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

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Abstract

Technology firms are increasingly moving to finance. They make use of 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. Therefore, 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. We adopt univariate extreme value theory (EVT) to determine equity tail risk. Our selection criteria is the market capitalisation and we choose top twenty technology and top twenty finance firms to evaluate tail risk and systemic risk. We find that 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 because technology firms are riskier than the finance firms. Our paper have phenomenal implications for both national and for global financial regulators.

JEL Classification: G21; G28; G29; G12; C49; N7; O3

Keywords: Banking; Systemic risk; Technology; Technological Change; Asymptotic dependence; Multivariate extreme value theory

1. Introduction

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

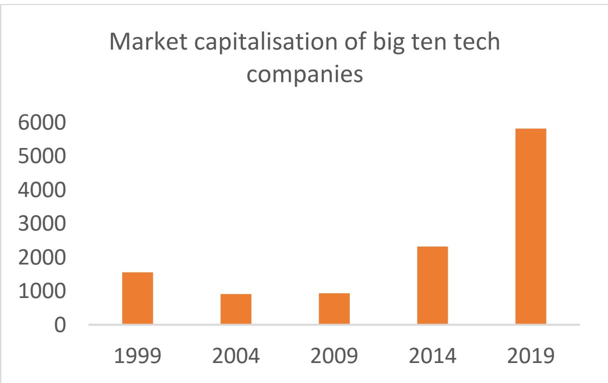

Figure 1: Market capitalisation of big ten tech firms
(Authors' Own Compilation)

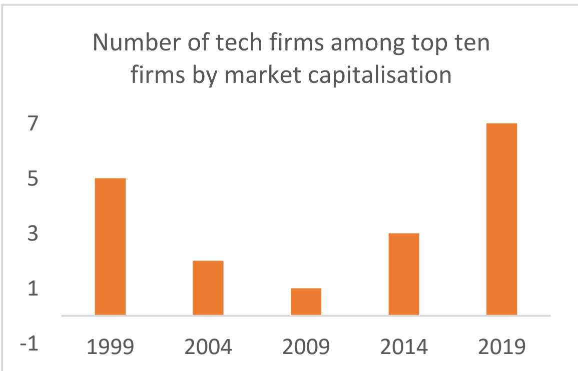

Figure 2: Number of tech firms among top ten firms by market capitalisation
(Authors' Own Compilation)

Technology is influencing the traditional business of banks, despite the consideration that banks are also adjusting to the digital world. It helps to perform the tasks more efficiently but in a unique and simple way. For example, like banks, crowdfunding platforms 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 the banking by lowering barriers to entry through mobile phones, which are substituting retail branch banking to develop 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 and Hu et al. 2019). Moreover, changing clients' behaviour and expectations also have influence on financial services providers.

The rapid growth in financial technology is causing risk and threats towards financial and economic system. BigTech firms provide three-fold risk to financial system. For instance, recent growth of "relatively small" Fintech firms has risk to control of highly concentrated financial market. Secondly, growth of BigTech industry establishes blurring boundaries between traditional financial system and other contemporary products for e.g. digital wallets and store credits, which is difficult for regulators to "segment and regulate" in economy. Finally, the Fintech firms are biggest risk to financial sector and economy through big data as compared with traditional financial system. Recently, the BigTech firms face tough legislation and resilient from politicians after selling consumer data to third parties without consumer consent (for e.g. Facebook chief executive Mark Zuckerberg forced to testify before the US congress in 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), the closer look in Fintech firms and by using extreme value theory (EVT) seems to have overlooked. Therefore, our study fulfils this gap.

The contribution of our paper is three fold. First, this is the first 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 in distress 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 that we need to implement tight standards and regulations for technology firms to safeguard the system from any global crisis in future. Our paper has phenomenal 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 cautious approach for investors whose portfolio contains finance and BigTech firms.

Our findings reveal that the average tail risk of technology firms is greater than the financial firms and it is less likely to be in distress from any surprise if it occurs. 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 years 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 organized as follows. Section 2 reviews the related literature on the impact of tail risk and systemic risk of technology firms on financial system and impact of technology firms on financial system and we have also examine the literature on impact of tail risk and systemic risk of finance firms on financial system. Section 3 provides 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 pose novel and complex trade-offs 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 system. Particularly, we explore the impact of tail risk and systemic risk of technology firms and finance firms on financial system.

2.1 Impact of technology firms on financial system

Technology firms have started playing an increasing role in financial system. The integration of technology firms and financial institution 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. The 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 instability of financial markets (These financial technologies refer to big data analytics, artificial intelligence and blockchain ledgers). This means such financial technologies enable to address risk management requirements and related costs more efficiently. Risk management includes political and economic risks, currency exchange risk, transfer risk, cultural differences, credit risk, legal risk, commercial risk, and changes in customer need (Ullah et al., 2019; Tanabandeh et al., 2019; Illiashenko, 2019). This has been support by Hua et al. (2019), who stress that FinTech promotes costs reduction, increases accessibility of customers, and manages risks more efficiently. Moreover, BIS annual economic report (2019) also states that big techs' entry into finance has the potential to create rapid change in the finance industry. It can expand financial services, use big data to analyse the network structure within industry and evaluate the risk of borrowers.

With these benefits, big techs could boost the efficiency of financial services provision, foster financial inclusion and stimulate economic activity. The additional cost advantage of FinTech firms due to loose regulatory structure by comparison to traditional banks as well as have more advance technologies enable FinTech firms to offer their services to wider customers who were inaccessible from bank services such as SMEs (Temelkov, 2018). Degryse et al (2007) also support that Fintech firms do not encounter with a complex corporate structure and high rank of administration, consequently, they can have lower operating costs. Fintech firms also benefit from lower physical location cost because they utilize technological advancement to contact clients rather than physical offices. Technology firms also play crucial role in promoting bank funds to broader group of borrowers. This has been support by the finding 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 did not have physical bank offices. Mills and McCarthy (2014 and 2016) and Schweitzer and Barkley (2017) also claim that FinTech lenders help reducing credit gap in small businesses borrowers by providing credit to those firms. By utilizing account-level data from a large FinTech lender, the Lending Club, and Y-14M bank, Jagtiani and Lemieux (2017) find that the Lending Club can provide funding to boarder areas in comparison to traditional banking which lose bank branches. 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 cost of operating business activities and decrease in capital expenditure. However, the collaboration might create disadvantage due to security, regulatory and agreement issues as well as degree of investment risk.

Overall, Zetzsche et al. (2017) point out that FinTech not only give major benefits to consumers, businesses, and economies but also pose problems referring to data privacy, funding security, and fairness of access. Giudici (2018) points out several key risk concerns regarding the development of the financial technologies. These include underestimation of creditworthiness, market risk 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. 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 involve in price discrimination and extract rents as they enable to collect big data at near zero cost which lead to digital monopolies or data-opolies (BIS annual economic report, 2019). Recent work of Zetzsche et al. (2020) have categorized related risks of artificial intelligence (AI) in finance context into four forms which are data risks, cybersecurity risks, financial stability risks, and ethical risks. Economic and financial system could be attacked, manipulated or threatened by AI. It could destabilize economy or send wrong signals to society which may lead to systemic risk.

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

2.2 Impact of tail risk and systemic risk of finance firms on financial system

Straetmans and Chaudhry (2015) apply 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. They find that both tail risk and systemic risk in the Eurozone are lower than in the US. This result is similar to earlier study by Hartmann et al. (2006), who apply multivariate extreme value theory to examine contagion risk and systemic risk of banks in the US and the euro zone. They find that bank spillover in the US seems to be significantly higher than in the euro area. This implies weak cross-border linkages in Europe. The increase of risk in the euro area seem to happen slowly from the integration of traditional banking firms. For the US, the strongest increases in extreme systematic risk seem to occur between the largest financial institutions and the main clearing banks.

Gilli and Kellezi (2006) use extreme value theory to compute tail risk measures 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 indicate that the left tail of all indices are heavier than the right tail. In asset markets, Kelly and Jiang (2014) use returns and sales growth data from 1963 to 2010 to assess the impacts of time-varying extreme event risk. They find that tail risk is a potentially crucial factor of asset prices because it has prophetic power for individual stocks' future extreme returns. 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 behavior 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) use extremal quantile regression and the CoVaR model to estimate the impact of state variables on the extreme risk and on systemic financial risk of financial institutions. Their samples include 33 financial listed institutions, banks, insurances, securities, and trust firms, in China. The findings indicate that state variables have different influence on the risk of financial institutions under different quantiles. Under extreme quantiles, spread of short-term liquidity risk has negative impacts on banks resulting in higher bank risk. This means banks have the extreme effects on financial systems. This result is consistent with the finding of systemic risk contribution which reveal higher risk contribution of banks to financial systems than other financial institutions. On the other hand, the value at risk measurement report lower risk contribution of banks to financial systems than securities. In addition, the findings show that the size and leverage of financial firms have positive relationship with systemic risk contribution. Financial institutions with larger sizes and higher leverage tend to have greater systemic risk contribution. By applying a dynamic analysis approach to examine the contagion of banking systemic risk, Gu et al. (2019) find that banking systemic risk contagion would be uncontrollable if banks have high risk contagion rate and low risk isolation protection rate.

Bank risk from a capital market perspective, Bessler et al. (2015) examine 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 indicate 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 the US bank holding firms to assess the relationship between tail risk and financial distress risk, Alzugaiby et al. (2019) find 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 study the relationship amongst tail risk measures and financial distress of the US publicly-traded firms during 1990 to 2016. More reviews on 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 on the broader financial system and broader economy. However, to authors' knowledge, none of those studies have compared the impact of tail risk and systemic risk of finance firms to big tech firms. Therefore, this paper aims to evaluate the tail risk and systemic risk of top twenty technology and top twenty finance firms by applying a univariate extreme value theory (EVT). The research hypothesis is "tail risk of technology firms is higher than the financial firms".

3. Data and Methodology

Our sample data consist of technology firms and for comparison we also evaluate the tail risk and systemic risk of finance firms. We download equity prices from April 2nd, 1992 to December 31st, 2019. Our selection criteria is top twenty technology and top twenty finance firms based on market capitalisation. We select only top twenty technology firms because after top twenty firms, the size becomes very small. Therefore, we select only top twenty technology firms and then to make the comparison fair, we also select top twenty finance firms. Furthermore, top forty firms make up major chunk of the index's market value. For example, 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 use 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 use six-year rolling data to calculate tail risk.

3.1 Measurement of tail risk

We examine the tail risk because of rapid decline in the equity indices of technology and finance firms. We adopt univariate extreme value theory (EVT) to determine equity tail risk. The univariate EVT compose of Generalised Extreme Value (GEV) distribution and consider as limit law for maxima of stationary method. We select Peaks-Over-Threshold (POT) method to measure the parameters of GEV distribution. We use semi-parametric method and match the distributional excess losses over a high threshold that leads to Generalised Pareto Distribution (GPD)[1].

We measure 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:

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

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

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

The parameter m examines how many extreme returns are evaluated in estimation. We adopt $m = 300$ for as our main investigation for technology firms and m = 175 for finance firms. We use sensitivity analysis by adjusting $m = 225$ and m = 350 for technology firms and m = 125 and m = 225 for finance firms. We measure m values by adopting Hill (1975) estimator. We arive at expected shortfall estimator by substituting the Hill (1975) equation (2) and tail quantile estimator in equation (1) as follows:

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

The theoretical explanation of the tail quantile (or tail-VaR) and tail expected shortfall given in equations (1) and (2) are our measures of tail risk for finance, technology and banking firms.

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

We calculate extreme quantiles for probability values ranging from 0.1% to 0.2%. This means that the corresponding tail quantile are expected to be violated every 500 days and every 1000 days, respectively. Furthermore, we also investigate 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 mean the more extreme expected shortfall measure when the extreme quantile estimates ($\hat{x}_p$) are lower than the x. Empirically, the framework in place here 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 measures with semi-parametric estimation procedures for systemic risk because with parametric probability distributions wrong distributional assumptions may severely bias the systemic risk estimations due to misspecification. We use the following equation for multivariate spillover risk:

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

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, *m* is the nuisance parameter as the parameter *m* in the Hill estimator, it 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 $q \to \infty$. However, when α = 1, as we impose throughout the paper, systemic risk is no longer influenced by changes in q.

We use another systemic risk measure and use the following equation to estimate that:

$$\hat{E}[\theta|\theta \geq 1] \approx \frac{N}{\frac{n1}{kn}\sum_{i=1}^{n} U_{i=1}^{N} X_i > X_{i,n-k}} \tag{5}$$

In the equation above, the denominator is an estimator of the stable tail dependence function l(.).[2] The upper order statistic $X_{i,n-k}$ estimates the quantile $Q_i\left(\frac{k}{n}\right)$ and $1\{.\}$ is the indicator

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

function . k is the nuisance parameter as m in the Hill estimator and represents the number of extremes in calculating risk measures.

The theoretical framework of systemic risk measures that are given in equations (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 use are the country market index and country industry index, which represents the based location of these firms. Moreover, we also link to a worldwide industrial sector and global market stock index. Next we also use the multivariate spillover risk with two-nuisance parameters m (representing the number of extremes used in estimation) for technology and finance industries. Empirically, for calculation of systemic risk, we use country market index, country industry index, global market index and global industry index as an independent variable and measure their impact on the stock price series of firms in technology, finance and banking sector. For calculation of spillover risk, we replace the country market index and other indices with another firm from 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. We also examine the indicators of extreme systematic risk (called as 'tail-β') under the different conditioning risk factors in section 4.2. Finally, we also check the robustness by adjusting the values of the nuisance parameter for three types of firms. Then, our results remain the same.

4.1. Downside risk estimates of technology and finance firms

Tables 1 and 2 demonstrate estimates of the tail index $\hat{\alpha}$ and corresponding values of tail-VaR and expected shortfall for all forty individual financial institutions from two categories such as finance and technology, respectively. The tail indices for finance sectors fluctuate 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 α (2.59) is lowest in the technology firms, which implies the fat tails. In contrast, the finance firms (2.68) have a thinner tails than technology firms do. It could be because of the exponential growth of technology firms in the recent past. Our finding also confirm the findings from Papanikolaou and Wolff (2014) that the regulatory changes and technological advances could be the potential sources of high risk of finance firms. In addition, the technology firms tend to overlook the risk control while the financial are likely to be active in managing their risk because of stricter regulations. The extant literature from Ellul and Yerramilli (2013) indicated that the financial institutions and banks experiencing the better risk management would have lower tail-risk exposure. Noticeably, Goldman (1982) also admitted that the technological firms have "short" product life cycle while the amount of investment is substantially large. Thus, making the growth of technology firms very fast, which comes with higher risk of these firms. Therefore, the tail-risk of technology firms is higher compared to finance firms in our empirical results which led us not to reject our null hypothesis.

When looking at specific firms, Alibaba, Paypal, Facebook and Bank of China exhibit the highest heavy tail from two categories such as finance and tech firms. It is important note that, two of these four organizations are located in China. It may be because of the high growth rate of China over the last decades, this market has an inherent risk, which has been captured in tail risk in our study. The previous study by Hou et al. (2014) indicate that 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 tail-risk among the top of big banks. Additionally, in the technology company list, the heavy-tail risk lies in Facebook and Alibaba. Facebook and Alibaba have frequently suffered from data breach events, and so the related bad news 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 risk in data privacy breach, which might cause a sharp decline in their returns. In another perspective, Alibaba is associated with the political connections, which might have an incentive to announce bad news at normal times and thus experience lower crash risk in the future in China. Meanwhile, the nature of this behavior also exhibits the potential risk in investing in the Chinese market. In addition, in our results, we also find that the technology firms with high likelihood of data protection breaches will experience the higher tail-risk in comparison with the other firms (Gatzlaff and McCullough, 2010; Eling and Loperfido, 2017; Wongchoti, 2020).

Another perspective, which we could observe the difference among these industries, is regulation. Although the previous studies such as Ellul and Yerramilli (2013) and Andrieş and Nistor (2016) indicated that the financial firms are regulated by the regulations while the technology firms have no much strict regulations, which induces more threat to these firms. However, it could be another explanation why the technology firms can pose riskier threat to this industry is that technology firms is both to the country they are headquartered as well as to the global financial system.

Upon comparing the tail quantiles and expected shortfalls across industries, the mean tail quantiles and expected shortfalls of technology firms exceed 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%) among forty firms. It implies that a daily erosion in the value of equity capital of this South Korean firm, which is doing semiconductor supplier of dynamic random-access memory (DRAM) chips and flash memory chips, with 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 of Alibaba among the full sample. The Alibaba expected shortfall value of 26.31% represents that once the tail-VaR of 13.50% (when $p = 0.1$%) exceeded, the "additional" expected loss given this exceedance 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 two industries, we observe that Alphabet among technology firms and AIA Group among finance firms exhibit lowest tail quantile and Microsoft among technology firms and Royal Bank of Canada exhibit lowest expected shortfall (ESx(p)). The study of Yu et al. (2019) indicates the potential reasons of high risk among technology firms are competition (Tong, 2015) and systematic risk among Internet Finance (Zhu and Hua, 2020).

When it comes to the truly time-varying tail risk measures by conditioning on rolling samples, Figure 3 demonstrates the evolution of (average) rolling Hill estimates and (average) rolling expected shortfalls for technology and finance firms. We use six-year rolling daily stock return data to plot time-varying tail risk measures and we report rolling tail quantile and rolling expected shortfall with p=0.2%.[3] In 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 crisis 2007-2008. However, the time-varying tail index of the tech firms exhibits the lowest values in 2014. The tail index of tech firms started falling from 2009 but the fall continued till 2014 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 and it rebounded already in 2011. The lower values of tail index implies that there is a fat tail in the return distribution of these firms. The average rolling tail quantile of technology firms show more variation across time compared to the rolling tail index and rolling expected shortfall. Although there is increase in the rolling tail quantile since the start of our sample in 1997 but there is exponential increase in the rolling tail quantile after dot com bubble in 2001 and keeps increasing till 2006 when it starts falling. However, it is interesting to note that the tail quantile remain stable during the global financial crisis in 2008-08. This is in contrast to the finance firms whose average rolling tail quantile has a sharp increase during the GFC while they were stable or even decreasing before the GFC. The average tail quantile decrease sharply after 2010 and keep falling till 2017 when it reaches pre-crisis level. This may be because of the stricter regulations for financial firms post GFC. The average tail quantile of technology firms is much higher than finance firms since 2011. This shows that the technology firms carry huge risk that needs to be addressed. This is more concerning given lack of regulations for technology firms despite their financial activities. The picture of average rolling expected shortfall for finance firms is very similar to the average rolling tail quantile as it remains very stable pre-crisis period, increases substantially during the GFC and then falls sharply post GFC at pre-crisis levels. However, the average rolling expected shortfall for technology firms remain stable with a slight increase during the dot com bubble and broadly remains at that level. It falls slightly in 2014 but recent data show upward trend. Nevertheless, the average rolling expected shortfall of technology firms is higher than finance firms since 2011, which again points to the need for regulation for technology firms.

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

4.2. Extreme systematic risk

In this subsection, we would like to estimate the exposure of the firms of two different industries such as technology and finance firms or technology and banks to large adverse movements in "aggregate" shocks. We would like to summarize our steps for these estimates. The first step is to employ the country market index and country industry index, which represents the based location of these firms. Moreover, we link to a worldwide industrial sector and global market stock index.

Tables 3 and 4 summarize extreme systematic risk (tail-βs) for technology firms and technology firms, respectively. We make a comparison between two nuisance parameter ($m = 300$ 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 the extreme systematic risk (tail-βs) than the other parameter ($m = 300$). We will interpret the economic intuition based on these figures. 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 herein the US market, is associated with a 41% probability that Apple faces a daily stock price decrease of comparable magnitude. Saying differently, a daily sharp drop in the S&P500 is expected to have the same drop with comparably large drop in the Apple stock nearly one out of two times. Furthermore, when we look at the financial firms, these institutions have higher exposure risk in extreme systematic risk with the country financial index. This reflects that the individual finance firms are more 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 a shock from the global market index.. Similarly, the technology companies also show the highest extreme systematic risk (tail-βs) to the respective country's technology index. It may be because of the fact the most of the big technology firms are based in the US and the US technology index better tracks performance of the whole industry. Therefore, a shock from the US technology index has more effect on the individual technology firms. Next to the US, the other big technology firms Chinese and have most of their business located in China. Hence, a shock from the Shanghai technology index has greater impact on individual technology firms compared to more general market index or global indices.

Although the biggest impact on the individual technology and finance firms is coming from their respective industry indices yet the impact from the respective global indices is also not ignorable. The mean extreme systemic risk (tail-βs) of technology firms conditional upon 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 respective country's tech index. Similarly, the mean extreme systemic risk (tail-βs) of finance firms conditional upon 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 respective country's financial index. Here we can note that the difference between extreme systemic risks of finance firms conditional upon respective country's industry index is not that much different compared to the extreme systemic risk conditional upon 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 concerns that the finance firms and more so technology firms not only need the local regulation but also need global regulation to mitigate the effects of extreme systematic risk. Recently, Nguyen et al. (2018) also 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 the large number of customers relatively to the other industries. Hence, it could see that these industries have the 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 Figure 4. The average rolling tail-βs of finance firms is about 0.80 and about 0.70, which are almost double than 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 fall more than the technology firms for all the conditioning factors. However, the fall in the tail-βs conditional upon respective industry index is not that sharp. Furthermore, the average rolling tail-βs of finance firms increase during the GFC and fall again after the GFC till 2013. After 2013, they continuously increase till 2018 and then they become a little bit until 2019. As we note above the variation in the technology firms are not very high, they remain high during the dot com bubble and then decrease until the GFC. During the GFC, the tail-βs of technology firms increase slightly and are the lowest in 2013 as was the case with finance firms. Similar to finance firms, the average rolling tail-βs of technology firms also increase but they are higher than the finance firms on average. Since 2013, the technology firms have higher the rolling tail-βs compared finance firms indicating higher extreme systemic risk of technology firms compared to finance firms. We also observe the higher risk in technology firms during the internet bubble in the beginning of 2000. Fong et al. (2008) indicate the existence of internet shocks that was followed by large losses from early 2000 while Cumming and Schwienbacher (2005) examined that banks and financial firms were prone to technological and liquidity risk. More interestingly, the role of technology and dot come bubble contributed to the systematic risk was found 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 dot come bubble rather than the global financial crisis. While the current literature speaks that the wake of global financial crisis contributed to tail risk and systemic risk of US and Eurozone financial institutions (Straetmans and Chaudhry, 2015), our study emphasizes that the severity of dot come bubble causes the co-crash risk among three industries namely technology and financial firms. Therefore, our findings are consistent with the study of Zouaghi et al. (2018) that the financial crisis does not negatively influence the technology firms with the 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 technology and finance industries. The economic interpretation of the point estimate of 1.75 reflects the expected number of technology firms in distress given there is one technology company is in distress. Similarly, the number of finance firms to be in distress is 2.12 if one finance firms goes into distress. The economic interpretation of the multivariate spillover risk of 0.04 for technology firms is that if one technology company goes into distress, there is 4% probability that all the twenty technology firms will go into distress. This number is 5% in case of finance firms. We observe that $E_{Finance} > E_{Tech}$ with $m = 170$ and $E_{Finance\ k} > E_{Tech}$ with $m = 160$. One explanation 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 those of 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 is found the previous empirical findings Similar to tail risk measures and extreme systemic risk measures, we also calculate time varying spillover risk measures. Figure 5 demonstrates the time varying systemic risk for technology and finance firms. Similar to tail-βs, the six-year rolling spillover risk measure 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 six-year rolling period compared to only 1.7 for the full sample. We find very similar pattern in the time-varying spillover risk for both technology and finance firms, however, the effect is more pronounced for finance firms. For technology firms, the crash likelihood is the highest (3.6 technology firms likely to be in distress given the distress of one technology company) during dot com bubble and lowest (only 2.9 technology firms crashing given one technology company crashes) just before the GFC. Only recently the crash likelihood for technology firms has started increasing and almost as high as the finance firms. For finance firms, four finance firms were likely to be in distress given one finance company in distress during the peak of the GFC. This likelihood goes down to 3.3 in 2013 and slightly increase after that. For the multivariate spillover risk, it is clear to see that the finance firms are consistently higher in comparison with the technology firms consistent with the findings of Teixeira et al. (2018). However, the multivariate spillover risk increases sharply after the dot com bubble for the technology firms and start decreasing after 2005. It reaches the lowest point (if one technology company goes into distress, only 13.5%

probability that all the technology firms go into distress) during the GFC and almost remains that this level until it starts increasing in 2019.

5 Regulations on Finance and Technology Firms

The financial services sector is one of the widely regulated sector, and considering the fact that after financial crisis of 2007-08 regulation has become more strict and vigilant. However, with the recent digitisation of the financial sector, the financial services firms are modifying significantly. This transformation has meaningful implications for policy and regulation (Garbellini and Okeleke, 2017).

5.1 Regulation and Fintech Innovation

The regulatory infrastructure has an important influence on innovation. Weak framework of regulation can discontinue innovation, and over regulated environment can deter innovation. Policy makers and Governments required to redesign financial regulations to accommodate the growing needs of Fintech industry, however, they need to maintain the compulsory balance to overcome negative influence on innovation while preserving the integrity that the industry requires. One of the significant factors to the development of innovation is the approach towards regulation. Asian Governments, for 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.

Another key aspect of Fintech start-ups to innovate and redesign the regulation and compliance in the financial services sector. Many firms expose to different challenges, based on the regulatory system or jurisdiction they are functional. Therefore regulation technology (Regtech) is revolution in the Fintech for regulation, because financial services sector needs better, faster and more transparent resources of reporting and ensuring compliance. Therefore, Regtech can deliver solutions to help financial sector to comply with regulations efficiently and effectively.

5.2 Importance of Regtech in Financial Services

Presently, the growing concern on financial institutions is to comply with more strict regulations and government and regulators are often implement new regulations, therefore Fintech enhance remarkable stress on the existing regulatory system which cannot address all compliance issues in a swift and efficient manner. Regtech can resolve cumbersome regulatory system through using new state of the art technologies. Regtech developed through innovations, for e.g. machine learning, biometrics and disabled ledgers. Regtech also translates complex regulation into programming codes and reduces the financial risk and human resources.

5.3 Challenges in regulation

Overall financial sector and new starts-ups in Fintech are facing variety of challenges in regulations. Although, solutions to improve due diligence and regulatory processes are convincing in Regtech for new start-ups, however, large institutional clients are reluctant and showing concern on adoption of key parts of Fintech systems, processes and risk and compliance management with new technology. On the other side, technology hurdles are key aspects, for example Fintech services require appropriate infrastructure and technology to start the financial services. Moreover, regulators are reluctant for over reliance on technology that could become operational risk on the sector and effects negatively 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 are mostly rely on collecting, handling or analysing clients' data and need to be aware of legal responsibilities on data-privacy around data usage and distribution.

6. Conclusion and Policy Implications

The huge growth in the BigTech firms over last one decade and their entry into financial services raise concerns about riskiness of BigTech firms and implications for financial stability, which has been rightly pointed by the Financial Stability Board in their report in 2019. Despite substantial growth and FSB's concern, no research has been done on measuring the risk of

BigTech firms. In this paper, we study the tail risk and systemic risk of BigTech firms by using novel extreme value theory. For the purpose of comparison, we also measure the tail risk and systemic risk of finance firms particularly because of the reason that BigTech firms are entering into the financial services. We assess whether BigTech firms are riskier than finance firms and whether there should be as strict regulations for tech firms as they exist for finance firms. To address this question, we use stock price data of top twenty technology firms and top twenty finance firms. Our selection criteria is the market capitalisation. For tail risk, we calculate tail tail index $\hat{\alpha}$ and corresponding values of tail quantile and tail expected shortfall. Extreme quantiles are calculated for probability values 0.1% and 0.2%. We also investigate the expected shortfall estimates conditioned on both the $\hat{x}_p$ (%) tail quantile and on crisis barriers x = 25% or 50%. For systemic, we estimate 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 calculate expected joint crashes and multivariate spillover risk. Our finding 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) like 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 review regulations of BigTech firms and find that currently there are hardly any regulations for BigTech firms and we conclude that similar to finance firms there should be tighter regulations for technology firms in order to avoid a global crisis in future so that taxpayers' money may not be used to bailout of these big firms.

When it comes to the policy implications, our findings and results could offer insights for national and global policymakers as well as for investors. First, the policy makers should be conscious of the bubble development and come up with appropriate regulations to mitigate the chances of any crash of BigTech firms. This is particularly important because the technological industry is likely to come even more powerful with the onset of COVID-19 pandemic, suggesting sudden reactions without persistent decline in tech-firms (Goodell and Huynh, 2020). Second, the investors whose portfolio consists of finance firms should be cautious due to the high likelihood of 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 for market crash. Finally, financial institutions tend to move with the "aggregate shocks" in our findings. Our findings emphasized the role of administrative department to continuously follow the market signals to timely intervene when the crash might be happened.

Our study covers the period from April 2nd, 1992 to December 31st, 2019 when the market has not experienced the external shocks from the pandemic, the negative crude oil prices (April, 2020). Therefore, what we found here should be considered a caveat when the market condition changed. Furthermore, we adopt univariate extreme value theory (EVT) to determine equity tail risk while the future works could extend 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. Furthermore, the applications of this methodology for another market, such as cryptocurrency (Yuneline et al., 2019) on the verge of the fourth industrial revolution can be a new direction. It is still a fruitful avenue.

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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**

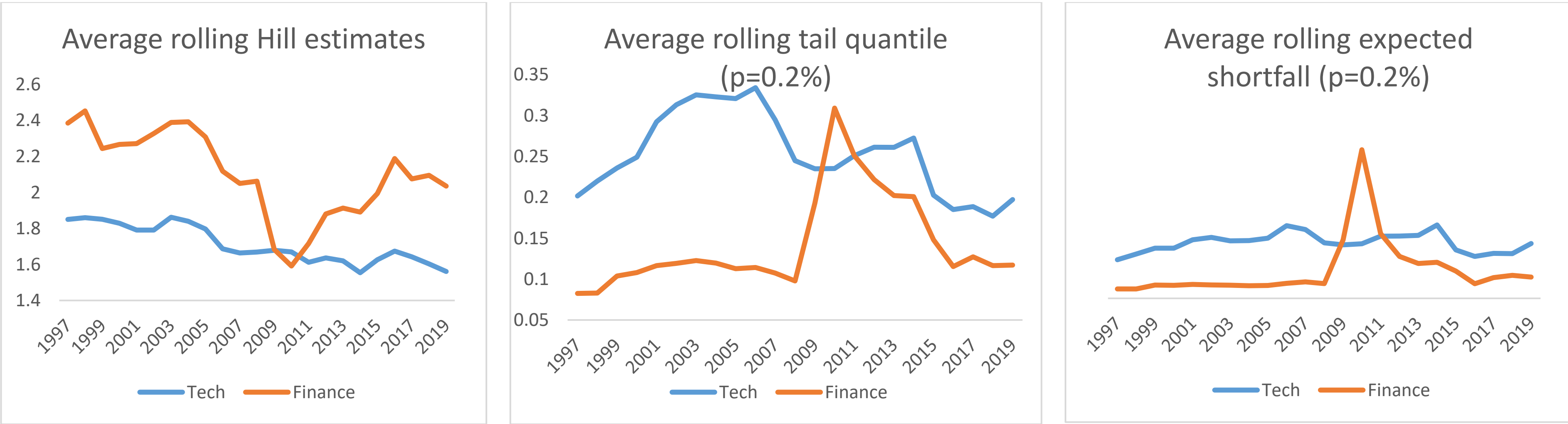

Figure 3. **The rolling tail risk of techonology and finance companies**

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**

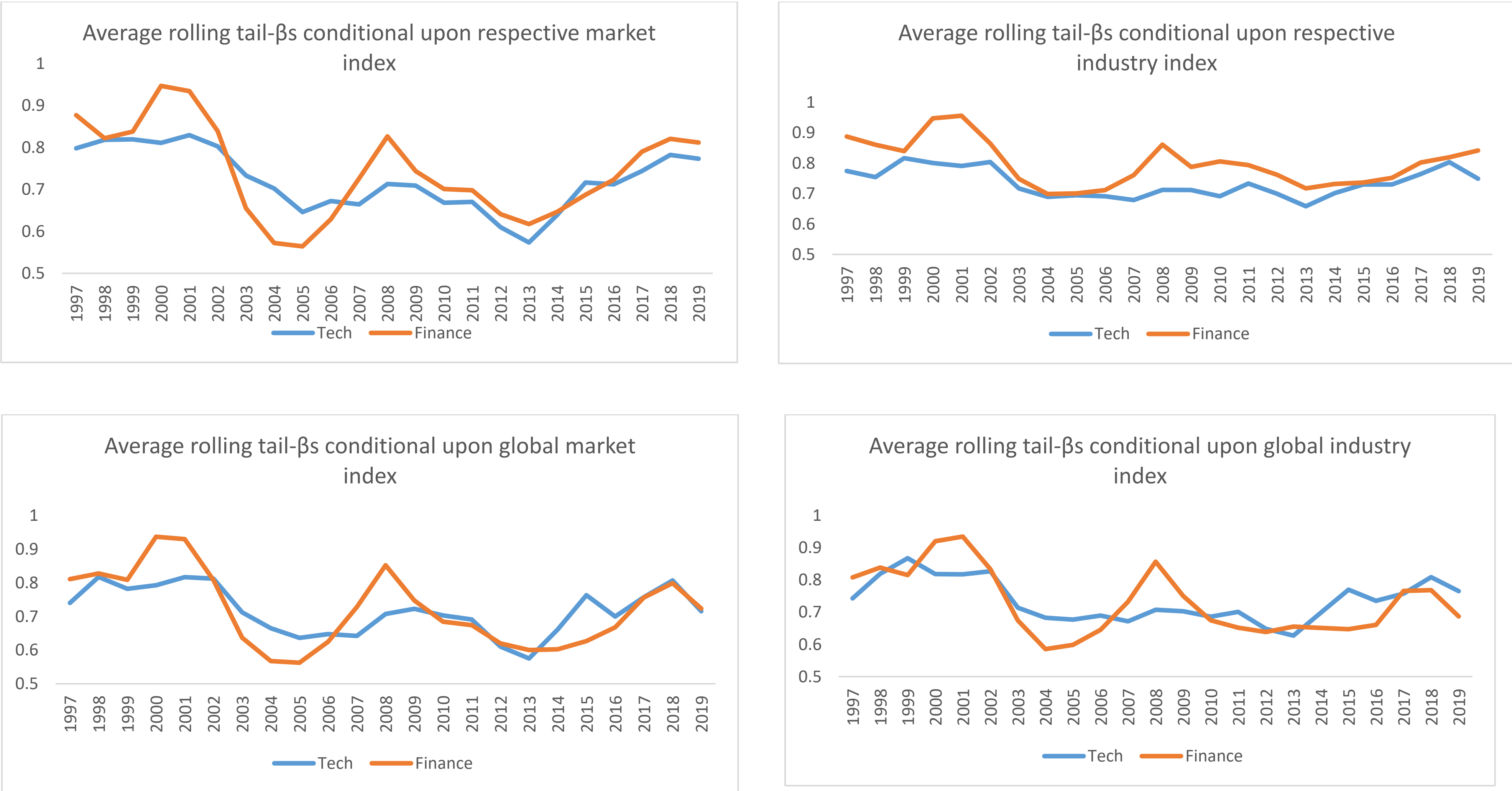

Figure 4. Time-varying systemic risk: (rolling) expected co-crash indicators and co-crash probabilities of technology and finance companies

Table 5. **Multivariate spillover risk**

	Parameters	Finance	Tech
E = Multivariate Gaussian	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.

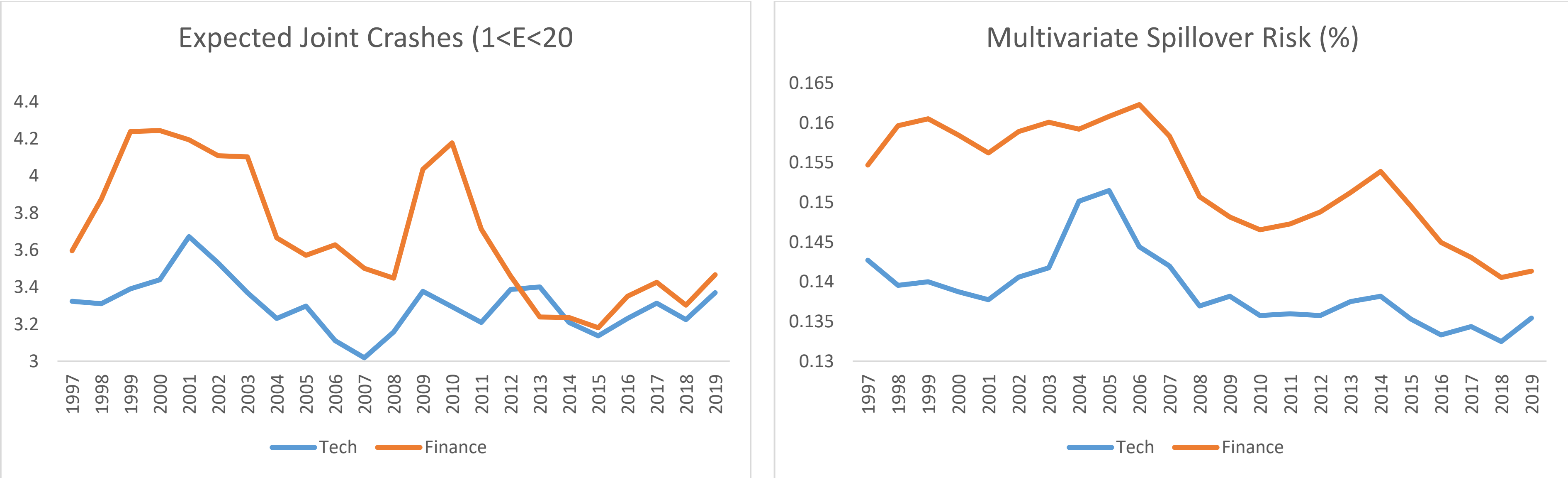

Figure 5. Time varying systemic risk: (rolling) expected co-crash indicators and co-crash probabilities for Finance, Technology companies and banks