposed approach for the construction of three types of spillover networks, namely downside-to-downside, upside-to-upside, and center-to-center, to estimate the risk spillovers across institutions in the bearish, normal and bullish cases respectively. More specifically, our methodology is based on a two-step approach. First, we estimate the risk spillovers between pairwise institutions in the abovementioned three cases by utilizing the Granger causality test across quantiles of Candelon and Tokpavi (2016). Second, based on the estimated risk spillovers, we build the three types of spillover networks and derive the network-based spillover indicators.

2.1 Risk spillover estimation

The first step in our analysis is the estimation of the three types of risk spillovers between pairwise institutions by implementing the Granger causality across quantiles to their stock returns. As a multivariate extension of the Granger causality in risk (Hong *et al.*, 2009), which is commonly utilized to estimate extreme risk spillover (see e.g. Wang *et al.*, 2017; Li *et al.*, 2019), the Granger causality across quantiles can identify the Granger causality in the entire distribution between two series. According to this method, the value at risk (VaR) for each institution should be estimated first. Then, the sets of event variables for each institution can be obtained through their VaRs for recording the risk information in the bullish, normal and bearish cases respectively. This will allow us to estimate the risk spillovers between pairwise institutions in the three cases.

2.1.1 VaR estimation

We follow Candelon and Tokpavi (2016) and, in the first step of our analysis, we estimate the value at risk (VaR). The VaR of an instrument is the maximum dollar loss within the θ_k-confidence interval (for more details about VaR, please see Jorion, 2007; Li *et al.*, 2018; and etc.). Let $r_{i,t}$ denote the stock return for institution $i=1,2,\ldots,N$. For institution i, the VaR at time t, denoted by $V_{i,t}$, is subject to

$$P\{r_{i,t} < V_{i,t}\} = \theta_k, \tag{1}$$

Mathematically, the $V_{i,t}$ is the θ_k-quantile of the conditional probability distribution of its returns $r_{i,t}$.

To estimate the VaR, we use the GARCH model, one of the most widely used methods in the literature (Alexander *et al.*, 2013; Candelon and Tokpavi, 2016; Peng *et al.*, 2018; among others). Following Xiao and Koenker (2009), we utilize the quantile regression estimation for the GARCH model. Formally, the return $r_{i,t}$ is described in a GARCH model as follows:

$$\begin{cases} r_{i,t} = \alpha_{i,0} + \sum_{j=1}^{l} \alpha_{i,j} r_{i,t-j} + u_{i,t}, \\ u_{i,t} = \sigma_{i,t} \cdot \varepsilon_{i,t}, \\ \sigma_{i,t} = \beta_{i,0} + \sum_{j=1}^{p} \beta_{i,j} \sigma_{i,t-j} + \sum_{j=1}^{q} \gamma_{i,j} \mid u_{i,t-j} \mid, \\ \varepsilon_{i,t} \sim N(0,1). \end{cases} \tag{2}$$

And the θ_k-th conditional quantile (VaR) $V_{i,t}(\theta_k) \equiv \hat{V}_{r_{i,t}}(\theta_k \mid \Omega_{i,t-1})$ of $r_{i,t}$ can be measured by

$$\hat{V}_{i,t}(\theta_k) = \hat{\mu}_{i,t} + \hat{\beta}_{i,0}(\theta_k) + \sum_{j=1}^{p} \hat{\beta}_{i,j}(\theta_k) \cdot \sigma_{i,t-j} + \sum_{j=1}^{q} \hat{\gamma}_{i,j}(\theta_k) \cdot \mid u_{i,t-j} \mid, \tag{3}$$

where $\hat{\mu}_{i,t} = \hat{\alpha}_{i,0} + \sum_{j=1}^{l} \alpha_{i,j} r_{i,t-j}$ is the AR model, estimated by the OLS method (see Peng *et al.*, 2018).

2.1.2 Granger causality across quantiles

Based on the VaR estimations, we obtain the set of event variables for each institution. Next, we estimate the risk spillovers between two institutions in the three cases, through the Granger causality test on their event variable sets.

Following Candelon and Tokpavi (2016), we consider a set $\Theta=\{\theta_1,\ldots,\theta_{m+1}\}$ that covers the distribution of the return $r_{i,t}$, with $0\le\theta_1<\ldots<\theta_{m+1}\le 100\%$. Then, a series of VaRs, $V_{i,t}(\theta_k)\le\ldots<V_{i,t}(\theta_{k+1})$, can be obtained. Consequently, the series of $r_{i,t}$ are divided into m regions, each related to the event variable

$$Z_{it,k}=1(V_{i,t}(\theta_k)\le r_{i,t}<V_{i,t}(\theta_{k+1})), k=1,\ldots,m, \tag{4}$$

where $1(\cdot)$ is the indicator function. Then a vector $\mathbf{Z}_{i,t}$ consisting of m event variables $\mathbf{Z}_{i,t}=\{Z_{it,1},\ldots,Z_{it,m}\}^T$ can be obtained. In particular, we obtain three types of vectors separately for the bearish, bullish and center case, namely $\mathbf{Z}_{i,t}^{downside}$ when $\Theta^{downside}=\{0,1\%,5\%,10\%\}$, $\mathbf{Z}_{i,t}^{upside}$ when $\Theta^{upside}=\{90\%,95\%,99\%,100\%\}$, $\mathbf{Z}_{i,t}^{center}$ when $\Theta^{center}=\{20\%,30\%,\ldots,80\%\}$. $\mathbf{Z}_{i,t}^{downside}$ and $\mathbf{Z}_{i,t}^{upside}$ individually includes the information of downside and upside risk, while $\mathbf{Z}_{i,t}^{center}$ includes the information of the center of the returns' distribution, removing the extreme events located on the left and right tails.

Let $\mathbf{Z}_{1,t}^{type}$ and $\mathbf{Z}_{2,t}^{type}$ denote the sets of event variables for institution 1 and institution 2 respectively, where $\text{type}\in\{\text{downside, center, upside}\}$ marks for the three different types of event variables. To test if the event variables of institution 2 affect those of institution 1, the null hypothesis of Granger causality across quantiles is formulated as:

$$H_0: E(\mathbf{Z}_{1,t}^{type}\mid\Omega_{1,t-1}^{type},\Omega_{2,t-1}^{type})=E(\mathbf{Z}_{1,t}^{type}\mid\Omega_{1,t-1}^{type}), \tag{5}$$

against

$$H_1: E(\mathbf{Z}_{1,t}^{type}\mid\Omega_{1,t-1}^{type},\Omega_{2,t-1}^{type})\ne E(\mathbf{Z}_{1,t}^{type}\mid\Omega_{1,t-1}^{type}), \tag{6}$$

where the $\Omega_{1,t-1}^{type}$ and $\Omega_{2,t-1}^{type}$ indicate the information sets of the event variables at time $t-1$. If the H_0 is rejected, namely H_1 is accepted, there are lagged effects of spillover from institution 2 to institution 1 considering their event variables.

Next, the null hypothesis of Granger causality across quantiles is examined based on nonparametric kernel-based test statistics. Let $\hat{\mathbf{Z}}_{1,t}^{type}$ and $\hat{\mathbf{Z}}_{2,t}^{type}$ be the estimated counterparts of the multivariate process of event variables $\mathbf{Z}_{1,t}^{type}$ and $\mathbf{Z}_{2,t}^{type}$ respectively. The sample cross-covariance matrix between $\hat{\mathbf{Z}}_{1,t}^{type}$ and $\hat{\mathbf{Z}}_{2,t}^{type}$ is defined as

$$\hat{C}^{type}(j) = \begin{cases} T^{-1}\sum_{t=1+j}^{T}(\hat{\mathbf{Z}}_{1,t}^{type} - \hat{\Pi}_1^{type})(\hat{\mathbf{Z}}_{2,t-j}^{type} - \hat{\Pi}_2^{type})^T, 0 \le j \le T-1 \\ T^{-1}\sum_{t=1-j}^{T}(\hat{\mathbf{Z}}_{1,t+j}^{type} - \hat{\Pi}_1^{type})(\hat{\mathbf{Z}}_{2,t}^{type} - \hat{\Pi}_1^{type})^T, 1-T \le j \le 0 \end{cases}, \tag{7}$$

where T is the sample size; the vector $\hat{\Pi}_1^{type}$ and $\hat{\Pi}_2^{type}$ is the sample mean of $\hat{\mathbf{Z}}_{1,t}^{type}$ and $\hat{\mathbf{Z}}_{2,t}^{type}$ respectively. The corresponding sample cross-correlation matrix is computed by

$$\hat{R}^{type}(j) = D(\hat{\Sigma}_{1,t}^{type})^{-1/2}\hat{C}^{type}(j)D(\hat{\Sigma}_{2,t}^{type})^{-1/2}, \tag{8}$$

where $D(\cdot)$ denotes the diagonal form of a matrix and $\hat{\Sigma}_{1,t}^{type}$ (or $\hat{\Sigma}_{2,t}^{type}$) are the sample covariance matrices of $\hat{\mathbf{Z}}_{1,t}^{type}$ ($\hat{\mathbf{Z}}_{2,t}^{type}$).

Thus, the test statistic can further be expressed as the following weighted quadratic form, such as

$$\hat{U}^{type} = \sum_{j=1}^{T-1}\kappa^2(j/M)\hat{Q}^{type}(j), \tag{9}$$

where $\kappa(\cdot)$ is a kernel function; M represents the truncation parameter; $\hat{Q}^{type}(j)$ is subject to

$$\hat{Q}^{type}(j) = T\mathrm{vec}(\hat{R}^{type}(j))^T((\hat{P}_1^{type})^{-1} \otimes (\hat{P}_2^{type})^{-1})\mathrm{vec}(\hat{R}^{type}(j)), \tag{10}$$

with $\hat{P}_1^{type}$ and $\hat{P}_2^{type}$ denoting the sample correlation matrices of $\hat{\mathbf{Z}}_{1,t}^{type}$ and $\hat{\mathbf{Z}}_{2,t}^{type}$ respectively. In accordance with Candelon and Tokpavi (2016), the Daniell kernel, $\kappa(x) = \sin(\pi x)/\pi x$, is utilized. Let $\Phi_T(M)$ and $\Psi_T(M)$ denote the location and scale parameters, written as

$$\Phi_T(M) = \sum_{j=1}^{T-1}(1 - j/T)\kappa^2(j/M), \tag{11}$$

$$\Psi_T(M) = 2\sum_{j=1}^{T-1}(1 - j/T)(1-(j+1)/T)\kappa^4(j/M). \tag{12}$$

Under the null hypothesis in equation (5), Candelon and Tokpavi (2016) propose that

$$\lambda_{2\to1}^{type} = \frac{\hat{U}^{type} - m^2\Phi_T(M)}{(m^2\Psi_T(M))^{1/2}} \to^d \mathrm{N}(0,1), \tag{13}$$

The null hypothesis is rejected when $\lambda_{2\to1}^{type}$ is greater than the right-tail critical value at a specified significance level. This indicates that there is risk spillover from institution 2 to institution 1. By implementing the nonparametric test to the three types of event variables, we can obtain the downside-to-downside, center-to-center, and upside-to-upside spillovers between the institutions. The three types of spillovers exactly reflect the risk spillovers in the bearish, normal, and bullish cases respectively.

2.2 Spillover networks construction

In this section, we introduce the construction of downside-to-downside, upside-to-upside, and center-to-center spillover networks. The nodes of the three types of networks are the institutions, and the edges in these networks are differentiated by the three different types of spillovers. In a downside-to-downside (/upside-to-upside/center-to-center) spillover network, a directional edge between two institutions is formed when there is a Granger causality from the downside (/upside/center) event variables of one institution to those of the other. Formally, considering that there totally are N institutions, the connections of the pairwise institutions are defined as

$$E_{i\to j}^{type} = \begin{cases} 1, \text{ if } i \neq j \text{ and the event variables of } i \\ \quad \text{Granger causes those of } j; \\ 0, \text{ otherwise} \end{cases} \tag{14}$$

where $\text{type} \in \{\text{downside, center, upside}\}$.

To estimate the total spillovers in the spillover networks, we require the total spillover index, based on the widely used network-based indicator, the network density (see e.g. Billio *et al.*, 2012; Wang *et al.*, 2017). To be specific, for a network consisting of N institutions, the total spillover index denoted as TS^{type} is computed by the ratio between the actual connections and all possible connections in the networks, written as

$$TS^{type} = \frac{1}{N(N-1)} \sum_{j=1, j\neq i}^{N} \sum_{i=1}^{N} E_{i\to j}^{type}. \tag{15}$$

The higher total spillover in a network means it is more likely to find pairwise institutions with Granger-causality, thus indicating that the spillover in the network is more intensive. This indicator can also be utilized to estimate the total spillover inside a specific sector by viewing the sector as a sub-network.

In addition, for estimating the spillover between different sectors, we propose a directional spillover index, which is measured as the ratio of the connections from one sector to another to all the possible linkages. Given sector α to β, the directional spillover from α to β, denoted as $DS_{\alpha\to\beta}^{type}$, is computed by

$$DS_{\alpha\to\beta}^{type} = \frac{1}{N_\alpha * N_\beta} \sum_{j\in\beta,\beta\neq\alpha} \sum_{i\in\alpha} E_{i\to j}^{type}, \tag{16}$$

where N_α and N_β denote the numbers of institutions in sector α and β. When the directional spillover value is higher, it's more likely to find there is a Granger-causality from an institution in α to an institution in β, indicating the effect of spillover from sector α to β is stronger.

3. Data

Our empirical analysis focuses on the U.S market as a setting to study the risk spillovers between FinTech firms and traditional financial institutions. Our first step is to identify and categorize FinTech institutions and traditional financial firms. As this is a rapidly developing sector, there are different ways in which the literature has tried to categorize FinTech institutions (Consumers International, 2017; Thakor, 2019). An important issue for our analysis is the existence of some overlap between traditional financial institutions and FinTech firms. For example, some startups or non-financial institutions utilize technology to provide financial services to customers. Similarly, some traditional financial institutions use financial technology to enhance products and services to customers. These institutions are labeled as cross-business institutions in this paper.

To obtain a representative sample of FinTech institutions, we select the institutions from the constituents of the well-known KBW Nasdaq Financial Technology Index (KFTX). The constituents of this index include both FinTech institutions and cross-business institutions. The total number of institutions in this index is 49. To allocate an institution to the correct group, we also check the business descriptions in the sample institutions' Form 10-K filings to make sure that (i) these institutions indeed provide FinTech services, and (ii) allocate the institutions providing only FinTech services to the category of FinTech institutions and the institutions providing both financial and FinTech services to the cross-business institutions. The business descriptions of the selected institutions are provided in Appendix A.

We also need to identify traditional financial institutions and classify them into sub-sectors. While there are many possible classifications (Wei et al 2019a; Wei et al 2019b), in this paper, we follow the Global Industry Classification Standard (GICS) and include the traditional financial industry four GICS sectors, namely banks (GICS code 4010), diversified financials (GICS code 4020), insurers (GICS code 4030) and real estate lenders (GICS code 4040 before 2016, and 6010 after 2016). Next, we select traditional financial institutions from the S&P 500 index. There are 101 financial institutions in the S&P 500 index. We then restrict the sample to include only to financial institutions that mainly engage in traditional financial services. This is important for our set-up, as some financial institutions also provide some innovative FinTech services and are therefore classified as cross-business.[1]

We then collect the daily stock returns of our sample institutions from January 2011 to June 2018, a period during which the FinTech in the U.S. has developed rapidly. To ensure that the number of observations of stock returns for all the institutions is consistent, we only include institutions that are listed during the whole sample period.

Our final sample is composed of 129 institutions, grouped as follows: (i) 17 banks; (ii) 18 diversified financials; (iii) 22 insurance companies; (iv) 33 real estate lenders; (v) 26 FinTech institutions and (vi) 13 cross-business institutions. The list of institutions included in our sample is provided in Appendix A. The sample institutions' daily stock prices are collected from the Thomson Datastream database. The statistics of the stock returns (daily logarithmic returns) of these institutions are shown in Appendix B.

[1]Note that eight financial institutions, such as American Express (AXP), Moody's Corp (MCO) and others, also provide innovative FinTech services and are therefore excluded from the sample list of traditional financial institutions.

4. Empirical results

In this section, we present the results of our empirical analysis. First, we analyze the risk spillover between pairwise institutions by implementing the Granger causality across quantiles to their stock returns in the bearish, normal and bullish cases. Then, we estimate the time-varying risk spillover, using a 500-day rolling window, for the three abovementioned cases. Finally, we present the results of the estimation of the correlation and causality between the risk spillover from FinTech firms to traditional financial institutions and the systemic risk of traditional financial institutions.

4.1 Risk spillover networks for FinTech and traditional financial institutions

In the first step in our empirical analysis, we estimate the risk spillover networks for all the institutions, banks, diversified financials, insurers, real estate lenders, FinTech and cross-business institutions, in the bearish, bullish and normal case. The risk spillovers are estimated by the Granger-causality across quantiles with the significance at the 5% level. The resultant networks are illustrated in Fig. 1. In each network, the nodes are the institutions, while the edges represent the risk spillover between the linked institutions. The institutions (nodes) in different sectors are distinguished by the color: green for banks, blue for diversified financials, yellow for insurers, light blue for real estate lenders, red for the FinTech institutions, and purple for the cross-business institutions. The risk spillover from each institution, i.e. the corresponding node's outgoing edge, is displayed by the same color as its sectors. From these networks, it can be observed that the linkages in the network in the bearish case (see Fig. 1 (a)) are closer than those in the normal and bullish cases (see Fig. 1 (b) and (c) respectively). Statistically, the values of the total spillover indices in the three types of spillover networks are 0.615, 0.162, and 0.148, respectively. These results indicate that the risk spillover across all the institutions is much stronger in the bearish case than the spillovers in the bullish and normal cases.

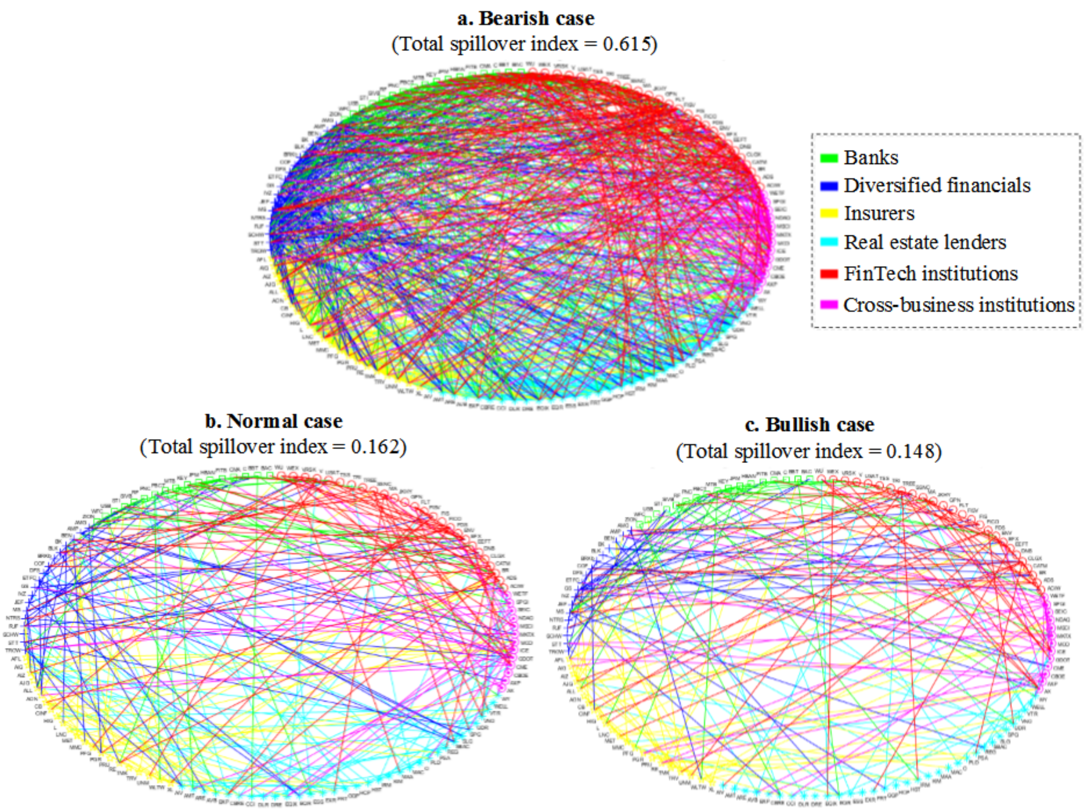

Fig. 1. Risk spillover networks for all the sample institutions during the three cases

Notes: Note that the figures only present 10% of the linkages between the institutions.

Based on the estimated risk spillover networks, we can then analyze the risk spillover between the institutions in different sectors. We compute the directional spillover indices between six non-overlapping sectors, i.e., banking, diversified financials, insurance, real estate lenders, FinTech and cross-business, and the total spillover index for each sector. The results for the bearish, normal and bullish cases are respectively shown in Panel A, B, and C in Table 1. In each panel, the non-diagonal elements represent the values of the directional spillover indices between the pairwise sectors, while the diagonal numbers are the values of the total spillover indices for the sectors. From Table 1, it can be seen that the values of the spillover indices in the bearish case are all over 0.460 (see Panel A), while those in the normal or bullish case are all below 0.265 (see Panel B and C). This indicates that the values of the spillover indices in the bearish case are significantly larger than those in the normal and bullish cases. To check if the differences between the values of the spillover indices in the bearish case and those in the normal (or bullish) case are statistically significant, we use the well-known Wilcoxon signed-rank test (Wilcoxon, 1945), to examine the differences between the matched samples (see e.g. Davies and Kim, 2009; Cohen *et al*., 2012; Chen and Wang, 2012). The results of the Wilcoxon signed-rank test indicate that the differences are statistically significant at the 1% level. Overall, the Wilcoxon signed-rank test results demonstrate that the risk spillovers between the subsectors or within each subsector in the bearish case are larger compared to normal and bullish cases. This confirms the results of the total spillovers in the whole network (see Fig. 1). Thus, we can conclude that both considering the whole network or the between (within) subsectors, the risk spillover in the bearish case is generally stronger compared to the bullish and normal cases.

Table 1: The values of directional spillover index across sectors and the values of the total spillover index within each sector

FROM	**TO**					
	Banks	Diversified financials	Insurers	Real estate lenders	FinTech institutions	Cross-business institutions
Panel A: Bearish case						
Banks	0.765	0.650	0.668	0.503	0.597	0.570
Diversified financials	0.873	0.748	0.841	0.653	0.756	0.726
Insurers	0.580	0.460	0.528	0.483	0.565	0.556
Real estate lenders	0.720	0.630	0.625	0.714	0.613	0.522
FinTech institutions	0.661	0.618	0.612	0.472	0.574	0.506
Cross-business institutions	0.710	0.632	0.626	0.522	0.607	0.526
Panel B: Normal case						
Banks	0.184	0.137	0.198	0.139	0.181	0.127
Diversified financials	0.157	0.131	0.164	0.152	0.186	0.192
Insurers	0.166	0.202	0.156	0.163	0.159	0.161
Real estate lenders	0.134	0.189	0.136	0.147	0.164	0.154
FinTech institutions	0.118	0.197	0.150	0.161	0.191	0.166
Cross-business institutions	0.172	0.205	0.129	0.172	0.180	0.135
Panel C: Bullish case						
Banks	0.180	0.137	0.139	0.119	0.138	0.145
Diversified financials	0.265	0.239	0.207	0.121	0.162	0.209
Insurers	0.152	0.139	0.158	0.156	0.150	0.154
Real estate lenders	0.128	0.106	0.121	0.098	0.148	0.166
FinTech institutions	0.127	0.162	0.159	0.125	0.172	0.172
Cross-business institutions	0.154	0.128	0.168	0.140	0.166	0.218

Note: The table presents the directional spillover indices between six non-overlapping sectors (banking, diversified financials, insurance, real estate, FinTech and cross-business), and the total spillover index for each sector. The results for the bearish, normal and bullish cases are respectively shown in Panel A, B, and C respectively. In each panel, the non-diagonal elements represent the values of the directional spillover indices between the pairwise sectors, while the diagonal numbers are the values of the total spillover indices for the sectors

In general, the results in Table 1 show that the risk spillovers from either the traditional financial firms or FinTech institutions are significant in the bearish case. However, there are still differences between the risk spillovers from different sectors. To evaluate whether these differences are statistically significant, we use the Wilcoxon signed-rank test for the pairwise spillovers. The results are shown in Table 2 and illustrate the p-value of the spillovers from each sector (from column to row and vice versa). For example, the spillovers from FinTech and banks are equal to 0.031. This indicates that the spillover effects from FinTech are lower than those from banks at the 5% significance level. In a similar way, we obtain the p-values of the Wilcoxon signed-rank test for the spillovers of all the other pairwise sub-sectors. Looking at the results in Table 2, we can see that the spillover effects from FinTech institutions are lower than most of the traditional financial firms, including banks, diversified financials, cross-business institutions, but not significantly higher than those from insurers. Indeed, we find that the spillover effects from insurers are significantly lower than those from other financial firms (i.e. banks, diversified financials, and real estate lenders) and cross-business institutions at 5% or 10% level. These findings show that, in general, the higher risk spillovers are from the diversified financials and the lowest from insurers.

Table 2: The p-values of the Wilcoxon signed-rank test for the risk spillovers from all the pairs of subsectors

	Banks	Diversified financials	Insurers	Real estate lenders	FinTech institutions	Cross-business institutions
Banks						
Diversified financials	0.031^{**}					
Insurers	0.031^{**}	0.031^{**}				
Real estate lenders	0.563	0.063^{*}	0.063^{*}			
FinTech institutions	0.031^{**}	0.031^{**}	0.313	0.031^{**}		
Cross-business institutions	0.219	0.031^{**}	0.063^{*}	0.438	0.031^{**}	

Notes: The table reports the Wilcoxon signed-rank test for the pairwise spillovers. **, *, represents the statistical significance at 5% and 10% respectively.

4.2 Dynamic risk spillover between FinTech and traditional financial institutions

This section analyzes the dynamic risk spillover between FinTech firms and traditional financial institutions by estimating the directional spillover indices in the three cases with a

500-day rolling time window. By doing so, we obtain the time-varying risk spillovers from December 28, 2012, to June 29, 2018. We then measure the dynamic risk spillovers between cross-business institutions and traditional financial firms during this period. These results are displayed in Fig. 2.

We can see that the risk spillovers between the FinTech and traditional financial institutions in the bearish case are more volatile compared to those in the bullish and normal cases. To be more specific, in the bearish case, the risk spillovers in both directions peaked at a high level, over 0.62 (see Panel A of Fig.2). This is potentially due to the destabilizing effects of the post-crisis economic cycle in the U.S. As the economy recovered, the risk spillover between FinTech firms and financial institutions significantly declined (from 0.62 to 0.26) after mid-2013. From the end of 2015 to mid-2016, we see a noticeable increase in the downside risk spillover from the FinTech to financial institutions. This might result from the steadfast growth of the U.S. the FinTech sector, spurred by the rapidly increasing investment in new technologies during this period (KPMG International, 2019). By contrast, during the whole sample period, the risk spillovers of both directions in the normal case generally fluctuate at around 0.20, while the risk spillovers in the bullish case range within [0.11, 0.43] (see Panel B and C in Fig. 2). Similar findings can be obtained from the results of the risk spillovers between cross-business and financial institutions. In sum, these findings reveal that the risk spillover in the bearish case is more volatile than that in the bullish and normal case.

In addition, while the values of bi-directional risk spillovers between FinTech firms and financial institutions in the normal (or bullish) case are quite similar during the sample period, the bi-directional spillovers in the bearish case are substantially different during certain periods. In particular, from the end of 2012 to the middle of 2013, the risk spillover from the traditional financial institutions to FinTech companies was larger than that in the opposite direction (see Panel A of Fig. 2). However, from the middle of 2015 to the end of 2017, the risk spillover from FinTech institutions to traditional financial firms was relatively more significant than the opposite directional risk spillover. Note that the results of the risk spillovers between the cross-business institutions and traditional financial institutions are generally similar to those between the FinTech firms and financial firms. These results demonstrate the asymmetry in the bi-directional risk spillovers between the FinTech (cross-business) firms and traditional financial institutions in the bearish case.

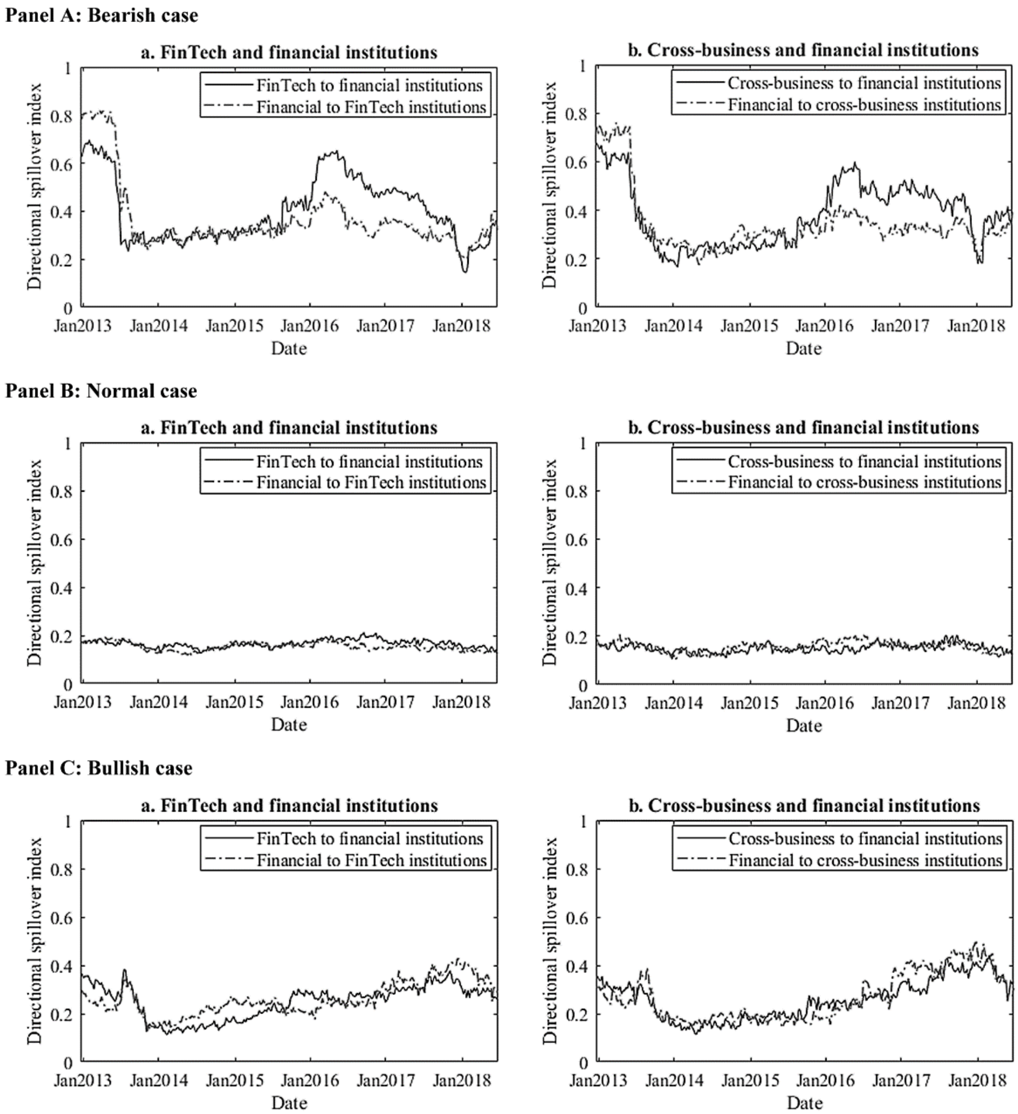

Fig. 2. Dynamic risk spillovers between FinTech (or Cross-business) institutions and traditional financial institutions

4.3 The relation between the risk spillover from FinTech and systemic risk

This subsection analyzes whether the risk spillovers from FinTech firms to traditional financial institutions contribute to an increase in the systemic risk contribution of the latter. We estimate the systemic risk of all the traditional financial institutions by employing the well-known Brownlees and Engle (2016)'s SRISK measure, which essentially captures the capital shortfall of the institutions, conditional on a severe market decline. We focus on the risk spillover in the bearish case, because of its high volatility. In this part, we consider only the risk spillover from FinTech institutions and exclude cross-business institutions which provide both FinTech services and traditional financial services. This is because it is difficult to exclude the risk spillover to financial institutions resulting from their traditional financial services. We therefore consider the average SRISK of the 90 traditional financial institutions in our sample. Fig. 3 presents the risk spillover from the FinTech institutions to traditional financial institutions and the systemic risk of these traditional financial institutions from December 28, 2012, to June 29, 2018. In line with Kamani (2018), we consider SRISK at the end of each time window.

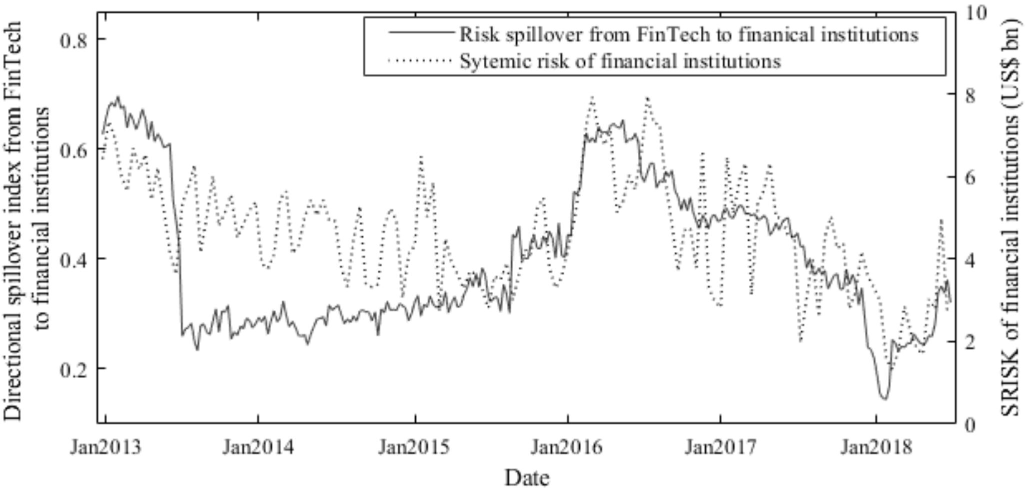

Fig. 3. The risk spillover from FinTech to financial institutions and the systemic risk of financial institutions

Notes: The figure shows the average SRISK of the 90 traditional financial institutions.

It is interesting to find that the tendencies of these two measures are similar. This indicates that there might be a positive relationship between the risk spillover from FinTech to financial institutions and the systemic risk contribution of financial institutions. We then examine this relationship by utilizing two commonly-used statistical methods, the Pearson correlation test and the Granger causality test. The Pearson correlation test is implemented to test whether the risk spillover from FinTech institutions is positively correlated with the systemic risk of traditional financial firms. The Granger causality test is employed to study if the risk spillover from FinTech institutions could cause systemic risk and vice versa. These tests are estimated for not only the whole traditional financial sector but also the different sub-sectors (banks, diversified financials, insurers, and real estate lenders). The summary statistics of all these measures are displayed in Table 3.

Table 3: Summary statistics of risk spillover from FinTech and financial institutions' systemic risk

Sectors	Directional spillover index from FinTech to financial institutions				SRISK financial institutions (US $ billion)			
	Mean	Min	Max	Std. Dev.	Mean	Min	Max	Std. Dev.
All financial institutions	0.401	0.144	0.696	0.133	4.608	1.227	8.183	1.396
Banks	0.473	0.161	0.817	0.145	12.605	1.148	24.785	4.909
Diversified financials	0.442	0.085	0.726	0.142	4.408	0.144	8.692	1.579
Insurers	0.422	0.166	0.720	0.112	5.503	3.484	7.799	0.803
Real estate lenders	0.327	0.121	0.622	0.163	0.000	0.000	0.000	0.000

Notes: This table reports the average SRISK in each sector. The total number of observations is 278.

Note that during the sample period, the systemic risk measured as SRISK of the real estate lenders is 0 because of their negative capital shortfalls (i.e. capital surpluses). This means that this sector is stable during this period. Thus, we do not estimate the Pearson correlation and Granger causality tests for real estate lenders. The results of the tests for the whole traditional financial sector as well as three sub-sectors (banking, diversified financials, and insurance), are shown in Table 4. Panel A of Table 4 displays the results of the Pearson correlation tests, while Panel B and C show the results of the Granger causality tests.

From Panel A in Table 4, we can see that both for the whole traditional financial sector and financial subsectors, the p-values of the Pearson correlation tests are 0.000, far less than 0.01, and the coefficients of the tests are positive. This indicates that the risk spillover from the FinTech to traditional financial institutions is positively correlated with the systemic risk of these financial institutions at the 1% significance. Panel B in Table 4 reports the Granger causality test for causality from FinTech risk spillover to systemic risk. We can see that the p-values of the Granger causality tests are all below 0.01. This indicates that the risk spillover from FinTech to traditional financial institutions is a potential cause of systemic risk for traditional financial institutions, at 1% significance. Panel C presents the results of Granger causality test for causality from systemic risk to FinTech risk spillovers. We can see that the p-values of the tests for the whole sector and the individual sub-sectors are all much larger than 0.10. Only the p-value of the test for the real estate lenders is 0.067, relatively lower than 0.10

but larger than 0.05. These results indicate that for most of the traditional financial institutions, their contribution to systemic risk does not cause an increase in the risk spillover from FinTech to traditional financial institutions.

Table 4: The correlations between risk spillover from FinTech and financial institutions' systemic risk

	All financial institutions	Banks	Diversified financials	Insurers
Panel A: Pearson correlation test for risk spillover from FinTech and systemic risk				
Coefficient	5.989***	18.682***	6.293***	4.314***
P-value	0.000***	0.000***	0.000***	0.000***
Panel B: Granger causality test for examining if risk spillover from FinTech causes systemic risk				
P-value	0.001***	0.003***	0.001***	0.000***
Panel C: Granger causality test for examining if systemic risk causes risk spillover from FinTech				
P-value	0.283	0.187	0.299	0.067*

Notes: Panel A reports the Pearson correlation for risk spillover from FinTech and SRISK in each sector. Panel B presents the Granger causality test for causality from FinTech's risk spillover to systemic risk, measured by SRISK. Panel C presents Granger causality test for causality from systemic risk to FinTech's risk spillover. ***, **, *, represents the statistical significance at 1%, 5% and 10% respectively.

Based on the above results we show that the risk spillover from FinTech firms to traditional financial institutions is positively correlated with the systemic risk of traditional financial institutions. In addition, when considering the causality between the two measures, we show that the risk spillover from FinTech to traditional financial institutions could cause the systemic risk of the traditional financial institutions, but not vice versa. These results provide empirical evidence that the spillover from FinTech could affect traditional financial institutions' systemic risk. These results have important policy implications and suggest that closer monitoring of the risk spillover from FinTech institutions to traditional financial firms is necessary for maintaining financial stability.

5. Conclusions

This study analyzes the risk spillovers between FinTech firms and several major types of traditional financial institutions, including banks, diversified financials, insurers, and real estate lenders, during a period of fast technological advances. By considering several different types of financial institutions, we provide a fuller picture of the complex interactions in the financial system and show how the emergence of new players impacts on risk spillovers. In addition, we provide an approach that constructs three types of spillover networks (downside-to-downside, center-to-center, and upside-to-upside) to study the risk spillovers. Using the stock returns of the institutions, we estimate pairwise risk spillovers by employing the Granger causality test across quantiles. This approach allows us to contribute to the literature by comprehensively examining the risk spillovers in multiple cases. In our empirical analysis, based on the stock returns of U.S. financial institutions and FinTech firms, we find that the risk spillovers between FinTech and traditional financial institutions are indeed different in the tails compared to the center of the distribution. In particular, we provide evidence of stronger spillovers during periods of downturn. Both the risk spillovers between FinTech and traditional financial sectors or those within sectors in the bearish case are the strongest. We also provide evidence that the risk spillover from the FinTech to traditional financial institutions has a positive relationship with, and even could be a potential cause of, the systemic risk of traditional financial institutions. We argue that the results of this study have important policy implications and suggest the need for closer monitoring of the risk spillover from FinTech institutions to traditional financial firms, particularly as supervisors aim at maintaining financial stability.

Appendix A

Table A.1: The list of our sample institutions

Banks (GICS code=4010)		Diversified financials (GICS code=4020)		Insurers (GICS code=4030)		Real estate lenders (GICS code=4040 before 2016, 6010 after 2016)		FinTech institutions		Cross-business institutions	
BAC	BANK OF AMERIC	AMG	AFFLTED MANAGE	AFL	AFLAC INC	AIV	APT INV MANAGE	ACIW	ACI WORLDWIDE IN	AX	AXOS FINANCIAL INC
BBT	BB&T CORP	AMP	AMERIPRISE FIN	AIG	AMER INTL GROU	AMT	AMER TOWER CP	ADS	ALLIANCE DATA	AXP	AMER EXPRESS
C	CITIGROUP	BEN	FRANKLIN RES	AIZ	ASSURANT	ARE	ALEXANDRIA RE	BR	BROADRIDGE FINL	CBOE	CBOE GLOBAL MK
CMA	COMERICA INC	BK	BANK NY MELLON	AJG	ARTHUR J GALLA	AVB	AVALONBAY COMM	CATM	CARDTRONICS PL	CME	CME GROUP INC
FITB	FIFTH THR BNCP	BLK	BLACKROCK INC	ALL	ALLSTATE CP	BXP	BOSTON PPTY	CLGX	CORELOGIC INC	GDOT	GREEN DOT CORP
HBAN	HUNTGTN BKSHR	BRKb	BERKSHRE CL B	AON	AON PLC	CBRE	CBRE GROUP INC	DNB	DUN & BRADSTREET	ICE	INTRCTNTL EXCH
JPM	JPMORGAN CHASE	COF	CAP ONE FINAN	CB	CHUBB LIMITED	CCI	CROWN CASTLE	EEFT	EURONET WORLDWID	MCO	MOODY'S CORP
KEY	KEYCORP NEW	DFS	DISCOVER FINAN	CINF	CINCINNATI FIN	DLR	DIGITAL REALTY	EFX	EQUIFAX INC	MKTX	MARKETAXESS
MTB	M&T BANK CRP	ETFC	E*TRADE FINCL	HIG	HARTFORD FINL	DRE	DUKE REALTY	ENV	ENVESTNET INC	MSCI	MSCI INC
PBCT	PEOPLE UNTD FI	GS	GOLDM SACHS GR	L	LOEWS CORP	EQIX	EQUINIX INC	FDS	FACTSET RESEARCH	NDAQ	NASDAQ INC
PNC	PNC FINL SVC	IVZ	INVESCO LTD	LNC	LINCOLN NATL	EQR	EQ RESIDENT	FICO	FAIR ISAAC CORP	SEIC	SEI INVESTMENTS
RF	REGIONS FINANC	JEF	JEFFERES FINAN	MET	METLIFE INC	ESS	ESSEX PROP TR	FIS	FIDELITY NATIONA	SPGI	S&P GLOBAL INC
SIVB	SVB FINANCIAL	MS	MORGAN STANLEY	MMC	MARSH & MCLENN	EXR	EXTRA SPACE ST	FISV	FISERV INC	WETF	WISDOMTREE INVES
STI	SUNTRUST BKS	NTRS	NORTHERN TRUST	PFG	PRINCIPAL FNAN	FRT	FED RLTY INV T	FLT	FLEETCOR TECHNOL		
USB	US BANCORP	RJF	RAYMOND JAMES	PGR	THE PROGRESSIV	GGP	GGP INC	GPN	GLOBAL PAYMENTS		
WFC	WELLS FARGO & CO	SCHW	CHRLS SCHWB CR	PRU	PRUDENTIAL FIN	HCP	HCP INC	JKHY	JACK HENRY		
ZION	ZIONS BANCORP	STT	ST STREET CP	RE	EVEREST RE GP	HST	HOST HOTL&RES	MA	MASTERCARD INC-A		
		TROW	T ROWE PRICE G	TMK	TORCHMARK CORP	IRM	IRON MOUNTAIN	SSNC	SS&C TECHNOLOGIE		
				TRV	THE TRAVELERS	KIM	KIMCO REALTY C	TREE	LENDINGTREE INC		
				UNM	UNUM GROUP	MAA	MID AM APT COM	TRI	THOMSON REUTERS		
				WLTW	WLS TWR WTSN L	MAC	MACERICH	TSS	TOTAL SYS SERVS		
				XL	XL GROUP LTD	O	REALTY INCM CO	USAT	USA TECHNOLOGIES		
						PLD	PROLOGIS	V	VISA INC-CLASS A		
						PSA	PBL STG MLD	VRSK	VERISK ANALYTI		
						REG	REGENCY CENTER	WEX	WEX INC		
						SBAC	SBA COMMS CORP	WU	WESTERN UNION		
						SLG	SL GREEN RLTY				
						SPG	SIMON PROP GRP				
						UDR	UDR INC				
						VNO	VORNADO REALTY				
						VTR	VENTAS INC				
						WELL	WELLTOWER INC				
						WY	WEYERHAEUSER C				

Notes: According to the GICS, the real estate lenders have been moved out of the financial sector to a newly created real estate sector since 2016. Considering that there is no significant change in the main businesses of the real estate institutions, they are included in our dataset to keep the sample consistent during the whole sample period.

Table A.2: The business description of the FinTech and cross-business institutions

Institution	Business description	GICS code
Panel A: Fintech institutions		
ACIW	ACI Worldwide, Inc. provides software products and services for facilitating electronic payments to banks, financial intermediaries, merchants, and corporates worldwide.	4510
ADS	Alliance Data Systems Corporation provides data-driven marketing and loyalty solutions worldwide. It operates through three segments: LoyaltyOne, Epsilon, and Card Services.	4510
BR	Broadridge Financial Solutions, Inc. provides investor communications and technology-driven solutions for the financial services industry worldwide.	4510
CATM	Cardtronics plc provides automated consumer financial services through its network of automated teller machines (ATMs) and multi-function financial services kiosks.	4510
CLGX	CoreLogic, Inc., together with its subsidiaries, provides property information, insight, analytics, and data-enabled solutions in North America, Western Europe, and the Asia Pacific.	4510
DNB	The Dun & Bradstreet Corporation provides commercial data, analytics, and insights for businesses worldwide. The company operates through two segments, the Americas and Non-Americas.	2020
EEFT	Euronet Worldwide, Inc. provides payment and transaction processing and distribution solutions to financial institutions, retailers, service providers, and individual consumers worldwide.	4510
EFX	Equifax Inc. provides information solutions and human resources business process outsourcing services for businesses, governments, and consumers. The company operates through four segments: U.S. Information Solutions (USIS), International, Workforce Solutions, and Global Consumer Solutions.	2020
ENV	Envestnet, Inc., together with its subsidiaries, provides intelligent systems for wealth management and financial wellness in the United States and internationally. It operates through Envestnet and Envestnet Yodlee segments.	4510
FDS	FactSet Research Systems Inc. provides integrated financial information and analytical applications to the investment community in the United States, Europe, and the Asia Pacific.	4020
FICO	Fair Isaac Corporation develops analytic, software, and data management products and services that enable businesses to automate, enhance, and connect decisions.	4510
FIS	Fidelity National Information Services, Inc. operates as a financial services technology company in the United States and internationally. It operates through Integrated Financial Solutions and Global Financial Solutions segments.	4510
FISV	Fiserv, Inc., together with its subsidiaries, provides financial services technology worldwide.	4510
FLT	FleetCor Technologies, Inc. provides commercial payment solutions in North America, Latin America, Europe, and Australasia. The company offers fuel payment solutions to businesses and government entities that operate vehicle fleets, as well as to oil and leasing companies, and fuel marketers.	4510
GPN	Global Payments Inc. provides payment technology and software solutions for card, electronic, check, and digital-based payments. The company operates in three segments: North America, Europe, and Asia-Pacific.	4510
JKHY	Jack Henry & Associates, Inc. provides technology solutions and payment processing services primarily for financial services organizations in the United States.	4510
MA	Mastercard Incorporated, a technology company, provides transaction processing and other payment-related products and services in the United States and internationally.	4510
SSNC	SS&C Technologies Holdings, Inc. provides software products and software-enabled services to financial services and healthcare industries in the United States, Canada, rest of the Americas, Europe, the Asia Pacific, and Japan.	4510
TREE	LendingTree, Inc., through its subsidiary, LendingTree, LLC, operates an online loan marketplace for consumers seeking loans in the United States. Its mortgage products comprise purchase and refinance products.	4010

Table A.2 (continued)

Institution	Business description	GICS code
TRI	Thomson Reuters Corporation provides news and information-based tools to professionals worldwide. It operates through five segments: Legal Professionals, Corporates, Tax Professionals, Reuters News, and Global Print.	2020
TSS	Total System Services, Inc. provides payment processing, merchant, and related payment services to financial and nonfinancial institutions worldwide. The company operates through three segments: Issuer Solutions, Merchant Solutions, and Consumer Solutions.	4510
USAT	USA Technologies, Inc. provides wireless networking, cashless transactions, asset monitoring, and other value-added services in the United States and internationally.	4510
V	Visa Inc. operates as a payments technology company worldwide. The company facilitates commerce through the transfer of value and information among consumers, merchants, financial institutions, businesses, strategic partners, and government entities.	4510
VRSK	Verisk Analytics, Inc. provides data analytics solutions in the United States and internationally.	2020
WEX	WEX Inc. provides corporate card payment solutions in North and South America, the Asia Pacific, and Europe. It operates through three segments: Fleet Solutions, Travel and Corporate Solutions, and Health and Employee Benefit Solutions.	4510
WU	The Western Union Company provides money movement and payment services worldwide. The company operates in two segments, Consumer-to-Consumer, and Business Solutions.	4510
Panel B: **Cross-business institutions**		
AX	Axos Financial, Inc. operates as the holding company for BofI Federal Bank that provides consumer and business banking products in the United States. The company offers deposits products, including consumer and business checking, demand, savings, and time deposit accounts.	4010
AXP	American Express Company, together with its subsidiaries, provides charge and credit payment card products, and travel-related services to consumers and businesses worldwide.	4020
CBOE	Cboe Global Markets, Inc., through its subsidiaries, operates as an options exchange in the United States. It operates in five segments: Options, U.S. Equities, Futures, European Equities, and Global FX. The Options segment trades in listed market indexes. The U.S.	4020
CME	CME Group Inc., through its subsidiaries, operates contract markets for the trading of futures and options on futures contracts worldwide.	4020
GDOT	Green Dot Corporation operates as financial technology and bank holding company in the United States. It operates in two segments, Account Services, and Processing and Settlement Services.	4020
ICE	Intercontinental Exchange, Inc. operates regulated exchanges, clearing houses, and listings venues for commodity, financial, fixed income, and equity markets in the United States, the United Kingdom, European Union, Asia, Israel, and Canada.	4020
MCO	Moody's Corporation provides credit ratings; and credit, capital markets, and economic research, data, and analytical tools worldwide. It operates through two segments, Moody's Investors Service and Moody's Analytics.	4020
MKTX	MarketAxess Holdings Inc., together with its subsidiaries, operates an electronic trading platform that enables fixed-income market participants to trade corporate bonds and other types of fixed-income instruments worldwide.	4020
MSCI	MSCI Inc., together with its subsidiaries, provides investment decision support tools for the clients to manage their investment processes worldwide.	4020
NDAQ	Nasdaq, Inc. provides trading, clearing, marketplace technology, regulatory, securities listing, information, and public and private company services worldwide.	4020
SEIC	SEI Investments Company is a publicly owned asset management holding company.	4020
SPGI	S&P Global Inc., together with its subsidiaries, provides ratings, benchmarks, analytics, and data to the capital and commodity markets worldwide.	4020
WETF	WisdomTree Investments, Inc., through its subsidiaries, operates as an exchange-traded funds (ETFs) sponsor and asset manager. It offers ETFs in equities, currency, fixed income, and alternatives asset classes.	4020

Notes: The business descriptions are obtained from the CRSP dataset and the Form 10-K fillings of the institutions reported on the SEC website.

Appendix B

Table B.1: The statistics of the stock returns of the sample institutions

Ticker	Mean (E-04)	Std	Min.	Max	Ticker	Mean (E-04)	Std	Min.	Max	Ticker	Mean (E-04)	Std	Min.	Max
Banks					***Diversified financials (continued)***					***Insurers (continued)***				
BAC	3.642	0.021	-0.227	0.155	BLK	5.118	0.016	-0.107	0.091	CINF	3.860	0.012	-0.077	0.064
BBT	3.341	0.014	-0.113	0.067	BRKb	4.467	0.011	-0.076	0.090	HIG	3.238	0.018	-0.154	0.144
C	1.653	0.020	-0.179	0.130	COF	3.945	0.016	-0.141	0.082	L	1.078	0.011	-0.061	0.055
CMA	4.001	0.018	-0.111	0.061	DFS	6.997	0.015	-0.096	0.088	LNC	4.001	0.021	-0.143	0.096
FITB	3.521	0.017	-0.121	0.087	ETFC	7.022	0.022	-0.158	0.128	MET	0.314	0.018	-0.113	0.086
HBAN	3.875	0.018	-0.105	0.085	GS	1.287	0.016	-0.106	0.090	MMC	5.802	0.011	-0.087	0.089
JPM	4.624	0.016	-0.099	0.081	IVZ	0.437	0.019	-0.147	0.099	PFG	2.419	0.017	-0.122	0.084
KEY	4.077	0.018	-0.110	0.083	JEF	-1.345	0.018	-0.132	0.110	PGR	5.723	0.012	-0.072	0.068
MTB	3.504	0.014	-0.081	0.066	MS	2.749	0.022	-0.156	0.154	PRU	2.293	0.018	-0.115	0.088
PBCT	1.326	0.012	-0.091	0.056	NTRS	3.234	0.014	-0.093	0.062	RE	5.279	0.012	-0.072	0.072
PNC	4.178	0.014	-0.085	0.065	RJF	5.282	0.017	-0.099	0.085	TMK	5.861	0.012	-0.098	0.082
RF	4.892	0.021	-0.145	0.135	SCHW	5.685	0.019	-0.127	0.096	TRV	4.163	0.011	-0.079	0.062
SIVB	8.809	0.021	-0.116	0.172	STT	3.556	0.016	-0.106	0.102	UNM	2.115	0.016	-0.186	0.096
STI	4.142	0.018	-0.149	0.080	TROW	3.014	0.015	-0.092	0.107	WLTW	2.584	0.012	-0.114	0.062
USB	3.283	0.013	-0.094	0.079	***Insurers***					XL	4.913	0.015	-0.091	0.256
WFC	2.986	0.015	-0.097	0.078	AFL	2.134	0.014	-0.108	0.083	***Real estate lenders***				
ZION	3.919	0.019	-0.115	0.100	AIG	0.458	0.017	-0.106	0.098	AIV	2.525	0.014	-0.095	0.078
Diversified financials					AIZ	5.226	0.014	-0.144	0.073	AMT	5.448	0.013	-0.083	0.061
AMG	2.068	0.019	-0.123	0.098	AJG	4.223	0.011	-0.076	0.071	ARE	2.794	0.013	-0.117	0.097
AMP	4.549	0.018	-0.132	0.124	ALL	5.522	0.012	-0.107	0.073	AVB	2.187	0.012	-0.064	0.076
BEN	-0.865	0.016	-0.134	0.117	AON	5.852	0.012	-0.072	0.084	BXP	1.809	0.013	-0.084	0.086
BK	2.970	0.016	-0.102	0.074	CB	3.784	0.011	-0.069	0.070	CBRE	4.354	0.020	-0.101	0.105

Table B.1 (continued)

Ticker	Mean (E-04)	Std	Min.	Max	Ticker	Mean (E-04)	Std	Min.	Max	Ticker	Mean (E-04)	Std	Min.	Max
Real estate lenders (continued)					***Real estate lenders (continued)***					***FinTech institutions (continued)***				
CCI	4.825	0.012	-0.072	0.059	VNO	0.888	0.013	-0.103	0.087	TREE	16.609	0.032	-0.348	0.353
DLR	4.039	0.015	-0.166	0.092	VTR	1.003	0.014	-0.080	0.083	TRI	0.289	0.012	-0.071	0.068
DRE	4.369	0.015	-0.154	0.087	WELL	1.369	0.013	-0.106	0.088	TSS	8.917	0.014	-0.159	0.069
EQIX	9.062	0.017	-0.096	0.124	WY	3.250	0.015	-0.076	0.061	USAT	13.592	0.038	-0.236	0.340
EQR	1.023	0.013	-0.082	0.097	***FinTech institutions***					V	10.698	0.014	-0.078	0.140
ESS	3.782	0.012	-0.067	0.086	ACIW	5.262	0.018	-0.101	0.146	VRSK	6.041	0.012	-0.100	0.091
EXR	9.120	0.014	-0.087	0.096	ADS	6.196	0.016	-0.215	0.099	WEX	7.434	0.019	-0.116	0.113
FRT	2.432	0.011	-0.067	0.096	BR	8.711	0.012	-0.066	0.053	WU	0.432	0.016	-0.343	0.062
GGP	1.541	0.016	-0.161	0.155	CATM	1.682	0.022	-0.201	0.137	***Cross-business institutions***				
HCP	-1.466	0.015	-0.182	0.118	CLGX	5.418	0.021	-0.369	0.256	AX	12.401	0.026	-0.359	0.177
HST	0.733	0.017	-0.132	0.073	DNB	2.187	0.015	-0.184	0.126	AXP	4.321	0.014	-0.129	0.086
IRM	2.638	0.016	-0.172	0.183	EEFT	8.307	0.020	-0.170	0.134	CBOE	7.838	0.014	-0.110	0.073
KIM	-0.414	0.015	-0.094	0.107	EFX	6.573	0.014	-0.158	0.082	CME	5.049	0.014	-0.106	0.080
MAA	2.406	0.013	-0.085	0.110	ENV	6.293	0.026	-0.431	0.197	GDOT	1.480	0.035	-0.945	0.340
MAC	0.889	0.015	-0.090	0.095	FDS	3.890	0.014	-0.131	0.092	ICE	5.979	0.014	-0.067	0.084
O	2.344	0.012	-0.068	0.111	FICO	11.166	0.018	-0.113	0.224	MCO	9.800	0.017	-0.117	0.106
PLD	3.764	0.015	-0.129	0.087	FIS	7.039	0.013	-0.131	0.084	MKTX	12.032	0.019	-0.112	0.132
PSA	4.162	0.012	-0.078	0.100	FISV	8.518	0.011	-0.074	0.055	MSCI	7.605	0.017	-0.312	0.104
REG	1.943	0.013	-0.098	0.082	FLT	10.257	0.018	-0.127	0.104	NDAQ	7.062	0.015	-0.137	0.103
SBAC	7.403	0.014	-0.092	0.072	GPN	8.283	0.016	-0.096	0.108	SEIC	5.088	0.016	-0.136	0.075
SLG	1.986	0.015	-0.100	0.114	JKHY	7.847	0.011	-0.074	0.078	SPGI	9.116	0.015	-0.148	0.079
SPG	3.099	0.012	-0.087	0.108	MA	11.596	0.015	-0.112	0.126	WETF	3.807	0.029	-0.159	0.231
UDR	2.402	0.013	-0.090	0.101	SSNC	8.731	0.017	-0.104	0.121					

Notes: The mean of the stock returns for each institution is expressed in scientific notation. The value of each institution's mean equals the product of the corresponding number in the table and 0.0001. It can be found that the mean of the stock return is close to 0, from -0.0001 and 0.0017. In addition, the minimums of stock returns of the sample institutions vary from -0.945 to -0.061, while the maximums change from 0.052 to 0.353. For 89% of all the sample institutions, their stock returns only range within [-0.200, 0.200]. This reflects that the changing magnitudes in the stock returns of most institutions are relatively small. Moreover, the standard deviations of these stock returns range from 0.011 to 0.038. Note that for 89% of the institutions, the standard deviations of their stock returns are not more than 0.020. This indicates that the stock returns of most institutions fluctuate moderately. Note that, there are still some institutions, like GDOT, ENV and etc., which have small minimums, large maximums, or even large standard deviations.

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