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Tail risk and systemic risk of finance and technology (FinTech) firms

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ABSTRACT

Technology firms are increasingly moving to finance. They are able to make use of a large stock of user data and offer a range of services that otherwise were not possible. This move may pose fresh challenges to financial stability. This paper empirically evaluates the tail risk and systemic risk of technology firms. Our data sample consists of technology firms, and for comparison we also evaluate the tail risk and systemic risk of finance firms. We use daily equity returns data from 2 April 1992 to 31 December 2019 and we adopt the univariate extreme value theory (EVT) to determine equity tail risk. Our selection criteria is the market capitalisation and we choose the top twenty technology and the top twenty finance firms to evaluate tail risk and systemic risk. We found that the tail risk of technology firms is higher than the financial firms, whereas they are less likely to be in distress conditional upon a shock from the system. However, this finding for technology firms reverses when we use recent data via our six-year rolling estimates. We conclude that, similar to finance firms, there should be tighter regulations for technology firms since technology firms are riskier than the finance firms. Our paper has significant implications for both national and global financial regulators.

1. Introduction

Financial technology (Fintech) is one of the stimulating and contemporary areas in global business today. The evolution of financial technology has, in a very short time, had a noticeable impact on how to carry out financial activities and transactions with customers. The investment in this industry is continuously increasing with no indication of stopping. KPMG (2017) report shows that there has been over US$ 100 billion invested into financial technology (firms?) during the last five years from 2011-2016. Similarly, since 2009, the market capitalisation (how the stock markets value firms) of the top ten BigTech firms have multiplied five times. (See Fig. 1). In 1999, there were only five tech firms among the top ten big firms by market capitalisation, which reduced to one in 2009. However, the number of BigTech firms in the top ten overall firms increased to seven in 2019. (See Fig. 2). With the entry of BigTech firms into the financial services market, the term Fintech has evolved to represent technology firms providing financial services. The BigTech companies' entry into the financial services market is based on the premise of innovation, efficiency and financial inclusion (FSB, 2019; BIS annual economic report, 2019). However, their entry poses risks to the financial system and has implications for financial stability (FSB, 2019). Despite the huge growth of BigTech and the certainty of their risk to the financial system, there is no empirical study measuring the extent of the risk that BigTech firms carry,= and how much risk they pose to the financial system, as well as how likely they are to be affected by unforeseen market events such as COVID-19, the dot com bubble or GFC. In this paper, we study the tail risk and systemic risk of BigTech firms. For the purpose of comparison, we also measure the tail risk and systemic risk of finance firms.

Technology is influencing the traditional business of banks, despite the fact that banks are also adjusting to the digital world. Organisations are increasingly seeking ways to perform their tasks more simply and

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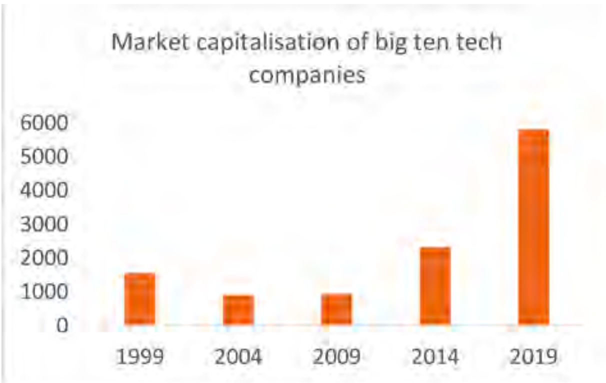

Fig. 1. Market capitalisation of big ten tech firms.

Fig. 2. Number of tech firms among top ten firms by market capitalisation.

efficiently. For example, like banks, crowdfunding platforms are able to convert savings into loans and lucrative investments by using the information established on big data, and not on long term relationships with customers; access to services is provided only through internet platforms; transformation of risk and maturity is not carried out; prospective lenders and borrowers opportunities are matched directly through internet platforms (For e.g. see Mills and McCarthy, 2014 & 2016; and Schweitzer and Barkley, 2017). Furthermore, technology is redesigning banking processes by lowering barriers to entry through mobile phones. This is then reducing the need for retail branch banking and shifting the focus to development of infrastructure through analytics, cloud computing, artificial intelligence and social technologies. Modern digital currencies and credit systems are also impacting retail banking and investment participants (Giudici, 2018). Moreover, the changing behaviour and expectations of clients also has influence on financial services providers.

The rapid growth in financial technology is causing risk for financial and economic systems. BigTech firms provide a three-fold risk to financial systems. For instance, the recent growth of some relatively small Fintech firms comes with risk regarding control for the highly concentrated financial market. Secondly, with the growth of the BigTech industry blurring boundaries have evolved between the traditional financial system and other contemporary products e.g. digital wallets and store credits, which is difficult for regulators to segment and control. Finally, the Fintech firms are the biggest risk to the financial sector through big data as compared with traditional financial systems. Recently, BigTech firms face tough legislation and regulations? from politicians after selling consumer data to third parties without consumer consent (e.g. Facebook chief executive Mark Zuckerberg was forced to testify before the US congress in the Cambridge Analytica case, Kozlowska, 2018). Although the current literature highlights the role of systematic risk among different financial assets (Huynh et al, 2020; Thampanya et al., 2020; Abbasi et al., 2020), a closer examination of Fintech firms using the extreme value theory (EVT) seems to have been overlooked. Our study fills this gap in the literature.

The contribution of our paper is threefold. First, this is the study that empirically evaluates the risk of BigTech firms, the risk they pose to the financial system and how likely they are likely to be affected if there is a systemic shock. Second, we compare the tail risk and systemic risk of BigTech with the tail risk and systemic risk of finance firms, which has also not been done before in the literature. Finally, our paper provides empirical evidence on the ongoing debate of introducing regulation for BigTech firms, and whether there is a need to implement tight standards and regulations for technology firms to safeguard the system from any global crisis in future. Our paper has significant implications for both national and global financial regulators as well as for investors. Given the risk these technology firms pose to regional and global financial stability, we argue for tighter regulations for technology firms (Goldman, 1982; Giudici, 2018) and a cautious approach for investors whose portfolio contains finance and BigTech firms.

Our findings reveal that the average tail risk for technology firms is greater than for financial firms and technology firms are less likely to be affected negatively by any unforeseen market events that may occur. Therefore, we do not reject our hypothesis that the the tail risk of technology firms is higher than that of finance firms. In other words, tail-β has lower values. However, the results for technology firms reverse when we use six year rolling estimates. Second, while measuring the systematic risk and multivariate spillover risk, we find finance firms are more related with each other and cause more distress in other finance firms in comparison with technology firms (Ellul and Yerramilli 2013).

The remainder of the paper is organised as follows. Section 2 reviews the related literature on the impact of tail risk and systemic risk of technology firms on financial systems as well as the impact of technology firms on financial systems. We have also examine the literature examining the impact of tail risk and systemic risk of finance firms on financial systems. Section 3 provides the data and methodology used in the empirical analysis. Section 4 reports the empirical findings and Section 5 provides the conclusion and policy implications.

2. Literature review

The entry of big technology firms into financial services poses novel and complex trade-offs within the market between financial stability, competition and data protection. These big technology firms, which offer financial services, can be either competitor or co-operator with banks. This paper focuses on the aspect of how technology firms as well as finance firms could impact financial systems. In particular, we explore the impact of tail risk and systemic risk on technology firms and finance firms in terms of the impact on the financial systems.

2.1. The impact of technology firms on financial systems

Technology firms have started playing an increasing role in financial systems. The integration of technology firms and financial institutions has created financial innovation known as financial technology or FinTech. This advancement of FinTech has brought disruptive changes to every aspect of financial services and is presently transforming the financial industry. Giudici (2018) states that financial technologies are changing the nature of the financial industry and generating many opportunities to access to financial services. Big data analytics, artificial intelligence and blockchain ledgers can lessen bias from credit scoring and increase peer-to-peer lending as well as measure and monitor systemic risk in peer-to-peer lending. In addition, these financial technologies can assess and monitor market risk and the instability of financial markets (These financial technologies refer to big data analytics, artificial intelligence and blockchain ledgers). This means such financial technologies are able to address risk management requirements and related costs more efficiently. Risk management includes political and economic risks, currency exchange risks, transfer risks, cultural differences, credit risks, legal risks, commercial risks, and changes in customer needs (Ullah et al., 2019; Tanabandeh et al., 2019; Illiashenko, 2019). This has been support by Hua et al. (2019), who stressed that FinTech promotes costs reduction, increases the accessibility of customers, and manages risks more efficiently. The BIS Annual Economic Report (2019) also states that BigTech's' entry into finance has the potential to create rapid changes in the finance industry. It can expand financial services, use big data to analyse the network structure within the industry and evaluate the risk of borrowers.

With these benefits, BigTech could boost the efficiency of financial services provision, foster financial inclusion and stimulate economic activity. The additional cost advantage of FinTech firms is gained by theirloose regulatory structure in comparison to traditional banks, as well as their more advanced technological capacity, meaning that FinTech firms can offer their services to a wider range of customers who were less accessible to banking services, such as SMEs (Temelkov, 2018). Degryse et al. (2007) further the argument by stating that Fintech firms do not encounter complex corporate structures and high ranking administrative layers, so consequently, they can have lower operating costs. Fintech firms also benefit from lower costs related to physical overheads because they utilise technological advancement to contact clients rather than maintaining physical offices. Technology firms also play a crucial role in promoting bank funds to a broader group of borrowers (e.g. see Li et al., 2020 and Xia et al., 2020). This is supported by the findings of Jagtiani and Lemieux (2016) which show that larger banks with advanced technology had a significant role in small business lending between 1997 and 2014, despite not having physical offices. Mills and McCarthy (2014 and 2016) and Schweitzer and Barkley (2017) also claimed that FinTech lenders help reduce the credit gap in small business borroweing by providing credit to those firms. By utilising account-level data from a large FinTech lender, the Lending Club, and Y-14M Bank, Jagtiani and Lemieux (2017) found that the Lending Club can provide funding to broader? areas in comparison to traditional banking with diminishing numbers of bank branches. The Lending Club's debtors pay less spreads on loans than borrowers from traditional lenders given the same default risk. On the other hand, Lending Club borrowers are, on average, riskier than traditional borrowers according to the same FICO scores. If there is a collaboration, Temelkov (2018) states that banks and Fintech firms could benefit from their cooperation in term of lower costs of operating business activities and a decrease in capital expenditure. However, the collaboration might create disadvantage due to security, regulatory and agreement issues as well as degree of investment risk.

Zetzsche et al. (2017) concluded that FinTech firms not only provide major benefits to consumers, businesses, and economies but also pose problems referring to data privacy, funding security, and fairness of access. Giudici (2018) pointed out several key risks regarding the development of the financial technologies which include underestimation of creditworthiness, market risk of non-compliance, fraud detection, and cyber-attacks, which may impede consumer protection and financial stability. The big technology firms may also create new risks and costs related to market power. For instance, they might increase barriers to entry for new technology firms by raising user switching costs or eliminating potential entrants. In addition, big technology firms can influence price discrimination and extract rents as they are able to collect big data at near zero cost which leads to digital monopolies or data-opolies (BIS annual economic report, 2019). The recent work of Zetzsche et al. (2020) categorised the risks of artificial intelligence (AI) in a financial context into four forms, which are data risks, cybersecurity risks, financial stability risks, and ethical risks. Economic and financial systems could be attacked, manipulated or threatened by AI. Similarly, AI could destabilise the economy or send the wrong signals to society which may lead to systemic risk. There are many papers which outline the role of FinTech in the finacial system (for e.g. see Huynh et al., 2020; Thampanya et al., 2020 and Huynh et al., 2020).

Existing studies show that there are a wide range of research papers on FinTech, however, the impact of tail risk and systemic risk of technology firms on financial systems has not yet been investigated. The accurate assessment of these risks will be advantageous for the authority to monitor and prevent related risks from FinTech firms to financial systems.

2.2. The impact of tail risk and systemic risk of finance firms on financial systems

Straetmans and Chaudhry (2015) applied statistical extreme value analysis to the tails of bank equity capital losses to estimate the likelihood of individual institutions'' financial distress as well as individual banks' exposure to risk?. They found that both tail risk and systemic risk in the Eurozone are lower than in the US. This result is similar to an earlier study by Hartmann et al. (2006), who applied the multivariate extreme value theory to examine contagion risk and systemic risk of banks in the US and the Eurozone. They found that bank spillover in the US seems to be significantly higher than in the Eurozone area. This implies weak cross-border linkages in Europe. The increase of risk in the Eurozone area seemed to occur slowly from the integration of traditional banking firms. For the US, the strongest increases in extreme systematic risk seemed to occur between the largest financial institutions and the main clearing banks.

Gilli and Kellezi (2006) used the extreme value theory to compute tail risk measurements and the related confidence intervals of six major stock market indices, which are Hang Seng, Dow Jones Euto Stoxx55, FTSE 100, Nikkei 225, Swiss Market Index, and S&P500. The findings indicated that the left tail of all indices are heavier than the right tail. In asset markets, Kelly and Jiang (2014) used returns and sales growth data from 1963 to 2010 to assess the impacts of time-varying extreme event risk. They found that tail risk is a potentially crucial factor of asset prices because it has prophetic power for future extreme returns for individual stocks. In addition, there is a high degree of commonness in time-varying tail exponents across firms. The aggregate tail risks are mathematically related to common dynamics in firm-level tails. The empirical studies of fat-tailed stock return behaviour and theoretical models of tail risk in the real economy are closely linked, as indicated by a significant drop in aggregate investment, output and employment after an increase in tail risk.

Wang et al. (2014) used extremal quantile regression and the CoVaR model to estimate the impact of state variables on extreme risk and on systemic financial risk of financial institutions. Their samples included 33 financial listed institutions, banks, insurance, securities, and trust firms, in China. The findings indicated that state variables have different influence on the risk of financial institutions under different quantiles. Under extreme quantiles, the spread of short-term liquidity risk has negative impacts on banks resulting in higher bank risk. This means that banks are subject to the extreme effects (of risk?) on (their?) financial systems. This result is consistent with the finding of systemic risk contribution which reveals a higher risk exposure of banks to financial systems than other financial institutions. On the other hand, the value at risk measurement reports a lower risk exposure of banks to financial systems than securities. In addition, the findings show that the size and leverage of financial firms have a positive relationship with systemic risk contribution. Financial institutions with larger sizes and higher leverage tend to have greater systemic risk. By applying a dynamic analysis approach to examine the contagion of banking systemic risk, Gu et al. (2019) found that the banking systemic risk contagion would be uncontrollable if banks have a high risk contagion rate and low risk isolation protection rate.

From a capital market perspective, Bessler et al. (2015) examined the time-varying systematic and idiosyncratic risk exposure of US bank holding firms by decomposing bank stock returns into systematic banking-industry risks, systematic market-wide risks, and individual bank risks. Their findings shed light on the time-varying systematic risk of the sample. Individual bank risk characteristics can be identified by idiosyncratic risk. Banks with lower equity capital, higher loan loss provision, and more exposure to real estate loans have significantly greater levels of idiosyncratic risk. By using accounting, market and macroeconomic data of US bank holding firms to assess the relationship between tail risk and financial distress risk, Alzugaiby et al. (2019) found a significant positive relationship between banks' tail risks and their risk of financial distress. This implies that financial distress is more likely to happen with banks that have more frequent extreme negative daily equity returns. This result is consistent with Gupta and Chaudhry (2019), who studied the relationship amongst tail risk measures and financial distress of US publicly-traded firms from 1990 to 2016. More analysis of systemic risk can be found in Bisias et al. (2012) and Benoit et al. (2017).

Previous studies have showed how systemic risk and tail risk could create significant damage to the broader financial system and broader economy. However, it appears that none of those studies have compared the impact of tail risk and systemic risk of finance firms to big technology firms. Therefore, this paper aims to evaluate the tail risk and systemic risk of the top twenty technology and top twenty finance firms by applying a univariate extreme value theory (EVT). The research hypothesis is "the tail risk of technology firms is higher than the financial firms".

3. Data and Methodology

Our sample data consists of technology firms, and for comparison we also evaluate the tail risk and systemic risk of finance firms. We downloaded equity prices from 2 April 1992 to 31 December 2019. Our selection criteria was top twenty technology and top twenty finance firms based on market capitalisation. We selected only top twenty technology firms, because after the top twenty firms, the size becomes very small. Therefore, we selected only the top twenty technology firms and top twenty finance firms. Furthermore, top forty firms make up major chunk of the index's market value. For example, the forty biggest firms make up about 60% of the index's market value in the S&P 500 and the size of big firms make up even more in China and other selected countries. Most of the selected firms are American and Chinese firms, but also include some Asian and European countries. For calculation of tail-β, we used datastream-calculated technology indices, financial indices, and market indices for each respective country, global technology indices, global financial indices and global market indices. For calculation of time-varying risk measures, we used a six-year rolling data source to calculate tail risk.

3.1. Measurement of tail risk

We examined the tail risk because there is often rapid decline in the equity indices of technology and finance firms. We adopted the univariate extreme value theory (EVT) to determine equity tail risk. The univariate EVT is comprised of Generalised Extreme Value (GEV) distribution and consideration of limit law for maxima of stationary method. We selected the Peaks-Over-Threshold (POT) method to measure the parameters of GEV distribution. We used the semi-parametric method to match the distributional excess losses over a high threshold that leads to Generalised Pareto Distribution (GPD)[2].

We measured the semi-parametric estimator of De Haan et al. (1994) to evaluate the quantile x for extremely low values of $p = P\{X.x\}$ as follows:

$$\widehat{x}_p = X_{n-m,n}\left(\frac{m}{np}\right)^{1/\alpha} \tag{1}$$

Where $X_{n-m,n}$ is representing the tail cut-off point of *(n-m)*th ascending order statistics from a sample size n such that $q > X_{n-m,n}$. We used the Hill (1975) estimator to derive α in the above tail quantile estimator set out in equation (1), which is as follows:

$$\widehat{\alpha} = \left(\frac{1}{m}\sum_{j=0}^{m-1} ln\left(\frac{X_{n-j,n}}{X_{n-m,n}}\right)\right)^{-1} \tag{2}$$

The parameter m examined how many extreme returns were evaluated in the estimation. We adopted $m = 300$ as our main investigation for technology firms and $m = 175$ for finance firms. We employed sensitivity analysis by adjusting $m = 225$ and $m = 350$ for technology firms, and $m = 125$ and $m = 225$ for finance firms. We measured m values by adopting Hill's (1975) estimator. We arrived at the expected shortfall estimator by substituting the Hill (1975) Eq. (2) and tail quantile estimator in Eq. (1) as follows:

$$\widehat{E}\left(X - \widehat{x_p}|X > \widehat{x_p}\right) = \frac{\widehat{x_p}}{\widehat{\alpha - 1}} \tag{3}$$

The theoretical explanation of the tail quantile (or tail-VaR) and tail expected shortfall given in Eqs. (1) and (2) are our measures of tail risk for finance, technology and banking firms. We calculated extreme quantiles for probability values ranging from 0.1% to 0.2%. This means that the corresponding tail quantile is expected to be violated every 500 days and every 1000 days, respectively. Furthermore, we also investigated the expected shortfall estimates conditioned on both the p (%) tail-VaRs and on crisis barriers x = 25% or 50%. Finally, expected shortfalls with the different threshold x represent the more extreme expected shortfall measurement when the extreme quantile estimates ($\widehat{x}_p$) are lower than the x. Empirically, the underlying framework in place is the calculation of extreme values from the median of the probability deviations, which are calculated in a temporal manner.

3.2. Measurement of systemic risk

We estimate our measurements with semi-parametric estimation procedures for systemic risk, because with parametric probability distributions, wrong distribution assumptions may severely bias the systemic risk estimations due to misspecification. We used the following equation to derivce multivariate spillover risk:

$$\widehat{P}_{N|1} = \frac{\widehat{P}_q}{p} = \frac{m}{n}\left(C_{n-m,n}\right)^{\alpha} q^{1-\alpha}, \tag{4}$$

For large but finite q = 1/p. For N = 2, this reduces to the tail-β estimator. $C_{n-m,n}$ is the $(n-m)^{th}$ "tail cut-off " ascending order statistic from the cross-sectional minimum series and m is the nuisance parameter. In the parameter m in the Hill estimator, m determines how many extreme returns are used in estimation, and n represents the total number of observations. When the original return vector exhibits tail independence (α > 1), the systemic risk estimator is a declining function of the threshold q and eventually reaches zero if $q \rightarrow \infty$. However, when α = 1, as we imposed throughout the paper, systemic risk is no longer influenced by changes in q.

We employed another systemic risk measure and used the following equation:

$$\widehat{E}[\theta|\theta \geq 1] \approx \frac{N}{\frac{n}{k}\frac{1}{n}\sum_{i=1}^{n} U_{i=1}^{N} X_i > X_{i,n-k}} \tag{5}$$

In this equation above, the denominator is an estimator of the stable

[2] See Jansen and de Vries (1991), Danielsson and de Vries (1997) and Straetmans and Chaudhry (2015), among others, for semi-parametric tail estimation approaches.

tail dependence function l(.).[3] The upper order statistic $X_{i,n-k}$ estimates the quantile $Q_i\left(\frac{k}{n}\right)$, l{.} is the indicator function and k is the nuisance parameter. In the parameter m in the Hill estimator k represents the number of extremes in calculating risk measures.

The theoretical framework of systemic risk given in Eqs. (4) and (5) are measured with the help of "tail-β", which is the estimate of the exposure of the firms of two different industries, such as technology, finance firms and banks, to an extreme shock large adverse movements in "aggregate" shocks. The aggregate shocks denote a macroeconomic (non-diversifiable) shock, which is mainly used to indicate the "extreme systematic risk" (or "tail-β") for different candidate-risk factors. The extreme systemic shock that we used are the country market index and country industry index, which represent the location of these firms. Moreover, we also linked to a worldwide industrial sector and global market stock index. Next used the multivariate spillover risk with two nuisance parameters m (representing the number of extremes used in estimation) for the technology and finance industries. Empirically, for the calculation of systemic risk, we used the country market index, country industry index, global market index and global industry index as an independent variable and measured their impact on the stock price for a series of firms in the technology, finance and banking sector. For the calculation of spillover risk, we replaced the country market index and other indices with another firm from the technology, finance or banking sector.

4. Empirical findings

We first discuss the tail risk proxies of three main categories: finance, technology firms and banks in section 4.1 below. We also examine the indicators of extreme systematic risk (called as 'tail- β') under the different risk factors in section 4.2 below. Finally, we check the robustness of the study by adjusting the values of the nuisance parameter for three types of firms whereby our results remain the same.

4.1. The downside risk estimates of technology and finance firms

Tables 1 and 2 demonstrate estimates of the tail index $\widehat{\alpha}$ and corresponding values of tail-VaR, as well as the expected shortfall for the top 20 financial institutions and the top 20 technology institutions, respectively. The tail indices for the finance sector fluctuates around 3, which confirms the findings of previous studies such as Straetmans and Chaudhry (2015), Hartmann et al. (2006), Jansen and de Vries (1991). In addition, the average value for α (2.59) is lowest in the technology firms, which implies the fat tails. In contrast, the finance firms (2.68) have thinner tails than technology firms. This could be as a result of the exponential growth of technology firms in the recent past. Our findings concur with Papanikolaou and Wolff (2014) who stated that regulatory changes and technological advances could represent the potential sources of high risk for finance firms. In addition, (we found that?) technology firms tend to overlook risk control while financial firms are likely to be active in managing their risk because of stricter regulations. Ellul and Yerramilli (2013) indicated that those financial institutions and banks with better risk management would have lower tailrisk exposure. Noticeably, Goldman (1982) also admitted that the technological firms have a "short" product lifecycle while the amount of investment is substantially large. This in turnmakes the growth of technology firms very fast, and this comes with higher risk for these firms. Therefore, the tail risk of technology firms is higher compared to finance firms in our empirical results which supports our hypothesis.

When looking at specific firms such as Alibaba, PayPal, Facebook and Bank of China, the highest heavy tail is exhibited from the finance and tech firms. It is important here note that two of these four organisations are located in China. It may be because of the high growth rate of China over the last decades that this market has an inherent risk, which has been captured in tail risk in our study. The previous study by Hou et al. (2014) indicated that the Bank of China is good at bias-corrected relative technical efficiency in China. However, our study provides contrary evidence that this bank has the highest exposure to tail risk among the top banks. Additionally, for these technology companies, the heavy-tail risk lies in Facebook and Alibaba. Facebook and Alibaba have frequently suffered from data breach events, and so the related disclosure of this is negative to its stock price (Yu and Huarng, 2019; Luo et al, 2016). Hence, technology firms doing business in innovation as well as E-commerce always have exposure to risk with regards to data privacy breach, which may cause a sharp decline in their returns. In another perspective, Alibaba is recognised to have political connections which might have an incentive to announce bad news at normal times and thus experience lower risk. Meanwhile, the nature of this behaviour has inherent risk with regard to investing in the Chinese marketplace. In regard to tail risk, our resultsfound that technology firms with higher likelihood of data protection breaches will experience higher tail risk in comparison with the other firms (Gatzlaff and McCullough, 2010; Eling and Loperfido, 2017; Wongchoti, 2020).

Another perspective from which we could observe and understand sector differences is regulation. Previous studies, such as Ellul and Yerramilli (2013) and Andrieş and Nistor, 2016, indicated that financial firms are strictly regulated while technology firms are not, inducing more threat to those firms without the strict regulations. However, there could be another explanation as to why technology firms incur more risk, and this is because technology firms are having both risks i.e. to the country they are headquartered as well as to the global financial system.

When comparing the tail quantiles and expected shortfalls across industries, the mean tail quantiles and expected shortfalls of technology firms exceeded the mean tail quantiles and expected shortfalls of finance firms. To interpret these results, it is worth noting that SK Hynix Company (in the technology group) has the highest 0.1% tail-VaR (28.62%) both top-20 firms. This implies, for this South Korean semiconductor supplier of dynamic random-access memory (DRAM) chips and flash memory chips, that a daily erosion in the value of the equity capital, of 28.62% or more, is expected to happen once every 1000 days (approximately 3.8 years). Regarding the expected shortfall, the highest expected shortfall ($p = 0.1\%$) is attributed to Alibaba among the full sample. Alibaba's expected shortfall value of 26.31% represents the fact that once the tail-VaR of 13.50% (when $p = 0.1\%$) is exceeded, the "additional" expected loss equals 26.31%. Furthermore, the tail quantile and expected shortfall of finance firms have a significant increase in the financial crisis, which denotes the extreme loss. When looking closer at the company level in the two industries, we observe that Alphabet (among technology firms) and AIA Group (among the financial firms) exhibited the lowest tail quantile. Meanwhile, Microsoft (among the technology firms) and Royal Bank of Canada exhibited the lowest expected shortfall (ESx(p)). There are some studies argue that the potential reasons for the higher risk among technology firms are competition (Tong, 2015) and systematic risk among Internet Finance (Zhu and Hua, 2020).

With regard to the time-varying tail-risk measurements obtained by conditioning on rolling samples, Fig. 3 demonstrates the evolution of the average rolling Hill estimates and the average rolling expected shortfalls for both technology and finance firms. We used six-year rolling daily stock return data to plot time-varying tail-risk measures and we reported rolling tail quantile and rolling expected shortfall with p=0.2%.[4] For the time-varying effect, we can see that there is a sudden downtrend in the tail index (increased tail-risk) for the finance firms after the financial

[3] For detail, see Straetmans and Chaudhry (2015).

[4] The average rolling tail quantile and rolling expected shortfall show very similar pattern we use p=0.1%.

Table 1
Tail risk indicators for technology companies.

Companies	α	x(p)		ES(X>s)		ES(x(p))	
		p = 0.1%	p = 0.2%	s=25%	s=50%	p = 0.1%	p = 0.2%
APPLE	2.8148	0.1607	0.1256	0.1378	0.2755	0.0885	0.0692
MICROSOFT	2.8931	0.1131	0.0890	0.1321	0.2641	0.0598	0.0470
ALPHABET INC.	2.3177	0.1072	0.0795	0.1897	0.3794	0.0813	0.0603
INTEL	2.6817	0.1507	0.1164	0.1487	0.2973	0.0896	0.0692
INTERTIOL BUS. MCHS. CORP.	2.6824	0.1118	0.0863	0.1486	0.2972	0.0664	0.0513
FACEBOOK	1.7244	0.1322	0.0884	0.3451	0.6902	0.1825	0.1221
CISCO SYSTEMS	2.7224	0.1633	0.1266	0.1451	0.2903	0.0948	0.0735
BROADCOM	2.2619	0.1083	0.0797	0.1981	0.3962	0.0858	0.0632
MICRON TECHNOLOGY	3.0116	0.2081	0.1653	0.1243	0.2486	0.1034	0.0822
HP	2.8226	0.1431	0.1120	0.1372	0.2743	0.0785	0.0614
QUALCOMM	2.9131	0.1758	0.1386	0.1307	0.2614	0.0919	0.0724
ORACLE	2.8639	0.1619	0.1271	0.1341	0.2683	0.0869	0.0682
ALIBABA	1.5130	0.1350	0.0854	0.4873	0.9747	0.2631	0.1664
TENCENT HOLDINGS	2.7071	0.1216	0.0941	0.1464	0.2929	0.0712	0.0551
BAIDU	2.2449	0.1734	0.1273	0.2008	0.4016	0.1393	0.1023
SAMSUNG ELECTRONICS	2.5779	0.1615	0.1234	0.1584	0.3169	0.1024	0.0782
SK HYNIX	2.3666	0.2862	0.2136	0.1829	0.3659	0.2094	0.1563
HON HAI PRECN. IND.	2.8753	0.1441	0.1132	0.1333	0.2666	0.0768	0.0604
TAIWAN SEMICONDUCTOR	3.3116	0.1454	0.1179	0.1082	0.2163	0.0629	0.0510
SAP	2.6195	0.1529	0.1174	0.1544	0.3087	0.0944	0.0725
ACCENTURE CLASS A	2.3220	0.1166	0.0865	0.1891	0.3782	0.0882	0.0654
Average	**2.5963**	**0.1528**	**0.1163**	**0.1772**	**0.3543**	**0.1065**	**0.0791**

Table 2
Tail risk indicators for finance companies.

Companies	α	x(p)		ES(X>s)		ES(x(p))	
		p = 0.1%	p = 0.2%	s=25%	s=50%	p = 0.1%	p = 0.2%
BERKSHIRE HATHAWAY	2.7162	0.0871	0.0675	0.1457	0.2913	0.0507	0.0393
VISA	2.4177	0.0906	0.0680	0.1763	0.3527	0.0639	0.0480
JP MORGAN CHASE & CO.	2.8973	0.1322	0.1041	0.1318	0.2635	0.0697	0.0549
BANK OF AMERICA	2.2702	0.1882	0.1387	0.1968	0.3936	0.1482	0.1092
MASTERCARD	2.6635	0.0996	0.0768	0.1503	0.3006	0.0599	0.0462
WELLS FARGO	2.4965	0.1396	0.1058	0.1671	0.3341	0.0933	0.0707
CITIGROUP	2.3439	0.1910	0.1421	0.1860	0.3720	0.1421	0.1058
PAYPAL HOLDINGS	1.7488	0.0852	0.0573	0.3338	0.6677	0.1137	0.0765
ICBC	2.4581	0.0844	0.0636	0.1715	0.3429	0.0579	0.0436
CHINA CONSTRUCTION BANK	2.4082	0.1071	0.0803	0.1775	0.3551	0.0760	0.0570
PING AN INSURANCE	2.5813	0.1190	0.0910	0.1581	0.3162	0.0752	0.0575
AGRICULTURE BANK	4.4336	0.1708	0.1461	0.0728	0.1456	0.0497	0.0425
BANK OF CHINA	2.1953	0.1008	0.0735	0.2092	0.4183	0.0843	0.0615
CHINA MERCHANTS BANK	2.5773	0.1126	0.0860	0.1585	0.3170	0.0714	0.0545
CHINA LIFE INSURANCE	2.6994	0.1159	0.0897	0.1471	0.2942	0.0682	0.0528
ROYAL BANK OF CANADA	3.3627	0.0693	0.0564	0.1058	0.2116	0.0293	0.0239
TORONTO-DOMINION BANK	3.1491	0.0805	0.0646	0.1163	0.2327	0.0375	0.0301
HSBC HOLDINGS	2.7048	0.1033	0.0800	0.1466	0.2933	0.0606	0.0469
AIA GROUP	2.7348	0.0630	0.0489	0.1441	0.2882	0.0363	0.0282
ALLIANZ	2.9008	0.1222	0.0962	0.1315	0.2631	0.0643	0.0506
Average	**2.6880**	**0.1131**	**0.0868**	**0.1613**	**0.3227**	**0.0726**	**0.0550**

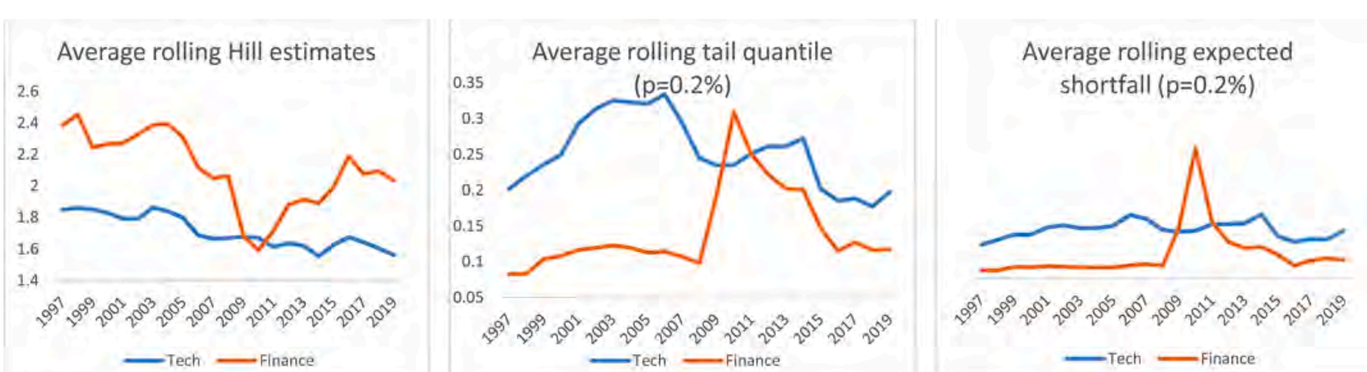

Fig. 3. The rolling tail risk of techonology and finance companies.

crisis 2007-2008. However, the time-varying tail index of the tech firms exhibited the lowest values in 2014. The tail index of tech firms started falling from 2009, but the fall continued until 2014. This is in contrast to the finance firms where the fall and rebound was very quick. The tail index of finance firms had a sharp fall in 2009 which quickly rebounded in 2011. The lower values of the tail index implies that there is a fat tail in the return distribution of these firms. The average rolling tail quantile of technology firms shows more variation across time compared to the rolling tail index and rolling expected shortfall. Although there is an increase in the rolling tail quantile since the start of our sample in 1997, there is exponential increase in the rolling tail quantile after the dot com bubble in 2001 which continues to increase until 2006 when it starts to fall. However, it is interesting to note that the tail quantile remained stable during the global financial crisis in 2008. This is in contrast to the finance firms, whose average rolling tail quantile experienced a sharp increase during the GFC while they were stable or even decreasing before the GFC. The average tail quantile decreased sharply after 2010 and continued to fall until 2017 when it reached pre-crisis level. This may be because of the stricter regulations for financial firms post GFC. (On the other hand, or simiilar to this?) the average tail quantile was much higher for technology firms than finance firms after 2011. This shows that technology firms carry a huge level of risk and there is a need for this to be addressed by regulators. This is even more concerning given the lack of regulations for technology firms despite their involvement in financial activities. The picture of the average rolling expected shortfall for finance firms is very similar to the the average rolling tail quantile, as it remains very stable pre-crisis period then increases substantially during the GFC before falling sharply post-GFC to pre-crisis levels. However, for technology firms, the average rolling expected shortfall remains stable with a slight increase during the dot com bubble where it broadly remains at that level. It falls slightly in 2014, but recent data shows an upward trend. Nevertheless, the average rolling expected shortfall of technology firms is higher than finance firms since 2011, and this again reaffirms the need for regulation for technology firms (in order to mitigate their much higher levels of risk?).

4.2. Extreme systematic risk

In this subsection, we estimate the exposure of the top-20 technology firms and the top-20 finance and banking firms to large adverse movements in "aggregate" shocks. We do this by employing the country market index and the country industry index respective to the location of these firms. Moreover, we link to a worldwide industrial sector and global market stock index.

Tables 3 and 4 summarise the extreme systematic risk (tail-βs) for technology firms and finance? firms, respectively. We make a comparison between two nuisance parameters ($m = 300$ and $m=400$) for four main categories such as the country market index, the country industry index, the global market index, and the global industry index. Overall, the nuisance parameter ($m = 400$) exhibits the higher extreme systematic risk (tail-βs) than the other parameter ($m = 300$). We interpreted the economic intuition based on these Fig.s. For instance, the number '0.41' for Apple in the 'Country market index' column implies that a very large downturn in the Apple return index, under the 'Country market index', specifically here in the US market, is associated with a 41% probability that Apple faces a daily stock price decrease of comparable magnitude. In other words, a sharp daily drop in the S&P500 is expected to have the same, comparably large drop in the Apple stock nearly one out of two times. Furthermore, when we look at the financial firms, these institutions have a higher exposure to extreme systematic risk with the country financial index. This means that the individual finance firms are more likely to be affected by a shock from the specific respective country's financial index compared to the more general respective country's market index or global indices. In fact, finance firms are least affected by such shocks from the global market index. Similarly, technology companies also show the highest extreme systematic risk (tail-βs) respective to the country's technology index. This may be because of the fact that most of the big technology firms are based in the US and the US technology index better tracks performance of the whole industry. A shock from the US technology index has more effect on the individual technology firms. Next to the US, the other big technology firms in our sample are Chinese and have most of their business located in China. Again, a shock from the Shanghai technology index has greater impact on individual technology firms compared to more general market indexes or global indices.

Although the biggest impact on the individual technology and finance firms arises from their respective industry indices, the impact from the respective global indices is also significant. [up to here]. The mean extreme systemic risk (tail-βs) of technology firms conditional upon the global tech index and global market index is 0.39 and 0.35 (with $m = 400$) compared to a mean tail-βs of 0.41 conditional upon the respective country's tech index. Similarly, the mean extreme systemic

Table 3
Extreme systematic risk (tail-βs) for technology companies.

Technology Companies	Country Market Index		Country Tech Index		Global Market Index		Global Tech Index	
	m=300	m=400	m=300	m=400	m=300	m=400	m=300	m=400
APPLE	0.41	0.42	0.45	0.49	0.33	0.37	0.42	0.46
MICROSOFT	0.35	0.50	0.57	0.61	0.40	0.42	0.53	0.56
ALPHABET INC.	0.52	0.40	0.31	0.34	0.33	0.36	0.32	0.34
INTEL	0.50	0.49	0.59	0.60	0.38	0.42	0.55	0.56
INTERTIOL BUS. MCHS. CORP.	0.40	0.47	0.51	0.53	0.38	0.40	0.48	0.50
FACEBOOK	0.46	0.21	0.17	0.20	0.19	0.21	0.18	0.20
CISCO SYSTEMS	0.54	0.49	0.58	0.60	0.38	0.41	0.55	0.56
BROADCOM	0.18	0.27	0.22	0.24	0.26	0.27	0.24	0.25
MICRON TECHNOLOGY	0.21	0.42	0.46	0.48	0.35	0.38	0.44	0.47
HP	0.23	0.47	0.48	0.52	0.38	0.41	0.47	0.49
QUALCOMM	0.21	0.40	0.44	0.47	0.34	0.37	0.42	0.45
ORACLE	0.19	0.45	0.52	0.53	0.36	0.39	0.50	0.51
ALIBABA	0.19	0.22	0.18	0.21	0.18	0.21	0.17	0.20
TENCENT HOLDINGS	0.28	0.30	0.27	0.29	0.26	0.30	0.23	0.26
BAIDU	0.24	0.27	0.23	0.25	0.33	0.35	0.30	0.32
SAMSUNG ELECTRONICS	0.56	0.60	0.41	0.44	0.29	0.32	0.29	0.31
SK HYNIX	0.42	0.43	0.36	0.38	0.28	0.30	0.28	0.31
HON HAI PRECN. IND.	0.48	0.37	0.37	0.41	0.27	0.30	0.27	0.30
TAIWAN SEMICONDUCTOR	0.36	0.37	0.32	0.34	0.28	0.30	0.28	0.29
SAP	0.46	0.49	0.41	0.44	0.37	0.41	0.40	0.43
ACCENTURE CLASS A	0.31	0.32	0.29	0.31	0.39	0.41	0.37	0.39
Average	**0.36**	**0.40**	**0.39**	**0.41**	**0.32**	**0.35**	**0.36**	**0.39**

Table 4
Extreme systematic risk (tail-βs) for finance companies.

Finance Companies	Country Market Index		Country Financials Index		Global market Index		Global Financials Index	
	m=300	m=400	m=300	m=400	m=300	m=400	m=300	m=400
BERKSHIRE HATHAWAY	0.41	0.41	0.43	0.43	0.36	0.39	0.36	0.39
VISA	0.35	0.35	0.36	0.36	0.32	0.32	0.32	0.32
JP MORGAN CHASE & CO.	0.52	0.54	0.62	0.63	0.43	0.46	0.46	0.48
BANK OF AMERICA	0.50	0.53	0.63	0.65	0.43	0.46	0.46	0.48
MASTERCARD	0.40	0.38	0.39	0.39	0.36	0.36	0.36	0.35
WELLS FARGO & CO	0.46	0.49	0.58	0.59	0.39	0.42	0.41	0.43
CITIGROUP	0.54	0.55	0.66	0.65	0.47	0.48	0.48	0.50
PAYPAL HOLDINGS	0.18	0.21	0.18	0.21	0.18	0.21	0.17	0.20
ICBC	0.38	0.38	0.40	0.41	0.25	0.27	0.27	0.28
CCB	0.31	0.33	0.30	0.33	0.30	0.32	0.32	0.33
PING AN INSURANCE (GP.) CO. OF CHINA	0.38	0.38	0.37	0.39	0.26	0.28	0.27	0.29
AGRICULTURE BANK	0.19	0.23	0.18	0.22	0.19	0.22	0.19	0.22
BANK OF CHINA	0.40	0.40	0.39	0.41	0.24	0.27	0.26	0.28
CHINA MERCHANTS BANK	0.43	0.44	0.50	0.51	0.25	0.28	0.26	0.28
CHINA LIFE INSURANCE	0.40	0.40	0.40	0.40	0.25	0.28	0.27	0.28
ROYAL BANK OF CADA	0.48	0.48	0.65	0.66	0.40	0.41	0.40	0.43
TORONTO-DOMINION BANK	0.47	0.48	0.59	0.61	0.38	0.40	0.39	0.40
HSBC HOLDINGS	0.34	0.36	0.36	0.37	0.36	0.37	0.38	0.39
AIA GROUP	0.24	0.26	0.23	0.26	0.21	0.24	0.22	0.24
ALLIANZ	0.61	0.63	0.52	0.53	0.46	0.48	0.49	0.50
Average	**0.40**	**0.41**	**0.44**	**0.45**	**0.32**	**0.35**	**0.34**	**0.35**

risk (tail-βs) of finance firms conditional upon the global finance index and global market index is 0.35 and 0.35 (with m = 400) compared to a mean tail-βs of 0.45 conditional upon the respective country's financial index. Here we can note that the difference between the extreme systemic risks of finance firms conditional upon the respective country's industry index is not that much different compared to the extreme systemic risk conditional upon the global indices. Nevertheless, both technology and finance firms seem to be global in nature as they are affected by a shock in the global indices. Therefore, our results also raise the concern that the finance firms, and more so the technology firms, not only need local regulation but also need global regulations to mitigate the effects of extreme systematic risk. Recently, Nguyen et al. (2018) indicated that an industry is a larger customer to the other industry; they are likely to have stronger tail risk connections. Thus, financial institutions and technology firms seem to have a larger number of customers relative to the other industries. Hence, it could be seen that these industries have high co-movement in tail-βs.

Similar to tail risk measures, we use six-year rolling daily stock returns data to calculate average rolling tail-βs, which are presented in Fig. 4. The average rolling tail-βs of finance firms is about 0.80 and about 0.70, which is almost double that of the full sample tail-βs. We observe more variation in the average rolling tail-βs of finance firms compared to technology firms for all conditional factors, i.e., respective country market index, respective industry index, global market index and global industry index. Even during the dot com bubble, the tail-βs of finance firms fell more than the technology firms for all the conditioning factors.

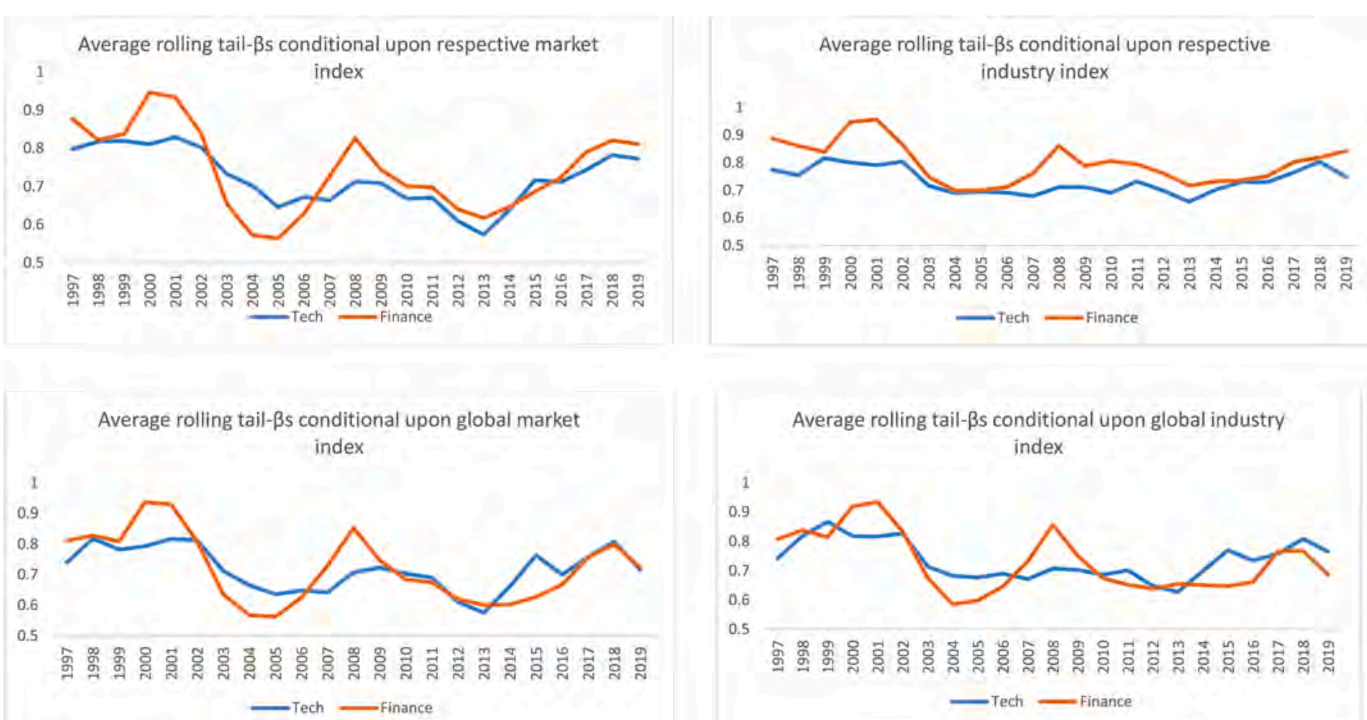

Fig. 4. Time-varying systemic risk: (rolling) expected co-crash indicators and co-crash probabilities of technology and finance companies.

However, the fall in the tail-βs conditional upon respective to the industry index was not pronounced . Furthermore, the average rolling tail-βs of finance firms increased during the GFC and fell again after the GFC until 2013. After 2013, they continuously increased until 2018 (where they remained steady?) until 2019. As highlighted above, the variation in the technology firms was not significant, remaining high during the dot com bubble and then decreasing until the GFC. During the GFC, the tail-βs of technology firms increased slightly and were the lowest in 2013, as was the case with finance firms. As with the finance firms, the average rolling tail-βs of technology firms also increased but remained on average higher than the finance firms. After 2013, the technology firms recorded higher the rolling tail-βs compared to finance firms indicating a higher extreme systemic risk for technology firms compared to finance firms. We also observe a higher risk for technology firms during the internet bubble in the beginning of 2000. Fong et al. (2008) highlighted the existence of internet shocks that was followed by large losses from early 2000 while other studies indicated that banks and financial firms were prone to technological and liquidity risk. Interestingly, the role of technology and the dot come bubble in contributing to the systematic risk was identified in the 2000s, which presents the higher time-varying systematic risk over the period from 1997 to 2002 in our approaches. Noticeably, the expected co-crash indicators and co-crash probabilities were observed at the highest value in the dot come bubble rather than the global financial crisis. While the current literature highlights that the global financial crisis contributed to the tail risk and systemic risk of US and Eurozone financial institutions (Straetmans and Chaudhry, 2015), our study emphasises the severity of the dot come bubble in causing the co-crash risk among the two industries, namely technology and financial firms. Therefore, our findings are consistent with Zouaghi et al. (2018) who stated that the financial crisis does not negatively influence the technology firms with strong resources in innovation.

Table 5 represents the multivariate spillover risk with two-nuisance parameters *m* (representing the number of extremes used in estimation) for the technology and finance industries. The economic interpretation of the point estimate of 1.75 reflects the expected number of technology firms in distress given that there is one technology company in distress. Similarly, the number of finance firms to be in distress is 2.12 should one finance firm go into distress. The economic interpretation of the multivariate spillover risk of 0.04 for technology firms is such that if one technology company goes into distress, there is a 4% probability that all twenty technology firms will go into distress. This number is 5% in the case of finance firms. We observed that $E_{Finance} > E_{Tech}$ with m = 170 and $E_{Finance\ k} > E_{Tech}$ with m = 160. One explanation for this could be that in a much more integrated financial system, the systemic risk may be higher because the financial sector is much more interdependent. Therefore, the multivariate spillover risk in finance firms is relatively higher than technology firms. By estimating the multivariate spillover risk, we can observe the broad picture about the systemic risk across these industries. Accordingly, the systematic risk is lowest in the technology firms, which supported in previous empirical findings, such as [insert]. Similar to tail risk measures and extreme systemic risk measures, we also calculated time-varying spillover risk measurements. Fig. 5 demonstrates the time-varying systemic risk for technology and finance firms. Similar to tail-βs, the six-year rolling spillover risk measurment is much higher compared to the full sample. For example, for technology firms, 3.3 technology firms on average are likely to be in distress if one technology company is in distress for a six-year rolling period compared to only 1.7 for the full sample. We found a very similar pattern in the time-varying spillover risk for both the technology and finance firms, however, the effect was more pronounced for finance firms. For technology firms, the crash likelihood was the highest (with 3.6 technology firms likely to be in distress given the distress of one technology firm) during the dot com bubble and lowest (only 2.9 technology firms crashing given one technology company crash) just before the GFC. Only recently, the crash likelihood for technology firms has started increasing to almost as high as the finance firms. For the finance firms, four were likely to be in distress given one finance company in distress during the peak of the GFC. This likelihood went down to 3.3 in 2013 and slightly increased after that. For the multivariate spillover risk, it is clear to see that the finance firms were consistently higher in comparison with the technology firms, consistent with the findings of Teixeira et al. (2018). However, the multivariate spillover risk increased sharply after the dot com bubble for the technology firms and started decreasing after 2005. It reached the lowest point (if one technology company goes into distress, there was only a 13.5% probability that all the technology firms would go into distress) during the GFC and remained around this level until it started increasing in 2019.

Table 5
Multivariate spillover risk.

E = Multivariate Gaussian	Parameters	Finance	Tech
	m = 160	2.123424	1.753653
	m = 170	0.052106	0.040081

Notes: The nuisance parameter m (representing the number of extremes used in estimation) for three industries.

5. Regulations on finance and technology firms

The financial services sector is one of the most widely regulated sectors, particularly since the financial crisis of 2007-08 where regulation became more strict and vigilant. However, the recent digitisation of the financial sector has significantly transformed the sector. This transformation has meaningful implications for policy and regulation (Garbellini and Okeleke, 2017).

5.1. Regulation and FinTech innovation

Regulatory infrastructure has an important influence on innovation. Weak regulatory framework can discourage innovation, and an over-regulated environment can deter innovation. Policymakers and governments are required to redesign financial regulations to accommodate the growing needs of the Fintech industry, however, they need to maintain the balance in overcoming the negative influence on innovation while preserving the integrity that the industry requires to flourish. One of the significant factors influencing the development of innovation is the approach towards regulation. Asian Governments, e.g. Hong Kong, Singapore and China, have been effective in innovation by developing regulatory sandboxes that permit start-ups to assess the feasibility of their ideas in an environment that confirms that the start-ups endure compliance and consumers are still fairly treated.

There are other key aspects of FinTech start-ups with regards to the innovation and redesign of regulation and compliance issues in the financial services sector. Many firms are expose to different challenges based on the regulatory system or jurisdiction they are functional within. Therefore regulation technology (Regtech) is revolutionary in the FinTech sector for regulation, because the financial services sector needs better, faster and more transparent resources of reporting and ensuring compliance. In this way, Regtech can deliver solutions to help the financial sector to comply with regulations efficiently and effectively.

5.2. Importance of Regtech in financial services

Presently, the growing concern for financial institutions compliance with increasingly strict regulations and the government and regulators frequently implement new regulations. Fintech firms are therefore exposed to remarkable stress to address all compliance issues in a swift and efficient manner. Regtech can resolve cumbersome regulatory systems through new, state-of-the-art technologies. Regtech has developed through innovations e.g. machine learning, biometrics and disabled

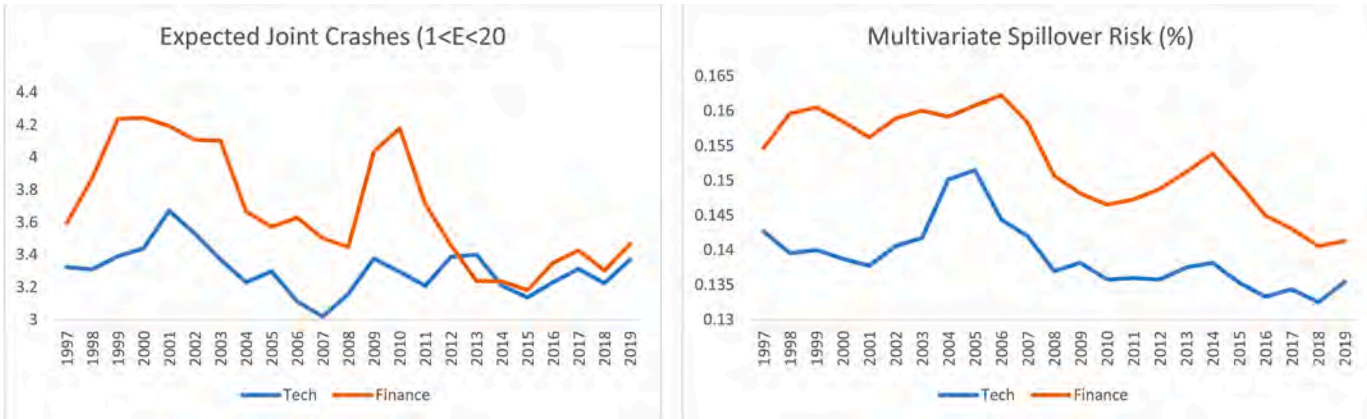

Fig. 5. Time varying systemic risk: (rolling) expected co-crash indicators and co-crash probabilities for Finance, Technology companies and banks.

ledgers. Regtech also translates complex regulation into programming codes and reduces financial risk and human resources.

5.3. Challenges in regulation

Overall, the financial sector and new starts-ups in Fintech are facing a variety of challenges with regards to the regulatory environment. Although solutions to improve due diligence and regulatory processes are convincing in Regtech for new start-ups, large institutional clients are reluctant and showing concern in adopting key parts of Fintech systems, processes and risk and compliance management with new technology. On the other hand, technological hurdles are also a key aspect, for example, Fintech services require appropriate infrastructure and technology to start the financial services. In addition, regulators are reluctant to see an over reliance on technology that could become an operational risk on the sector and negatively affect the financial market reputation (K & L Gates, 2017).

Another key barrier is data-privacy jurisdictional differences among cross-border products and restricting cross-border data analysis. Fintech services mostly rely on collecting, handling or analysing clients' data and need to be aware of their legal responsibilities on data-privacy, usage and distribution.

6. Conclusion and policy implications

The huge growth in the BigTech firms over last decade and their entry into financial services raises concerns about the riskiness of BigTech firms and the implications for financial stability, which has been aptly highlighted by the Financial Stability Board (FSB) in their report in 2019. Despite substantial growth and concern from the FSB, no research has been done to measure the risk of BigTech firms. In this paper, we studied the tail risk and systemic risk of BigTech firms by using the novel extreme value theory. For the purpose of comparison, we also measured the tail risk and systemic risk of finance firms since BigTech firms are increasingly entering into the financial services sector. We assess whether BigTech firms are riskier than finance firms and whether there should be similarly strict regulations for tech firms as for finance firms. To address this question, we used the stock price data of the top twenty technology firms and top twenty finance firms. Our selection criteria was the market capitalisation. For tail risk, we calculated tail index $\widehat{\alpha}$ and corresponding values of tail quantile and tail expected shortfall. Extreme quantiles were calculated for probability values 0.1% and 0.2%. We also investigated the expected shortfall estimates conditioned on both the $\widehat{x}_p$ (%) tail quantile and on crisis barriers $x = 25\%$ or 50%. For systemic risk, we estimated the exposure of technology and finance firms to large adverse movements in "aggregate" shocks. This extreme systemic risk is denoted as tail-β. Furthermore, for systemic risk we also calculated expected joint crashes and multivariate spillover risk. Our findings show that the average tail risk of technology firms is higher than the financial firms whereas they are less likely to be in distress conditional upon a shock from the system, meaning they have smaller values of tail-β. Therefore, we do not reject our hypothesis that the the tail risk of technology firms is higher than that of finance firms. However, this finding for technology firms reverses when we use recent data via our six-year rolling estimates. Our other measure of systemic risk (or spillover risk), such as expected joint crashes and multivariate spillover risk, show that finance firms are more connected as they cause distress in other finance firms more than the technology firms. We also reviewed the regulations of BigTech firms and find that currently there are few regulations for BigTech firms. We conclude that there should be tighter regulations for technology firms, similar to the strict regulations of finance firms, in order to avoid a global crisis in the future and to avoid a situation whereby taxpayers' money is used to bail out these big firms.

With regard to policy implications, our findings could offer insights for national and global policymakers as well as for investors. First, policymakers should be conscious of the (dot com?) bubble development and come up with appropriate regulations to mitigate the chances of any crash for BigTech firms. This is particularly important because the technological industry is likely become even more powerful with the onset of the COVID-19 pandemic, suggesting sudden reactions without persistent decline in tech-firms (Goodell and Huynh, 2020). Second, investors whose portfolio consists of finance firms should be cautious due to the high likelihood of a crash. The same perspectives still hold for the BigTech firms. Thus, the supervising regulations to avoid the 'bubble development' could be useful to mitigate the chances of a market crash. Finally, financial institutions tend to move with the "aggregate shocks" in our findings. Our findings emphasised the important role of the administrative department to continuously follow market signals to allow for a timely intervention before any potential crash.

Our study covered the period from 2 April 1992 to 31 December 2019, prior to the market experiencing the external shocks from the pandemic, and the negative crude oil prices (April, 2020). Therefore, these findings should be considered a caveat to when the market condition changed. Furthermore, whilst we adopt the univariate extreme value theory (EVT) to determine equity tail risk while, future studies could be extended to use the machine-learning, deep-learning (Wang et al., 2020) or the intersection between econophysics and economics to aggregate all relevant factors to compute the tail risk. Finally, the applications of this methodology for other markets, such as cryptocurrency sit on the verge of the fourth industrial revolution, remains a positive future direction of study.

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