Technological Forecasting & Social Change 217 (2025) 123968

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

On the risk commonality of US tech firms: Relevance and determinants

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ARTICLE INFO

JEL classification:
D43
D62
G21
G29
O33

Keywords:
Digitalization
Risk commonality
Technological change
Banking

ABSTRACT

Technology firms serve as critical data and service intermediaries, which may pose new challenges to financial stability. We apply market-based systemic risk measures designed initially for financial firms to measure the risk commonality of tech firms included in the S&P 500 index. First, we find that, on average, the level of total risk commonality of tech firms is larger than for non-tech firms/non-banks. The difference between the level of risk commonality of tech firms and non-tech firms/non-banks increases over time. Second, we observe a high intra-group risk commonality for tech firms. Third, we find that the intra-group risk commonality of tech firms is driven to a larger extent by exposure to systematic risk factors than this is the case for banks. Fourth, in contrast, there is weak evidence that the inter-group risk commonality of tech firms is driven to a larger extent by non-systematic risk factors (e.g., direct business relationships) than this is the case for banks. Fifth, we hardly find balance-sheet or other firm-specific variables that are significantly associated with the level of total risk commonality of tech firms. Our results indicate that regulators should also look for risk accumulation outside the traditional financial world.

1. Introduction

In recent years, the political debate about the potential risks stemming from the size and market influence of digitally-oriented tech companies (tech companies/firms, in the following) has intensified. Calls to split large tech companies[1] since their size, market power, and complexity make it hard to get them under the control of regulatory authorities have recently seen a new spike.[2] A closer look at the policy debate highlights that regulators are not only worried about the size, market power, and complexity per se but also about the potential transmission of shocks from tech firms to other industries (Rogoff (2019); Tirole (2020), Crisanto et al. (2022)). This policy debate is supported by various recent research papers that identify and analyze the systemic relevance of industries outside the financial system (see, e.g., Welburn et al. (2020) or Li et al. (2020)). That is why there are first attempts to measure the risk commonality within the technology sector as well as between the technology sector and other sectors (see, e.g., Chaudhry et al. (2022) or Dungey et al. (2022)). For example, this risk commonality can emerge if tech companies are interconnected to other industries, and the value-added they provide to these other industries is not easily substitutable by other firms. An example of this transmission channel is the dependence of almost all industries on digital infrastructure offered by tech firms, such as telecommunication, IT, cloud services, digital marketing channels, and the corresponding digital payment options. This dependence was highlighted during the Covid-19 crisis when the functioning of societies crucially depended on the reliability of the services provided by tech firms.[3]

A crucial prerequisite for regulating tech firms based on the risk commonality they exhibit is the existence of suitable metrics. So far, regulators are equipped with very few quantitative tools when assessing the magnitude of the risk commonality with respect to tech firms. This paper aims to close this gap and contribute to a better understanding of this risk commonality by empirically analyzing its magnitude and determinants.

For identifying systemically important banks that bear the risk of exhibiting a considerable risk commonality with other banks, financial

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[1] Lee et al. (2019).

[2] https://www.politico.com/news/2020/12/09/facebook-breakup-suits-zuckerberg-444100.

[3] The hearing at the US congress of the CEOs of the largest four tech companies in July 2020 is a prominent example of the raised policy makers' attention to the debate.

https://doi.org/10.1016/j.techfore.2024.123968
Received 17 July 2023; Received in revised form 14 October 2024; Accepted 28 December 2024
Available online 24 April 2025

regulators employ an indicator-based approach with several qualitative dimensions (see Basel Committee of Banking Supervision, 2013). These dimensions include size, interconnectedness, lack of readily available substitutes or financial institution infrastructure, global activity, and complexity. Although originally formulated for the financial industry, each of these dimensions can also be found in the context of tech firms. This is because tech companies are also interconnected (both between each other and to other industries), offer not easily substitutable outputs, and jointly provide but are also jointly exposed to digital infrastructure so that if these companies are in distress or even default, problems for other companies that use the tech firms' products might arise. Further, as financial institutions, large tech firms are complex, globally active entities. More generally, the analogy between the financial and the tech sector can be illustrated by the fact that while the financial sector is the major intermediary of capital, the tech industry enables the intermediation of data and digital processes. Hence, tech companies might also exhibit a large risk commonality among each other and with firms outside the tech sector, even though some channels that are perceived as the obvious sources of risk commonality between financial institutions (e.g., interbank exposures, informational contagion, or fire sales) are formally lacking in non-financial sectors. In Section 3, we outline in detail which features of tech firms can lead to risk commonality and highlight the parallels to financial firms.

Leaning on the analogy to financial institutions, we use measures computed from stock return data that before have extensively been used in the academic literature to measure the systemic risk of financial institutions (see, e.g., Engle et al. (2015), Engle (2018), Girardi and Ergün (2013), Gravelle and Li (2013), López-Espinosa et al. (2012, 2015), Weiß et al. (2014a, 2014b)) to measure the risk commonality of tech firms. Essentially, these measures reflect conditional tail-risks of entities. More specifically, we use as quantitative systemic risk measures the Marginal Expected Shortfall (MES) proposed by Acharya et al. (2012, 2017) and the ΔCoVaR exposure and contribution measures introduced by Adrian and Brunnermeier (2016).[4] While the ΔCoVaR contribution measure identifies those firms whose collapse would have the most harmful effect on the system (contribution to systemic risk), MES and the ΔCoVaR exposure measure identify those firms that would be most significantly affected by systemic distress (exposure to systemic risk). We compute the risk commonality for firms in the S&P 500 with a particular focus on the sample of tech firms and, for comparison, on the sample of banks in the S&P 500. We focus on the US because there is a large share of tech companies in the total economic output, which implies that systemic influences of the industry are most likely to be found in the US market.[5] In our baseline analysis, the system is proxied by the whole S&P 500 which yields the total risk commonality. To analyze to which extent the total risk commonality can be explained by intra-group risk commonality and inter-group risk commonality, we additionally compute the risk commonality measures based on different indices proxying the system. For analyzing intra-group and inter-group risk commonality, we consider as a system all firms in the S&P 500 that belong to a specific sector and all firms in the S&P 500 that do not belong to a specific sector, respectively. Then, the percentage change of the risk commonality measures that results from switching the system from the S&P 500 to one of the other indices is interpreted as a proxy of intra-group and inter-group risk commonality, respectively.

Our main results are as follows: First, on average the level of total risk commonality of tech firms is larger than for non-tech firms/non-banks. Further, the difference between the level of risk commonality of tech firms and non-tech firms/non-banks increases over time. Second, we observe a high intra-group risk commonality for tech firms. Third, we find that intra-group risk commonality of tech firms is driven to a larger extent by an exposure to systematic risk factors than this is the case for banks. Fourth, in contrast, there is weak evidence that the inter-group risk commonality of tech firms is driven to a larger extent by non-systematic risk factors (e.g., direct business relationships[6]) than this is the case for banks. Fifth, we hardly find balance-sheet or other firm-specific variables that are significantly associated with the level of total risk commonality. Some significance of firm-specific variables is found in the case when we consider the level of inter-group and intra-group risk commonality.

Our results contribute to the academic and political debate on the need to regulate tech firms by pointing to the growing potential of such firms to generate risk spillovers to other sectors. Further, they are related to the literature on the impact of FinTechs on financial stability that typically argues that FinTechs have a lower impact on financial stability than traditional banks (see, e.g., Li et al. (2020)) or that they can even (due to efficiency gains) contribute to financial system stabilization (see, e.g., Daud et al. (2022)). Contrary to this line of research but consistent with Franco et al. (2020), we find that FinTechs (in our case, we look at payment service providers only) can have a detrimental systemic effect as some dimensions of their risk commonality are relatively high.

The remainder of the paper is organized as follows: Section 2 gives an overview of the related literature. Section 3 motivates the transmission channels for risk commonality between the tech industry and the remaining economy. In Section 4, we present the methodology for measuring risk commonality, explain our definition of tech firms, and describe the data set. In Section 5, we present the empirical results for tech firms' risk commonality. In Section 6, we carry out robustness checks, whereas Section 7 discusses implications and further research. Section 8 contains our conclusion.

2. Literature review

Up to now, the existing academic literature about systemic risk has only paid very limited attention to the systemic risk of non-financial firms. Not only is the literature that deals with the systemic risk of non-financial institutions (especially tech firms) relatively scarce, but many of the existing studies on the systemic relevance of non-financial companies do not use the elaborated measurement techniques (e.g., MES or ΔCoVaR) which, in the meantime, have become standard in studying the systemic risk of financial firms.

For example, Oh and Patton (2018) calculate a new copula type for 100 US companies in stress (defined as firms whose credit default swap spread lies above some threshold) and show that systemic risk has decreased since 2009. Anufriev and Panchenko (2015) calculate a network model with (partial) correlations and a 'centrality index'. They find evidence for strong links between the four major Australian banks, the real estate sector, and other sectors of the economy. In another paper studying the systemic risk of non-financial sectors, Muns and Bijlsma (2011) use the measure 'expected additionally failing firms' (EAF) to compare the systemic risk of US companies from the insurance, construction and food sector to the one of banks. These authors find that

[4] Since the computation of the third broadly used systemic risk measure, SRISK proposed by Brownlees and Engle (2017), crucially depends on the role of required bank capital (either in regulatory or in economic terms), and as it is less clear how much capital the market requires from non-financial firms, we presume that this measure might not properly reflect risk commonality in the case of non-financial firms and do not incorporate it in the analysis, analogous to Dungey et al. (2022).

[5] US tech firms account for approximately 60 % of all tech companies in the EIKON database, measured by market capitalization in 2019, and therefore represent the most important corporate tech market.

[6] The term 'direct business relationships' has to be understood in a broad sense. As data intermediaries and hardware providers, tech firms warrant the functionality of subsequent products and services in other sectors. Therefore, idiosyncratic events at an individual tech company, such as server failures or semiconductor shortages, can lead to the (temporary) failure of other firms outside the tech sector.

systemic risk is highest in the banking sector. Also using EAF, Kerste et al. (2015) find, based on Australian data, that there is a risk of contagion within the energy sector as well as from the energy sector to the banking sector. Dungey et al. (2017) get a similar result for the Australian mining industry based on a correlation analysis. Pankoke (2014) and Mamaysky (2016) both add more sophisticated measures (e.g., MES, ΔCoVaR, Granger-causality networks) to the set of simple systemic risk indicators (e.g., market capitalization, implied volatility, credit spreads, correlations) and apply these to non-financial firms. The focus of their studies is on the differences between sophisticated and simple measures. They do not use the computed measures to draw conclusions regarding the differences in systemic risk measures across industry sectors.

A further strand of literature exclusively employs sophisticated measures of systemic risk for analyzing the difference between sectors, but without a clear focus on digital or tech firms. For example, Brownlees and Engle (2017) calculate for non-financial firms the systemic risk measure SRISK they have initially proposed for financial firms. They use the computed measures to analyze whether SRISK for non-financial firms also has some predictive power for macroeconomic distress or whether this predictive power is only a feature of financial firms' SRISK. They find that the effect of non-financial firms' SRISK is hardly significant. Zhu et al. (2019) investigate the contribution of China's non-financial firms to systemic risk in the entire financial market, represented by the China Securities Index 300 (CSI 300), which includes the 300 largest Chinese companies by market capitalization. They show significant spillover effects from China's non-financial firms to the financial sector caused by massive credit risk exposures. The systemic risk level for every single company is derived from an extreme value theory (EVT)-based copula version of MES. Further, they introduce a test for a 'significant contribution to positive systemic risk' for their MES. They find significant systemic risk contributions for non-financial firms and conclude that these deserve more attention in terms of macroprudential regulation. However, Zhu et al. (2019) have no special focus on a specific sector, in particular not on the tech sector. Bühler and Prokopczuk (2010) compute parametric estimators of lower tail dependencies and empirically compare the systemic risk in the US banking sector with those of twelve other industries. This study is related to our research as two of these twelve industries are the technology and telecommunication sectors, which are also of particular interest to us. Based on the sector-specific differences in bivariate and multivariate lower tail dependencies, these authors conclude that systemic risk in the banking sector is significantly higher than in all other sectors. However, they only use the five largest companies per sector, and their analysis encompasses only data up to 2006. Furthermore, this study does not explore the determinants of systemic risk. Wu (2019) examines the sectoral contributions to systemic risk as measured by the MES and component ES. They focus on data from the Wind Financial Database between 2009 and 2018. The sample consists of companies from 11 Chinese sectors, with the IT sector accounting for <1 % by market capitalization. They find that the information technology sector is the most important contributor to systemic risk in the whole sample period. They argue that the authorities should pay closer attention to sector-wide contributions to systemic risk and impose proper prudential regulation. In contrast to our work, the authors focus on the Chinese market and employ only variants of the exposure measure MES. Finally, Borri (2019) investigates the conditional tail-risk of cryptocurrencies. The results indicate that the conditional tail-risk of cryptocurrencies as measured by ΔCoVaR is indeed high.

As we study the risk commonality of tech firms, which also encompass the universe of FinTechs, our study is also related to the growing strand of literature exploring the impact of FinTechs on financial stability. Daud et al. (2022) analyze 63 countries between 2006 and 2017 and examine whether the emergence of FinTechs has an impact on financial stability as measured by banks' z-score. The authors find that FinTechs contribute to financial stability when the banking market is highly concentrated. According to the authors, this stability is achieved through artificial intelligence, cloud computing, and data technology that encourages efficiency and financial inclusion. Li et al. (2020) use pairwise Granger causality tests and network spillover indicators to analyze the relationship between FinTechs and traditional financial institutions (in particular banks, insurers, diversified financials and real estate) in different market phases. They hypothesize that FinTechs are connected to the financial stability of traditional financial institutions through multiple interconnections. These channels can be competition, cooperation or investments in FinTechs by traditional financial institutions, in particular banks. The results show that the risk spillovers from FinTechs to traditional financial institutions are lower than those from traditional financial institutions to FinTechs in normal and bullish times, but that the risk spillovers from FinTechs to traditional financial institutions are higher than those from traditional financial institutions to FinTechs in bearish phases. The authors recommend a closer monitoring of FinTechs. Franco et al. (2020) analyze a US and a European sample of (Fin-)Tech companies between 2010 and 2017 using an expansion of the ΔCoVaR by Adrian and Brunnermeier (2016) and compare the results with those of banks. They find no enhanced risk of tech companies compared to banks, but within tech companies, software and information technology companies have the highest risk in Europe, while payment services have the highest risk in the US. Factors that contribute to systemic risk of tech firms are size, contagion, correlation, concentration, structure and context.

The studies most closely related to ours are the parallel works by Chaudhry et al. (2022) and Dungey et al. (2022). Chaudhry et al. (2022) compute tail and systemic risk (measured by extreme value theory (EVT)-methods[7]) for a sample of the 20 worldwide largest (with respect to market capitalization) tech and financial companies. They find that tail risk is higher for tech firms than for financial firms in an observation period from 1992 to 2019 but that this result is not robust to a six-year rolling window estimation. Bhatti et al. (2022) apply the same methodology to the analysis of the impact of FinTechs on financial stability during the Covid-19 crisis. These authors find that the risk contribution of FinTechs is lower than in Chaudhry et al. (2022). Dungey et al. (2022) analyze the systemic risk of 1145 US non-financial firms between 2005 and 2018 using MES and ΔCoVaR. They find that non-financial US firms are vulnerable to systemic shocks and contribute to system-wide risk. They also show that the characteristics of systemically important non-financials and banks are different.

We extend the above mentioned work by studying a more specific group of firms and providing a more detailed analysis of the transmission channels for risk commonality in the tech industry. Further, we perform an in-depth analysis of intra- and inter-group risk commonality of firms in the tech sector.

3. Transmission channels for tech industry's risk commonality

The main contribution of this paper is the application to tech companies of risk commonality measures initially developed to quantify the risk commonality arising from financial firms. To defend the application of this approach to tech firms, in this section, we discuss the channels through which the performance of tech companies can affect other tech and non-tech firms. For this purpose, we first discuss the analogies to financial firms' risk commonality channels, then briefly point to potential differences.

Our point of departure is the dimensions through which, according to BCBS (2013), financial institutions can exhibit risk commonality termed in the literature as systemic risk. As mentioned before, these dimensions are size, interconnectedness, lack of readily available substitutes or financial institution infrastructure, global activity, and complexity. Even

[7] For a more detailed overview of EVT methods to measure systemic risk, see, e.g., Straetmans and Chaudhry (2015).

though the theory on the emergence of risk commonality generated by tech firms is less developed relative to the one on the systemic risk of banks, some key narratives have already been made. The growth of tech firms is partially due to the scale and network effects observed in the tech sector, leading to the emergence of natural monopolies (Katz (2020, p. 2) or Bamberger and Lobel (2017, p. 1062 f.)) and making the services provided by these firms particularly difficult to replace. By expanding various ranges of business lines, tech firms, similar to banks, also develop into complex institutions. More specifically, the similarities and differences between banks and tech firms along the lines of the risk commonality dimensions proposed by BCBS (2013) can be summarized as follows.

3.1. Size

Tech companies are among the largest in the US economy, with market capitalizations well above those of banks.

3.2. Interconnectedness

As argued by Welburn et al. (2020, p. 6 ff.), tech companies, just like financial firms, take a central position in the economy-wide input and output networks.[8] Welburn et al. (2020, p. 9 ff.) develop a formal model for supplier-customer linkages at a firm level, which works similarly to those for banks. The theoretical difference, however, is that they focus on 'production' and 'demand' in those linkages between firms rather than on counterparty refinancing or mutual assets.[9] Further, as banks increasingly rely on the performance of technology that tech firms offer, tech firms could have system-wide effects indirectly through banks as well (see, e.g., Chaudhry et al. (2022) or Crisanto et al. (2022)).

3.3. Lack of readily available substitutes

More generally, the analogy between the financial and the tech sectors can be illustrated by the fact that while the financial sector is the primary intermediary of capital, the tech industry enables the intermediation of data and digital processes. On the one hand, tech firms provide the infrastructure that enables data flows, which are essential to most modern economic activities.[10] On the other hand, they deliver tools for data processing. Just as with financial firms the services provided by tech firms cannot easily be substituted. For example, marketing at many firms nowadays relies on data tools provided by large tech firms like Facebook or Google. This argument of lack of readily available substitutes has first been raised in a more general context by Hellström (2003). Hellström's (2003) point of departure is the observation that all critical US infrastructure is increasingly dependent on information and telecommunication services. The author then argues that information and telecommunication services bear a high risk of causing severe disruption due to the high risk of computer viruses (as the typical example of cyberattacks twenty years ago) and due to their complex interconnectivity. Moreover, even minor disturbances can lead to a cascade of issues leading to regional outages, thus becoming systemic. Similarly, Renn et al. (2022) argue more recently that the tech industry is steadily building up its potential for complex, multi-causal and ongoing malfunctions (e.g., related to data storage and computing capacities) which can contribute to the collapse of critical infrastructure.

3.4. Global activity

Financial globalization is a well-documented phenomenon affecting systemic risk. However, there are still national champions in financial services in most jurisdictions. In contrast, the tech industry is featured by global players, hence this dimension of risk commonality can be even more pronounced for the tech industry. The low redundancy in the technology sector is related to the global market dominance of individual tech companies. The growth of tech firms is largely due to the economies of scale and network effects observed in the tech sector, which lead to the development of global natural monopolies and make the services provided by these companies particularly difficult to replace. Given the low interoperability and high interdependencies within these companies, they create the potential for vulnerabilities to spread widely across the global economy.

3.5. Complexity

The systemic impact of a bank's distress or failure is likely to be positively related to its overall complexity, i.e., its business, structural and operational complexity. Examples of circumstances that can create complexity are a large portion of illiquid financial assets and liabilities that are difficult to value, or opaque and complex securitizations. Similarly, tech firms also have to cope with various kinds of complexity. Examples are large and complex software that cannot be overviewed by a single person any more, or production planning processes that depend on the just-in-time availability of production factors. Complex systems are error-prone so that the likelihood of the occurrence of distress events which might have systemic consequences increases with complexity.

3.6. Recent examples and further discussion

Numerous recent episodes have highlighted the significant potential of disruptions in tech firms' production process or service for generating negative risk spillovers. These serve as modern examples of the issues described by Hellström (2003) and Renn et al. (2022). To start with a popular example, the failure of the semiconductor industry to correctly predict demand dynamics between 2021 and mid-2023 has caused adverse effects across many industries, with automotive being a notorious example.[11] Further, disruptions in the operations of cloud service providers have generated negative consequences for other sectors. For example, a 2017 incident at Amazon Web Services (AWS) led to operation challenges for a substantial number of internet retailers, generating financial damage equal to approximately 150 million USD (see Curran (2020, p. 253)). Furthermore, cyber security attacks have generated substantial negative risk spillovers by affecting digital infrastructure. Examples in this direction range from the DDoS[12] attack on Dyn (internet domain registration company) resulting in a disruption of the services of Twitter, Amazon, Spotify, PayPal, Reddit, and Airbnb (Curran (2020, p. 251)) to the NotPetya ransomware attack that disrupted energy and transportation logistics across the world in 2017.[13] A further example is the hacking of Microsoft Exchange Services in early

[8] These authors explore the role of input-output interdependencies across industries as a source of potential systemic risk outside the financial sector. Their analysis is not explicitly focused on the tech industry.

[9] The literature on theoretical models for explaining the systemic relevance of banks is by far much more extensive than that one for non-banks (see, e.g., Acemoglu et al. (2015), Aikman et al. (2011), Allen and Gale (2000), Battiston et al. (2012a, 2012b, 2012c), Eisenberg and Noe (2001), Gai and Kapadia (2010), Gai et al. (2011), Georg (2013), Glasserman and Young (2015), Iori et al. (2006), Krause and Giansante (2012)).

[10] The change in the organisation of work during the Covid-19 pandemics substantially expanded the set of economic interactions depending on the flow of data (videoconferencing, etc.).

[11] See, e.g., Li (2022) and Brinley (2023).

[12] Distributed-Denial-of-Service (DDoS) is the deliberate blocking of a particular internet service by a number of attacking sources (usually many hacked computers). This makes it impossible to identify and block the attacker, so that the service usually has to be temporarily taken offline.

[13] For example, FedEx lost 300 million USD in the first quarter of 2017 due to NotPeyta (see Badkar (2017)).

2021, which affected the operations of thousands of firms and authorities (the European Banking Authority is the most prominent example).[14] The most recent example of the immense externalities of a tech glitch is the global disruption caused by the CrowdStrike software failure in July 2024 (see, e.g., Stacey and Hodgson (2024)). This example demonstrates how the rapidly increasing interconnection of the real economy in many areas is fundamentally dependent on the digital services provided by just a few companies.

We have argued that tech companies can exhibit risk commonality for reasons similar to those of banks. However, as mentioned before, there are also differences in the underlying channels. A major difference consists in the fact that while shocks to financial firms can be generated by shifts in expectations and valuation effects, shocks to and from tech firms are typically rooted in business interruptions caused by ransomware, human error, or a technical failure (AGCS, 2020, p. 5). Company-specific business interruption events can generate a systemic event mostly via observable input-output networks. For example, a failure of Windows-related products will only affect those companies that also work with Windows. Unlike in the case of banks, these effects are less likely to be exacerbated by information contagion. In the framework of Welburn et al. (2020, p. 37), this argument implies that while 'production network' links drive the systemic importance of tech firms, they are less relevant for banks. We highlight the validity of this argument by showing that the inter-group risk commonality of tech firms with firms outside the tech sector is driven to a larger extent by non-systematic risk factors (e.g., direct business relationships) than this is the case for banks.

4. Methodology and data

In this section, we discuss the employed measures of risk commonality, our data, and our definition of tech firms.

4.1. Measures of risk commonality

Following the literature on measuring the systemic risk of financial institutions, we use risk commonality measures (RCM) that show how the equity return of an individual firm reacts to stress of the entire market[15] (exposure RCM) and how the market equity return reacts to stress of an individual firm (contribution RCM), respectively.

4.1.1. Measures of total risk commonality

As an example of an exposure RCM, the Marginal Expected Shortfall (MES), proposed by Acharya et al. (2017), is defined as the negative value of the expected equity return $r_{i,t}$ of firm i on day t conditional on the system log-return $R_{m,t}$ being smaller than some low quantile (e.g., 5 %-quantile[16]):

$$MES_{\alpha}^{i,t} = -\mathbb{E}_{t-1}\left(r_{i,t} \,\middle|\, R_{m,t} < q_{\alpha}(R_{m,t})\right) \tag{1}$$

where $q_{\alpha}(r)$ denotes the α-quantile of the return distribution. This measure reflects the extent to which an individual firm is affected by a market-wide downturn. The negative sign ensures that larger values of MES go along with a larger level of measured risk commonality.

The exposure ΔCoVaR measure (EXP_ΔCoVaR) of firm i as proposed by Adrian and Brunnermeier (2016) corresponds to the increase of the conditional Value-at-Risk (CoVaR) of firm i, given that the system return switches from its median to values at some low quantile $q_{\alpha}(R_{m,t})$:

$$\Delta CoVaR_t^{i|R_{m,t}} = -\left(CoVaR_t^{i|q_{\alpha}(R_{m,t})} - CoVaR_t^{i|q_{0.5}(R_{m,t})}\right). \tag{2}$$

As MES, the exposure ΔCoVaR measures the extent to which an individual firm is affected by market-wide distress. Again, the negative sign ensures that larger values of this measure go along with a larger level of total risk commonality. The contribution ΔCoVaR (CON_ΔCoVaR), as (also) proposed by Adrian and Brunnermeier (2016), represents the increase of the Value-at-Risk of the market conditional on firm i being in distress. Formally, CON_ΔCoVaR is defined as:

$$\Delta CoVaR_t^{m|r_{i,t}} = -\left(CoVaR_t^{m|q_{\alpha}(r_{i,t})} - CoVaR_t^{m|q_{0.5}(r_{i,t})}\right) \tag{3}$$

where $CoVaR_t^{m|\,q_{\alpha}(r_{i,t})}$ is the Value-at-Risk of the system m conditional on the equity return of firm i being at its α-quantile $q_{\alpha}(r_{i,t})$. Both the contribution and exposure ΔCoVaR measures can be computed either using time series approaches (dynamic volatility and correlation models; see for example Brownlees and Engle (2017)) or employing quantile regressions (see Adrian and Brunnermeier (2016)). Since we need the time series approach to calculate MES, we apply this method also for computing both versions of ΔCoVaR (see Benoît et al. (2013) and Appendix A). In the robustness section, we show that very similar results can be derived using a quantile regression approach.

4.1.2. Measures of non-systematic risk commonality

Further, we analyze whether our measures of total risk commonality are mainly driven by the sample firms' common reaction to systematic risk factors or by non-systematic risk factors, such as direct interactions between the tech firms and between the tech firms and other firms in the sample, respectively (e.g., resulting from business relationships). For this, we follow Muns and Bijlsma, 2011[17] and regress the firm-specific equity returns $r_{i,t}$ of each firm i in our sample on the daily log-return $R_{m,t}$ of the S&P 500 index:

$$r_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \varepsilon_{i,t}. \tag{4}$$

Thus, using the return of the S&P 500 index as a proxy for all systematic risk factors, we filter out the common exposure of the individual equity returns to these factors. Our measures of non-systematic risk commonality are then calculated using the residual returns $\varepsilon_{i,t} = r_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i \cdot R_{m,t}$ of the above market model. For this, we employ the market capitalization-weighted index of residual returns as system index.[18]

If Eq. (4) would represent the true data generating process of the sample firms' equity returns, the residual returns $\varepsilon_{i,t} = r_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i \cdot R_{m,t}$ were noise and the measures of risk commonality based on them should be zero. Thus, applying this procedure, we implicitly assume that the true data generating process is slightly more complex and also encompasses a direct effect of a significant idiosyncratic event at some firm k on the equity return of some other firm $i \neq k$:

$$r_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \underbrace{\sum_{k=1}^{N} \gamma_{i,k} \cdot 1^{t}_{\{significant\ idiosyncratic\ event\ at\ firm\ k\}} + \eta_{i,t}}_{=\varepsilon_{i,t}}. \tag{5}$$

[14] See, e.g., European Banking Authority (2021) or Duffy (2021).

[15] The terms 'market' and 'system' are synonymously used in the following.

[16] See Silva-Buston (2019, p. 191) or Banulescu and Dumitrescu (2015, p. 578).

[17] A related idea is applied by Silva-Buston (2019, p.188 ff.) who distinguishes between an 'excess' and a 'systematic' component of systemic risk. However, her allocation is based on the assumption that there is a necessary 'desired' component of systemic risk in the banking sector. By diversifying their assets, banks approach a 'systemic portfolio', which exposes them to common risks, at least to a certain degree. No such mechanism exists for non-banks, making the approach not applicable in our case.

[18] As robustness check, we also use the S&P 500 as system index to calculate these measures. We find no qualitative difference with respect to the sample of tech firms. Results can be found in the supplementary data.

Table 1
Definitions of risk commonality measures.

Risk commonality measure (RCM)	Definition
Total risk commonality	
$RCM(r_i; R_{S\&P\ 500})$	RCM based on equity returns and the S&P 500 as a system (see Section 4.1.1)
Non-systematic risk commonality	
$RCM(\varepsilon_i; R_{\varepsilon_i(S\&P\ 500)})$	RCM based on residual equity returns and the sample index of the residual returns of all firms in the S&P 500 as a system (see Section 4.1.2)
Risk commonality without a specific sector g	
$RCM(r_i; R_{S\&P\ 500\ without\ sector\ g})$	RCM based on equity returns and the sample index of the returns of all firms in the S&P 500 that do not belong to sector g as system
$RCM(\varepsilon_i; R_{\varepsilon_i(S\&P\ 500\ without\ sector\ g)})$	RCM based on residual equity returns and the sample index of the residual returns of all firms in the S&P 500 that do not belong to sector g as system
Risk commonality only in a specific sector g	
$RCM(r_i; R_{S\&P\ 500\ only\ sector\ g})$	RCM based on equity returns and the sample index of the returns of all firms in the S&P 500 that belong to sector g as system
$RCM(\varepsilon_i; R_{\varepsilon_i(S\&P\ 500\ only\ sector\ g)})$	RCM based on residual equity returns and the sample index of the residual returns of all firms in the S&P 500 that belong to sector g as system

Here, $R_{m,t}$ again denotes the log-return of the S&P 500 index (capturing market-wide effects), $1^t_{\{significant\ idiosyncratic\ event\ at\ firm\ k\}}$ is an indicator variable being 1 if a significant idiosyncratic event at firm k occurs in period t and 0 otherwise, $\gamma_{i,k}$ is a constant representing the sensitivity of firm i with respect to a significant idiosyncratic event at firm k, and $\eta_{i,t}$ is the non-modelled error term of firm i. Using the residuals from the market model in Eq. (4) for computing the measures of risk commonality, reduces the potential causes of the measured risk commonality to the significant idiosyncratic events that influence the financial well-being of other firms. Examples of such significant idiosyncratic events that could spill over to other firms could be errors in software produced by a software company and used by many other firms in the sample, server failures of cloud providers, payment service failures, or interrupted supply chains due to faulty production of processors and electronic components (see also the discussion in the previous Section 3). We will refer to the measures of risk commonality based on the above residual returns as 'non-systematic risk commonality' and denote them by D_MES, D_EXP_ΔCoVaR and D_CON_ΔCoVaR.

4.1.3. Measures of intra- and inter-group risk commonality

Next, we analyze to which extent the RCM introduced so far can be explained by intra-group risk commonality and by inter-group risk commonality, respectively. In particular, we are interested in the risk commonality within the tech sector and in the risk commonality between tech firms and non-tech firms. For this purpose, we compute the RCM introduced so far based on different indices proxying the system. While in the default case, the system consists of all firms in the S&P 500, for analyzing intra-group and inter-group risk commonality, we consider as a system all firms in the S&P 500 that belong to a specific sector and all firms in the S&P 500 that do not belong to a specific sector, respectively. In both cases, a market capitalization-weighted sample index of the returns of all relevant companies is employed for computing the RCM. Then, the percentage change of the RCM that results from switching the system from the S&P 500 to one of the other indices is interpreted as a proxy for intra-group and inter-group risk commonality (see Sections 5.4 and 5.5 for details). Table 1 shows the different RCMs we employ for the empirical analysis.

4.2. Data

4.2.1. Data sources

We focus our analysis on companies included in the US S&P 500 index.[19] Our US centric focus is driven by several considerations. First, most of the policy debate has been focused on potential risk spillovers from large tech firms listed in the US. This is most likely related to the fact that the US tech industry dominates the global tech market with approximately 60 % market share (measured by market capitalization). Second, focusing on the US allows us to estimate the models for firms that operate in the same legal, regulatory and macroeconomic environment. Expanding the sample to include tech firms from other jurisdictions will complicate the analysis as some differences in these environments might not be observable so that we cannot control for those. However, in Section 5.2, we also present some tests including a global sample of semiconductor firms.

We collect data on market returns (with a daily frequency) and on firm accounting reports (with annual frequency) from Thomson Reuters Datastream (now LSEG Data & Analytics) for all S&P 500 firms for the period January 1, 2010, to December 31, 2019. Our sample starts in 2010 for two reasons. First, it is unlikely that we can observe any market awareness of risk commonality of tech companies before 2010. Second, the values of RCM for banks, which we use as a reference, may have been distorted in earlier periods due to the financial crisis of 2007/2008. Further, we would like to exclude any Covid-19-implied biases. That is why we restrict our sample to the end of 2019.[20] We calculate the measures of risk commonality using a time series approach as proposed and implemented by Benoît et al. (2013). Thus, we need a burn-in phase of about 500 data points corresponding to about two years.[21] That leaves us with an eight-year investigation period running from 2012 to 2019.

4.2.2. Sector definitions

We define an S&P 500 company as a tech firm using the sectoral classification by the GICS (Global Industry Classification Standard) of MSCI (Morgan Stanley Capital International). The GICS specification is annually updated for every covered company. It is, therefore, more suitable for considering a changing sector classification of a firm than, for example, NAICS codes (North American Industry Classification

[19] We use the composition of the S&P 500 from 01.06.2020. We are aware of a potential survivorship bias due to this procedure. Anyhow, literature has mainly shown an insignificant association between performance measures (like ROA or ROE) and systemic risk measures (see, e.g., the overview in the online appendix of Abendschein and Grundke (2022)). Therefore, we do not expect a survivorship bias in our results due to delisted firms.

[20] WHO was naming Covid-19 a pandemic on 11.03.2020.

[21] See, e.g., Kabaila and Mainzer (2018, p. 32).

System, an extension to SIC codes), which are only updated every five years.[22] A GICS code is assigned to a company depending on its primary business activity.[23] Further, Hrazdil and Scott (2013) show that GICS codes result in more homogenous groupings for financial research than other schemes.[24] We identify tech firms as all companies operating in the sectors defined by GICS as 'information technology', 'communications services', and 'internet & direct marketing retail'. This results in a sample of 97 tech companies. From this sample, we then exclude the GICS subgroups 'movies & entertainment'[25] (e.g., Walt Disney and Discovery, four companies in total) and 'publishing & advertising' (e.g., News Corp., four companies in total) because neither their business area nor their products are prominently related to digitalization. The resulting sector of tech firms consists of 89 companies. The list of these companies is presented in Table 2.

Since NAICS codes are also widely used in academic research,[26] we verify that all companies that we have identified as tech firms by GICS are also classified as tech firms according to this alternative classification approach.[27] The only difference that we observe is that we also consider payment service providers to be tech companies. To deal with this issue, we also provide specifications where we control for possible overlaps with the financial sector by removing the payment service providers (e.g., PayPal) from our tech sample (see Section 5.2).

Next, we construct a benchmark sample of banks that belong to the S&P 500. In order to create a reference sample similar to the traditional banking literature, we follow the classification of Hautsch et al. (2015), who define an S&P 500 firm as a financial institution if it enters with one of the SIC codes 60, 62, and 67.[28] Then, we exclude all non-bank financial institutions (e.g., shadow banks like insurance companies or financial exchanges, 35 firms in total) from this sample. The resulting sample consists of 32 banks.

Finally, we define the sector REST as a reference group for the comparison of tech firms' risk commonality with that of other non-tech firms/non-banks. This sector includes all S&P 500 companies not classified as tech firms or banks, as defined before. Furthermore, we also exclude non-bank financial firms from the sector REST because their increased systemic risk (relative to non-financial firms; see Banulescu and Dumitrescu (2015), Brownlees and Engle (2017), Bühler and Prokopczuk (2010) or Muns and Bijlsma (2011) can bias the values of this reference group. This procedure yields 344 companies in the sector REST. In total, our sample consists of 465 firms (encompassing all three sectors).[29]

In our default setting, we consider the universe of all S&P 500 firms as a system when we compute the RCM of tech firms.[30] This choice is driven by our goal to analyze risk commonality not only in the tech sector but also across different sectors. In contrast, most research on systemic risk of financial institutions focuses on intra-industry risk spillover effects and, hence, employs a sample index of banks or financial institutions as a system for computing the RCM.[31] Later on, for our analysis of intra-group and inter-group risk commonality, we employ various modified definitions of the system (see Section 4.1.3).

5. Results

5.1. Level of tech firms' total risk commonality

Fig. 1 and Table 3 show the cross-sectional means and medians of the various measures of total risk commonality and their evolution over time for all three sectors - tech firms, banks, and REST.

As shown in Fig. 1, the time patterns of the sector-specific means of the various measures of total risk commonality are quite similar. However, the level of these measures is higher for the tech sector and for banks than for the sector REST. Furthermore, this level is largest for banks. In almost all cases, these visual impressions are also confirmed by t-tests (results can be found in the supplementary data) of the statistical significance of the corresponding differences.

Looking at the dynamics of the RCM depicted in Fig. 1, we observe that the level of the RCM of tech firms converges towards that of banks in the 2017 to 2019 period (at least for MES and EXP_ΔCoVaR). This finding motivates a more detailed analysis of the time trend of the differences between the mean RCM for pairs of sectors. For this purpose, for each RCM, we regress the daily mean difference of this measure between two sectors $g, k \in \{tech\ firms, banks, REST\}$ on a time variable t:

$$RCM_t^g - RCM_t^k = \alpha_{g,k}^{RCM} + \beta_{g,k}^{RCM} \cdot t + \varepsilon_t \tag{6}$$

where t are the days in ascending order. Thus, $\beta_{g,k}^{RCM} > 0$ indicates a growing mean difference in the measure of total risk commonality between the two sectors g and k. The results of this time trend analysis with robust standard errors exhibited in Table 4 show that, on the one hand, the mean differences in all RCM between the sectors banks and tech firms are significantly decreasing over time. On the other hand, the mean differences between the tech sector and REST are significantly increasing.

In sum, these results imply that tech firms show, at least on average, a larger risk commonality with the whole economy than non-tech firms/non-banks and that this effect is increasing over time. They also imply that in the lapse of time, tech firms become more similar to banks in terms of risk commonality than non-tech firms/non-banks.

Next, we extend the analysis to a more granular level and estimate panel regressions to confirm our previous visual and descriptive results with respect to the level of risk commonality shown in various sectors. More specifically, we examine whether tech firms and banks exhibit significantly different levels of risk commonality after controlling for observable firm-level characteristics. Since balance sheet data is available with only an annual frequency, we aggregate our daily RCM values by the arithmetic mean over the corresponding years. We use the following baseline random-effects panel regressions with dummies indicating whether a firm is a tech firm (TECHS) or a bank (BANKS):

$$\begin{aligned} RCM_{i,t} = & \alpha + \lambda_t + \gamma_1 \cdot BANKS + \gamma_2 \cdot TECHS + \delta \cdot CONNECT_{i,t-1} \\ & + \sum_{k=1}^{M} \beta_k \cdot CONTROLS_{k,i,t-1} + u_{i,t} \end{aligned} \tag{7}$$

where $RCM_{i,t}$ denotes the mean value in year t of the respective measure of risk commonality (MES, EXP_ΔCoVaR or CON_ΔCoVaR) of firm i, λ_t are year-fixed effects, and $CONTROLS$ is a vector of firm-specific control variables that have been found to be associated with our measures of risk

[22] See Phillips and Ormsby (2016, p. 4).
[23] Phillips and Ormsby (2016, pp. 15).
[24] Hrazdil and Scott (2013, p. 16).
[25] We deviate from this general rule in one case, NETFLIX, since this firm has a completely digital business model (unlike, e.g., Walt Disney, where Disney+ is just a minor area of business during the period under investigation).
[26] Phillips and Ormsby (2016, p. 10).
[27] We do this by comparing our classification to the one presented by Barefoot et al. (2018).
[28] We performed a plausibility check for the sector of banks with GICS codes (performed with sectoral assignment as of 27.05.2020). First, we include all companies in the S&P 500 which are classified by GICS as 'Financials'. We then define banks as the GICS subgroups 'Asset Management and Custody Banks', 'Consumer Finance', 'Diversified Banks', 'Investment Banking and Brokerage' and 'Regional Banks'. The conformity of the sector of banks according to SIC codes and GICS codes is around 93 %.
[29] Due to missing data for various variables the number of firms in the baseline regressions might differ.
[30] As a consequence, non-bank financials are included in the system but not in the reference group rest.
[31] An exception is for example Acharya et al. (2017) who also use the S&P 500 as system index.

Table 2
Composition of the companies in the sectors of the S&P 500.

BANKS					
Ameriprise Finl.	Bank of America	Bank of New York Mellon	Capital One Finl.	Charles Schwab	Citigroup
Citizens Financial Group	CME Group	Comerica	E Trade Financial	Fifth Third Bancorp	First Republic Bank
Franklin Resources	Goldman Sachs GP.	Huntington Bcsh.	Invesco	JP Morgan Chase & Co.	Keycorp
M&T Bank	Morgan Stanley	Northern Trust	Peoples United Financial	PNC Finl. Svs. Gp.	Raymond James Finl.
Regions Finl. New	State Street	SVB Financial Group	T Rowe Price Group	Truist Financial	US Bancorp
Wells Fargo & Co	Zions Bancorp.				

TECHS					
Accenture	Activision Blizzard	Adobe (NAS)	Adv. Auto Parts	Akamai Techs.	Alliance Data Systems
Alphabet	Amazon.com	Amphenol	Analog Devices	Ansys	Apple
Applied Mats.	Arista Networks	AT&T	Autodesk	Automatic Data Proc.	Booking Holdings
Broadcom	Broadridge Finl. Sltn.	Cadence Design Sys.	CDW	CenturyLink	Charter Comms.
Corning	Dish Network	DXC Technology	eBay	Electronic Arts	Expedia Group
Cisco Systems	Citrix Sys.	Cognizant Tech. Sltn.	Comcast	Corning	Dish Network
DXC Technology	eBay	Electronic Arts	Expedia Group	F5 Networks	Facebook
Fidelity Nat. Info. Svs.	Fiserv	Fleetcor Technologies	FLIR Systems	Fortinet	Gartner
Globe Life	Hewlett Packard Enter.	HP	Intel	International Bus. Mchs.	Intuit
IPG Photonics	Jack Henry &Associates	Juniper Networks	Keysight Technologies	KLA	Lam Research
Leidos Holdings	Mastercard	Maxim Integrated Prds.	Microchip Tech.	Micron Technology	Microsoft
Motorola Solutions	NetApp	Netflix	NortonLifeLock	NVIDIA	Oracle
Paychex	Paycom Software	PayPal	Qorvo	Quanta	Salesforce.com
Seagate Tech.	ServiceNow	Skyworks Solutions	Synopsys	Take Two Intact. Sftw.	TE Connectivity
Texas Instruments	T-Mobile US	Twitter	Verisign	Verizon Communications	Visa
Western Digital	Western Union	Xerox Holdings	Xilinx	Zebra Technologies	

TECH subgroups								
GAFA	Platforms	Payment service provider (PSP)	Cloud computing	PC hardware	Software	Semiconductors and electronic components	IT-infrastructure	IT-service and consulting
Alphabet	Alphabet	Alliance Data System	Amazon	Hewlett Packard	Activision Blizzard	Charter Communication	Arista Networks Inc.	Accenture Plc
Amazon	Amazon	Fidelity National Inf	Alphabet	HP Inc.	Adobe Inc.	Cisco Systems Inc.	AT&T Inc.	Akamai Technologies
Facebook	Facebook	Fiserv Inc.	Hewlett Packard	Intel	Autodesk Inc.	Comcast Corporation	CenturyLink	Automatic Data Proc
Apple	Apple	Fleetcor Technologies	Intl Business Machs	Nvidia Corp	Cadence Design Syst	Dish Network	CDW Corp	
	Booking Holdings	Mastercard	Microsoft	Seagate Technology	Citrix Systems Inc.	Juniper Networks Inc.	Cognizant Technology	
	eBay Inc.	PayPal Holdings	Oracle		Electronic Arts Inc.	Micron Technology	DXC Techno	
	Expedia Group	Visa Inc.	Salesforce		Intuit Inc.	Motorola Solutions	F5 Networks Inc.	
	Microsoft	Western Union			Microsoft	Nividia Corporation	Fortinet Inc.	
	Netflix	Jack Henry &Associates			Nortonlife	Quanta Services Inc.	Gartner Inc.	
	Oracle				Oracle	Qorvo Inc.	Int'l Business Machs	
	PayPal				Paycom Software Inc.	TE Connectivity	Jack Henry &Associates	
	Twitter				Service	Texas Instruments	Leidos Holdings Inc.	
					Synopsys Inc.	Verizon Communications	Verisign, Inc.	
						Xilinx Inc.		
						Zebra Technologies		

commonality in earlier empirical studies on the systemic risk of financial institutions. Our variables of interest (BANKS and TECHS) are sector-fixed effects, which are exogenous, as the grouping is externally specified by GICS codes and reflects the industries where the respective firms are active. These are time-constant and cannot be estimated by a fixed-effects panel regression. Hence, we employ a random-effects estimation. To control for confounding factors and tighten the identification, we include a set of firm-level and industry-level variables that are available for all three sectors and can be a source of observable heterogeneity. These variables are:

- SIZE, computed as the natural logarithm of total assets. We expect that a firm's degree of risk commonality increases with its size because larger firms are more likely to offer goods or services used by a significant fraction of firms in the market.
- INT-ASSET-RATIO, computed as the ratio of intangible to total assets, is a proxy for the opaqueness of the business model.[32] Intangible assets are exposed to valuation risks, especially during a crisis. Due to their opaque nature, they are more challenging to value 'fairly' than

[32] See Jones et al. (2013, p. 703).

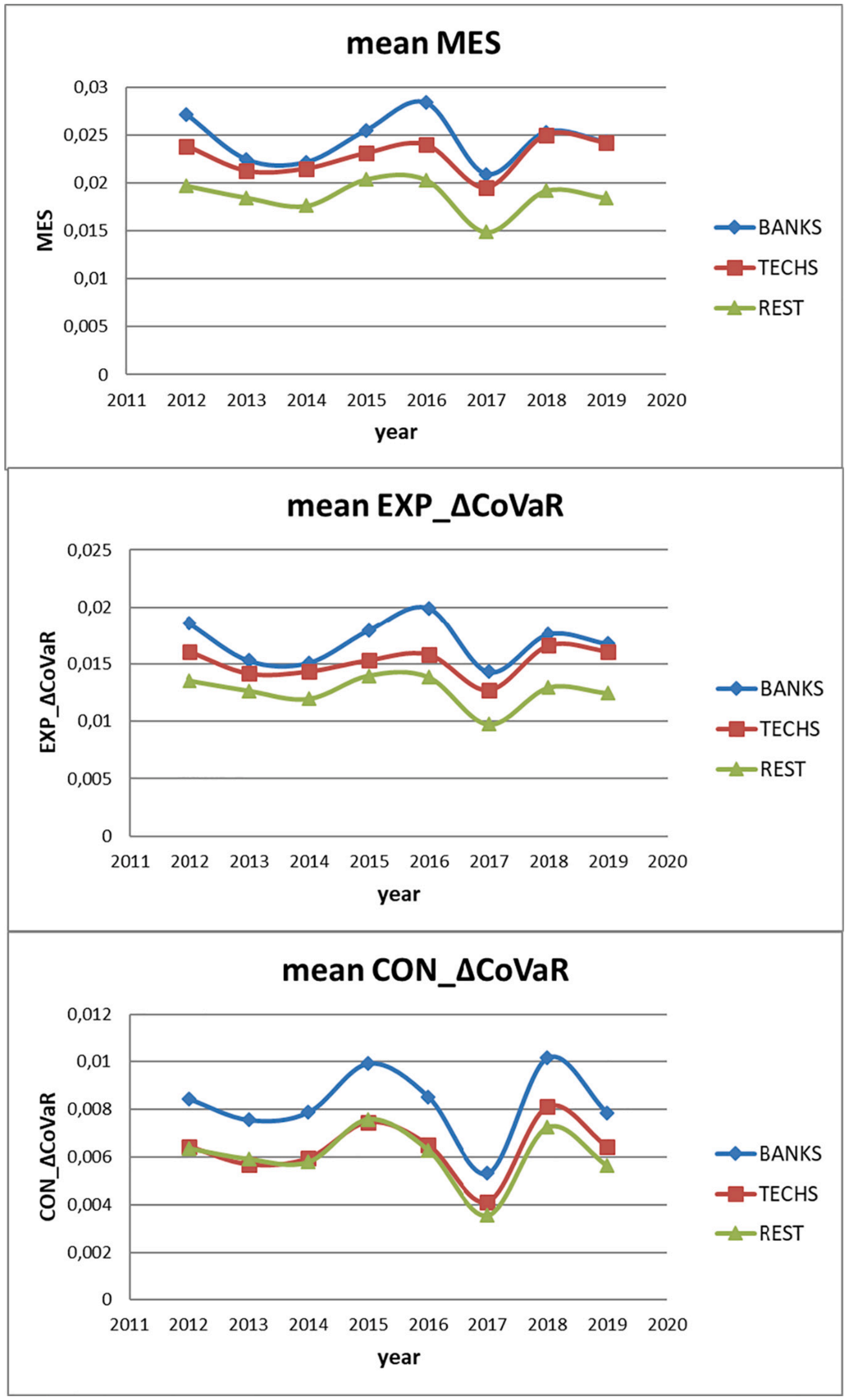

Fig. 1. Evolution over time of the various measures of total risk commonality.
This figure shows the evolution over time of the sector-specific cross-sectional means of the various measures of risk commonality between 2012 and 2019. These measures are calculated using the equity returns $r_{i,t}$. The employed system index is the return of S&P 500 index.

other assets, and in times of high uncertainty, these assets are devalued more than others.[33] This can lead to a negative 'price contagion' in times of a crisis, which can result in financial instability. Accordingly, Jones et al. (2013) find that a high proportion of opaque assets leads to higher systemic risk for banks. Therefore, we also expect a positive regression coefficient for the variable INT-ASSET-RATIO with respect to our measures of risk commonality for non-banks.

- EQUITY-RATIO, defined as common equity divided by total assets, is a proxy for the financial health of a firm because equity can absorb adverse shocks. Highly leveraged firms might be forced to deleverage by selling assets at fire sale prices in response to increased credit rationing by creditors facing liquidity constraints. That is why we expect, as mentioned in the literature (see, e.g., Zhang et al. (2015)

[33] See Jones et al. (2013, p. 693).

Table 3
Means/Medians of the various measures of total risk commonality per sector.
This table shows the sector-specific means and medians of the various measures of total risk commonality (MES: Marginal expected shortfall, EXP_ΔCoVaR: exposure ΔCoVaR, CON_ΔCoVaR: contribution ΔCoVaR) across firms and time between 2012 and 2019. Unreported *t*-tests confirm a significant difference in the mean/median values between all sectors at the 1 %-significance level (results can be found in the supplementary data). The only exception is the difference between the median values of CON_ΔCoVaR for tech firms and non-tech firms/non-banks. Furthermore, all means and medians are statistically different from zero.

Measure of risk commonality	Banks	Tech firms	Non-tech firms/non-banks
Mean MES	0.0243	0.0228	0.0186
Median MES	0.0241	0.0222	0.0189
Mean EXP_ΔCoVaR	0.0169	0.0151	0.0126
Median EXP_ΔCoVaR	0.0168	0.0149	0.0127
Mean CON_ΔCoVaR	0.00814	0.00634	0.00605
Median CON_ΔCoVaR	0.00815	0.00622	0.00608
Observations:	253	689	2651

Table 4
Time trend analysis of the pairwise mean differences in the measures of total risk commonality.
This table shows the results for the slope coefficients of OLS regressions where for each pair of measures of risk commonality (MES: marginal expected shortfall, EXP_ΔCoVaR: exposure ΔCoVaR, CON_ΔCoVaR: contribution ΔCoVaR), the daily mean pairwise differences in 2012–2019 are regressed on a time variable. A positive regression coefficient indicates an increasing mean difference between the corresponding sectors over time. The regression coefficients and standard errors are multiplied by 10.000 for readability (°). *** (**;*) indicates significance at 1 % (5 %; 10 %); heteroskedastic robust standard errors in parenthesis.

Dependent variable	MES (°)	EXP_ΔCoVaR (°)	CON_ΔCoVaR (°)
Difference banks − tech firms	−0.013*** (0.00133)	−0.0107*** (0.00001023)	−0.0032*** (0.0004)
Difference tech firms − non-tech firms/non-banks	0.0151*** (0.0005)	0.0110*** (0.0004)	0.0061*** (0.0001)
Difference banks − non-tech firms/non-banks	0.0020 (0.00129)	0.0003477 (0.0010)	0.00286*** (0.0005)

for banks) that higher equity ratios are associated with a lower level of risk commonality.

- MARKET-TO-BOOK-RATIO, defined as the ratio of the market value of equity to the book value of equity, allows for comparison of the market (i.e., forward-looking) view on a firm with the accounting-based view. Döring et al. (2016) find a significant negative association between MARKET-TO-BOOK-RATIO and banks' systemic risk. However, in the banking literature (see, e.g., Weiß et al. (2014a)), MARKET-TO-BOOK-RATIO is also used as a proxy for the overconfidence of managers who want to run their companies as 'glamorously' as possible and therefore take excessive risks. Thus, the expected sign for MARKET-TO-BOOK-RATIO is not immediately apparent.
- SHARE is a proxy for the market share of the firm within a particular submarket, measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket. We have classified our sample into the sectors TECHS, BANKS, and REST. Due to the high diversity of the sector REST, for computing the variable SHARE, we divide it into 9 subgroups (X1, …, X9) using the GICS codes. Thus, we get the subgroups $SG = \{TECHS, BANKS, X1, \dots, X9\}$. For each year $t \in \{2010, \dots, 2019\}$, the sum $SUM_{SG}^{t}(MC)$ of the market capitalization (MC) of the companies in the respective subgroup SG is calculated. The measure SHARE of firm i is then given by $SHARE_i^t = \frac{MC_i^t}{SUM_{SG}^{t}(MC)}$. We expect a positive regression coefficient for SHARE indicating that a higher level of risk commonality is associated with a higher market share of firm i.
- STRUCTURE is a sector-specific control variable, measuring the market concentration per year and per sector. The measure is computed analogously to Silva-Buston (2019), where the variable is used only for systemic risk analysis in the banking sector. As before for the variable SHARE, we first calculate the total market capitalization $SUM_{SG}^{t}(MC)$ in each subgroup SG for each year t. Then, within each subgroup for each year t, we rank the companies by their market capitalization. We then compute the sum of the market capitalization of the three largest companies (in each SG) by market capitalization and divide this sum by the market capitalization of all companies (in each SG). The inclusion of this control variable allows us to identify the risk commonality once the impact of market structure is controlled for.[34]

To address any potential reverse causality issues, we use the one-year lagged values for all balance sheet variables.[35] Further, we control for unobservable variation across time by including time-fixed effects. In the robustness section, we will discuss further tests designed to tighten the identification.

Including the above control variables allows us to check whether belonging to one of the sectors is still significant for explaining the level of risk commonality even after controlling for observable features that might be associated with these measures. These controls help us to overcome omitted variable biases, especially since, due to the time invariability of the firms' sector dummies, we cannot estimate the panel regressions with fixed effects.

Furthermore, following Mühlnickel and Weiß (2015) and Bostandzic and Weiß (2018), we also analyze whether the differences in risk commonality across sectors persist after controlling for interconnectedness ($CONNECT$). For this purpose, we follow the approach proposed by Billio et al. (2012)[36] and carry out pairwise linear Granger causality tests on firms' equity returns in a given year with lag length selection based on the BIC criterion to compute the variable $CONNECT_{i,t}$. More specifically, we define.

[34] Due to the similarity to the variable SHARE by design, we only use that part of the variation of STRUCTURE which is not already explained by SHARE. For this purpose, we regress the variable STRUCTURE on the variable SHARE and employ the residual term for STRUCTURE. Doing this, we avoid potential multicollinearity problems.

[35] In contrast to the other control variables, we employ SHARE and STRUCTURE as a non-lagged variable. However, we re-ran our baseline regressions with lagged SHARE and STRUCTURE. This does not alter our results qualitatively. Results can be found in the supplementary data.

[36] It is by far not the only way to measure interconnectedness. Meanwhile, a number of other approaches and extensions exist, such as Ahelegbey et al. (2016) or Diebold and Yilmaz (2014). However, since we include CONNECT only as a control variable, we stick to the initial method.

Table 5
Variable definitions and descriptive statistics.
The table reports definitions and summary statistics for the dependent variables, firm-specific controls, and explanatory variables employed in the empirical analyses.

Variables	Definition	(1) N	(2) Mean	(3) Median	(4) Std	(5) Min	(6) Max
MES	Marginal expected shortfall of firm *i*	3593	0.0198	0.0200	0.00661	0.000987	0.0550
CON_ΔCoVaR	Contribution ΔCoVaR of firm *i*	3593	0.00625	0.00623	0.00201	−0.000373	0.0124
EXP_ΔCoVaR	Exposure ΔCoVaR of firm *i*	3593	0.0134	0.0135	0.00458	−0.00322	0.0398
D_MES	Marginal expected shortfall of firm *i* based on residual equity returns and the sample index of the residual equity returns of all firms in the S&P 500 as a system	3593	0.0005	0.0003	0.00341	−0.01013	0.0209
D_CON_ΔCoVaR	Contribution ΔCoVaR of firm *i* based on residual equity returns and the sample index of the residual equity returns of all firms in the S&P 500 as a system	3593	0.000006	0.00001	0.00007	−0.00033	0.00036
D_EXP_ΔCoVaR	Exposure ΔCoVaR of firm *i* based on residual equity returns and the sample index of the residual equity returns of all firms in the S&P 500 as a system	3593	0.00034	0.00037	0.00223	−0.00866	0.01394
BANKS	Dummy variable that equals 1, if firm *i* is classified as a bank, 0 otherwise	3720	0.0688	0	0.253	0	1
TECHS	Dummy variable that equals 1, if firm *i* is classified as tech firm, 0 otherwise	3720	0.191	0	0.393	0	1
PLATFORMS	Dummy variable that equals 1, if firm *i* is classified as a platform economy, 0 otherwise	3720	0.0258	0	0.159	0	1
GAFA	Dummy variable that equals 1, if firm *i* is classified as GAFA, 0 otherwise	3720	0.00860	0	0.0924	0	1
PSP	Dummy variable that equals 1, if firm *i* is classified as payment service provider (PSP), 0 otherwise	3720	0.0172	0	0.130	0	1
GIN	Normalized number of firms which Granger cause the equity return of firm *i* in year *t*	3720	0.119	0.101	0.0736	0	0.684
GOUT	Normalized number of firms which are Granger caused by firm *i* in year *t*	3720	0.119	0.100	0.0817	0	0.998
SIZE	Ln of total assets (in USD thousands) *i* in year *t*	3685	16.64	16.56	1.373	11.57	21.71
EQUITY-RATIO	Common equity / total assets *i* in year *t* (in %)	3671	35.74	36.88	26.61	−337.1	100.9
MARKET-TO-BOOK-RATIO	Market value of equity / book value of equity	3551	1.814	2.850	67.91	−2343	1407
RD-RATIO	Research and development costs / total assets	1739	0.054	0.030	0.066	0.0002	0.637
BUP-RATIO	Gross value of brands, patents, and trademarks / total assets	1851	0.050	0.021	0.073	0.0004	0.579
WC-RATIO	Working capital (defined as the difference between current assets and current liabilities) / total assets	3472	0.127	0.082	0.175	−0.342	0.771
INT-ASSET-RATIO	Intangible assets / total assets	3685	0.251	0.196	0.230	0	0.902
SHARE	Ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket	3621	0.024	0.017	0.024	0.00016	0.214
STRUCTURE	Ratio of the sum of the market capitalization of the three largest firms (by market capitalization) in a submarket to the market capitalization of the (corresponding) total submarket	3720	0.0876	0.062	0.063	0.043	0.562

$$(j \rightarrow i)_t = \begin{cases} 1, & \text{if } j \text{ granger causes } i \text{ in year } t \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

and sum up the results of these bivariate tests for all firms i. We distinguish between $GIN_{i,t} = \sum_{i \neq j} (j \rightarrow i)_t$ as a measure for the influence of other firms *j* on firm *i* in year *t* and $GOUT_{i,t} = \sum_{i \neq j} (i \rightarrow j)_t$ as a measure for the influence of firm *i* on other firms *j* in year *t*. We normalize these measures by dividing $GIN_{i,t}$ and $GOUT_{i,t}$ by the corresponding number of firms with sufficient data in the relevant year. For the exposure measures, MES and EXP_ΔCoVaR, the variable $CONNECT_{i,t}$ is set equal to $GIN_{i,t}$, and for the contribution measure CON_ΔCoVaR, it is defined as $GOUT_{i,t}$. We expect a positive association between the interconnectedness of a firm and its measures of risk commonality.

The definitions of all employed dependent and independent variables are summarized in Table 5, together with their descriptive statistics.

Our previous visual and descriptive results are confirmed by the results of our baseline panel regressions exhibited in Table 6. These show that tech firms are associated with significantly higher levels of risk commonality than firms in the sector REST. This is true for all employed measures.[37,38] Furthermore, it can be seen that being a bank is also significantly positively associated with all measures of risk commonality. Banks, on average, exhibit the highest level of risk commonality.

The coefficients of the control variables in our baseline regressions are mostly insignificant. When they are significant, they exhibit the expected sign (e.g., positive and significant coefficients for INT-ASSET-RATIO and STRUCTURE with respect to exposure RCM and positive and significant coefficients for SIZE, CONNECT and SHARE with respect to contribution RCM).

5.2. Are some tech firms special?

Next, we analyze how the level of total risk commonality differs across various subgroups of tech firms. For this purpose, we first focus on

[37] For the sake of brevity, in the tables following Table 6 we usually do not present the regression coefficients of the control variables.

[38] Notably, the R^2 of the CON_ΔCoVaR regression is much higher than the R^2 of the other models. In unreported tests (results can be found in the supplementary data), we re-run the baseline regressions without year-fixed effects and find that the R^2 are similar across all models. We hence presume that the difference in the R^2 is driven by the fact that for CON_ΔCoVaR the time-fixed effects explain a larger share of the variation.

Table 6
Results of the baseline panel regressions.
The table shows the results of the baseline random-effects panel regressions. Dependent variables are the various firm-specific measures of total risk commonality (MES: Marginal expected shortfall, EXP_ΔCoVaR: exposure ΔCoVaR, CON_ΔCoVaR: contribution ΔCoVaR). The variables of interest are the dummy variables TECHS and BANKS, which are 1 when a firm belongs to the corresponding sector and 0 otherwise. CONTROL variables are: SIZE measured by ln (total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, GIN as a measure of interconnectedness counting the number of firms that Granger cause the equity return of a firm, GOUT as a measure of interconnectedness counting the number of firms that are Granger caused by the equity return of a firm, SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket and STRUCTURE measured by the ratio of the sum of the market capitalization of the three largest companies (by market capitalization) in a submarket to the market capitalization of the (corresponding) total submarket. Further, we control for year-fixed effects. R^2 (within) describes how much variation within firms is captured by the model, R^2 (between) describes how much variation between firms is captured by the model, and R^2 (overall) is the weighted average of both. The regression coefficients and standard errors are multiplied by 100 for readability (°). Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	(1)	(2)	(3)
	MES (°)	EXP_ΔCoVaR (°)	CON_ΔCoVaR (°)
TECHS	0.404***	0.235***	0.035**
	(0.0622)	(0.0407)	(0.0176)
BANKS	0.657***	0.467***	0.183***
	(0.0940)	(0.0676)	(0.0240)
SIZE	−0.0275	−0.0108	0.0108**
	(0.0165)	(0.0113)	(0.0048)
INT-ASSET-RATIO	0.144**	0.0887*	0.0243
	(0.0697)	(0.0508)	(0.0194)
EQUITY-RATIO	−0.0006	−0.0002	−0.00008
	(0.0006)	(0.0004)	(0.0001)
MARKET-TO-BOOK-RATIO	0.00004	0.00002	0.00002
	(0.0001)	(0.0001)	(0.00003)
GIN	−0.0423	−0.030	
	(0.0581)	(0.0425)	
GOUT			0.0532***
			(0.0156)
SHARE	−1.28	−0.484	0.414***
	(0.923)	(0.629)	(0.233)
STRUCTURE	2.10*	1.43*	−0.191
	(1.08)	(0.815)	(0.324)
Constant	2.45***	1.530***	0.431***
	(0.260)	(0.1780)	(0.0752)
Observations	3505	3505	3505
Number of firms	454	454	454
Year FE	Yes	Yes	Yes
R^2 (overall)	0.173	0.174	0.417
R^2 (between)	0.134	0.117	0.138
R^2 (within)	0.340	0.350	0.764

the largest tech firms (Google, Amazon, Facebook and Apple; GAFA), which have been at the center of most of the political debate. Second, we turn our attention to platform firms whose two-sided novel business model may be associated with a stronger potential for risk commonality. Third, we explore the analogy to banks by analyzing whether tech firms that are payment service providers (PSP) have a higher level of risk commonality. Finally, we perform a more general analysis of whether tech firms from different subindustries (according to the Thomson Reuters Business Classification[39] - TRBC, Datastream Code: TRN5) show different levels of risk commonality. The tech subgroups matched by TRBC are: 1) IT-Service and Consulting, 2) Semiconductors and Electronic Components, 3) IT-Infrastructure, 4) Computer Hardware, 5) Cloud Computing, 6) Software. As some companies have several major business areas, e.g., Amazon as a market platform and cloud services provider or Microsoft as a software and cloud services provider, we allow for multi-classification in this section. As before, the sector REST includes all other companies from our sample that do not belong to the sectors TECHS (or its subgroups mentioned above) and BANKS. This ensures that sector REST remains unchanged for all subgroup analyses.

Table 7
Tech subgroup analysis.
The table shows the results of the baseline random-effects panel regressions. Dependent variables are the various firm-specific measures of total risk commonality (MES: Marginal expected shortfall, EXP_ΔCoVaR: exposure ΔCoVaR, CON_ΔCoVaR: contribution ΔCoVaR). The variables of interest are the respective tech subgroup dummies, which are 1 when a firm belongs to the corresponding tech subgroup and 0 otherwise. All firms that belong to the sector TECHS but not to the respective tech subgroup are excluded from the sample for the respective regression. This ensures a constant control sector REST for all regressions. CONTROL variables are: SIZE measured by ln(total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, GIN as a measure of interconnectedness counting the number of firms that Granger cause the equity return of a firm, GOUT as a measure of interconnectedness counting the number of firms that are Granger caused by the equity return of a firm, SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket, and STRUCTURE measured by the ratio of the sum of the market capitalization of the three largest companies (by market capitalization) in a submarket to the market capitalization of the (corresponding) total submarket. Further, we control for year-fixed effects. The international sample of semiconductors (outside US) consists of: HAMAMATSU PHOTONICS, INFINEON TECHNOLOGIES, MEDIATEK, NANYA TECHNOLOGY, NOVATEK MICROELECTRONICS, REALTEK SEMICONDUCTORS, RENESAS ELECTRONICS, ROHM, SAMSUNG ELECTRONICS MECHANICS, SEMICONDUCTOR MANUFACTORING INTERNATIONAL, SK HYNIX, SOITEC, ST MICROELECTRONICS, SUMCO, TAIWAN SEMICONDUCTOR MANUFACTORING COMPANY, UNITED MICRO ELECTRONICS, ZHEN DING TECHNOLOGY HOLDING. The regression coefficients and standard errors are multiplied by 100 for readability (°). For the sake of readability, we just report the range of R^2 (0.138–0.516), number of observations (2863-2969), and number of companies (370–383) in the regressions here because these values vary in each regression due to the different subgroup quantities. Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	(1)	(2)	(3)
	MES (°)	EXP_ΔCoVaR (°)	CON_ΔCoVaR (°)
GAFA	0.566***	0.295***	−0.0249
	(0.0732)	(0.0539)	(0.0552)
PLATFORMS	0.532***	0.208***	−0.0726
	(0.0962)	(0.06260)	(0.0466)
PSP	0.0912	0.0258	0.131***
	(0.119)	(0.0583)	(0.0490)
IT-SERVICES	0.231**	0.112*	0.0417
	(0.1080)	(0.0632)	(0.0359)
IT_INFRASTRU	0.138	0.0121	−0.0492
	(0.1490)	(0.101)	(0.0307)
HARDWARE	0.619***	0.362***	−0.0342
	(0.203)	(0.1430)	(0.0505)
SEMICOND	0.666***	0.513***	0.109***
	(0.1120)	(0.0685)	(0.0282)
CLOUD	0.361***	0.210***	0.0382
	(0.1140)	(0.0847)	(0.0466)
SOFTWARE	0.498***	0.252***	0.0416
	(0.1310)	(0.0569)	(0.03303)
INT_SEMICOND	−1.06***	−0.848***	−0.481***
	(0.319)	(0.198)	(0.0696)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

[39] The TRBC, in contrast to GICS, offers a fifth hierarchical level (895 activities) and is, therefore, highly appropriate to be used for very detailed classifications (see, e.g., Refinitiv (2020) and Phillips and Ormsby (2016, pp. 17)).

The results are presented in Table 7.

The results concerning GAFA show that GAFA companies are not distinctively different from other tech companies. For our measures of risk commonality, the size and significance of the regression coefficients of the dummy GAFA are similar to those of the dummy TECHS in the baseline regressions, except for CON_ΔCoVaR, for which, surprisingly, we lose significance. This is also true for those companies within the S&P 500 that are typically considered to be online platforms (PLATFORMS).[40]

Our definition of tech firms also includes payment service providers (PSP; e.g., Visa, Mastercard, PayPal). Due to their business model these service providers have a solid link to the banking sector. They could, therefore, exhibit particularly high risk commonality, which could drive the results for tech firms in the baseline regressions. That is why we examine this subgroup separately. As can be seen in Table 7, we hardly observe any significance of the regression coefficients corresponding to the dummy PSP. Only the contribution measure CON_ΔCoVaR is significantly positively associated with being a PSP. This result suggests that the PSP belong to those companies in the tech sector that are responsible for the significant positive association between the dummy TECHS and the contribution measure CON_ΔCoVaR in the baseline regressions. These findings on PSP seem to be partly in conflict with the results of the literature on FinTechs, which in some cases argues that FinTechs can even, due to efficiency gains, contribute to financial system stabilization (see Section 2). We have not examined the stabilizing or destabilizing effect of FinTechs on the financial system, but our results show that PSP have a destabilizing effect (in terms of contribution to systemic risk) on the US economy as a whole.

With respect to the TRBC tech subgroup classification, the semiconductor and electronic parts industry results are most striking. As Table 7 shows, the regression coefficients for the dummy SEMICOND with respect to our exposure measures even exceed those of banks (compare with the results shown in Table 6). All regression coefficients for the dummy SEMICOND, including that one with respect to the contribution measure, are positive and highly significant. This is consistent with the observation that while media attention in the past has been focused on the platforms, recent media reports indicate that the semiconductor industry does indeed generate a relevant level of risk commonality with the real (US) economy.[41] This observation may be due to the fact that almost all components (e.g., for computer chips) and services of other companies (both those of other tech firms and those of other firms) cannot be offered without the products of the semiconductor industry. At the same time, these companies are also vulnerable to aggregate market distress that might cause a reduction in the demand for the subgroup's products.

We next dig deeper into the finding that US semiconductor producing firms represent the subgroup of TECH companies with the most substantial risk commonality. While most technology companies relevant to US firms are also listed in the US, anecdotal evidence suggests that this is not the case for semiconductor manufacturers. Some major semiconductor firms are not listed in the US and are hence not included in the analysis presented in Table 7. TSMC, a highly relevant firm from Taiwan, is a prominent example. To increase the representativeness of our results, we next offer an additional set of results regarding the systemic relevance of semiconductor producers using an international (non-US) sample. We proceed as follows: We first identify a global sample of semiconductor manufacturers using the 'Refinitiv Global excluding US SEMICONDUCTORS' index from EIKON. We sort the companies listed there in descending order by market capitalization in USD in 2019.[42] Then, we include the 17 largest companies by market capitalization in our sample, given that we also have 17 US semiconductors in the US sample and the market capitalizations are similar.[43] This avoids a potential bias due to different sample sizes in the US and the international sample. We then calculate our RCM using the S&P 500 index as a system indicator (all values in USD). In other words, we examine the risk commonality of international semiconductor manufacturers with the US stock market. We also re-calculate all sample-dependent variables (such as CONNECT) and re-estimate the regression equation with the dummy variable INT_SEMICOND which equals 1 if the firm belongs to our international sample of semiconductors and 0 otherwise. The estimation results reported in Table 7 show a negative and significant coefficient for the dummy variable INT_SEMICOND. This means that international semiconductor-producing firms have less risk commonality with US-listed firms relative to the average of the US companies in the group REST. In other words, the US semiconductor producers are the major drivers of systemic effects. That is why we return to our baseline sample of US-listed firms for the remaining tests.

5.3. Level of tech firms' non-systematic risk commonality

In the next step, we re-run the baseline regressions, but now, we employ the measures of non-systematic risk commonality (as introduced

Table 8
Results of the baseline panel regressions for non-systematic risk commonality.
The table shows the results of the baseline random-effects panel regressions for measures of non-systematic risk commonality. Dependent variables are the various firm-specific measures of non-systematic risk commonality (D_MES: non-systematic Marginal expected shortfall, D_EXP_ΔCoVaR: non-systematic exposure ΔCoVaR, D_CON_ΔCoVaR: non-systematic contribution ΔCoVaR). The variables of interest are the dummy variables TECHS and BANKS, which are 1 when a firm belongs to the corresponding sector and 0 otherwise. CONTROLS encompass: CONNECT as granger-based measure for interconnectedness, SIZE measured by ln(total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket, and STRUCTURE measured by the ratio of the sum of the market capitalization of the three largest companies (by market capitalization) in a submarket to the market capitalization of the (corresponding) total submarket. Further, we control for year-fixed effects. R^2 (within) describes how much variation within firms is captured by the model, R^2 (between) describes how much variation between firms is captured by the model, and R^2 (overall) is the weighted average of both. The regression coefficients and standard errors are multiplied by 100 for readability (°). Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	(1)	(2)	(3)
	D_MES (°)	D_EXP_ΔCoVaR (°)	D_CON_ΔCoVaR (°)
TECHS	0.293***	0.159***	0.0036***
	(0.0474)	(0.0296)	(0.0008)
BANKS	−0.295***	−0.287***	−0.0112***
	(0.0434)	(0.0281)	(0.0009)
Constant	0.501***	0.330***	0.0074***
	(0.153)	(0.0996)	(0.0028)
Observations	3505	3505	3505
Number of firms	454	454	454
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2 (overall)	0.236	0.267	0.325
R^2 (between)	0.247	0.292	0.355
R^2 (within)	0.040	0.040	0.076

[40] Bamberger and Lobel (2017) outline the success of new platform industries leading to growing market dominance and anticompetitive practices.

[41] See, e.g., Vakil and Linton (2021) or King et al. (2021).

[42] We also checked that their TRBC is in line with 'semiconductors'.

[43] The lowest log market capitalization in USD for US semiconductors is above 8.9 and for the international semiconductors it is above 8.1.

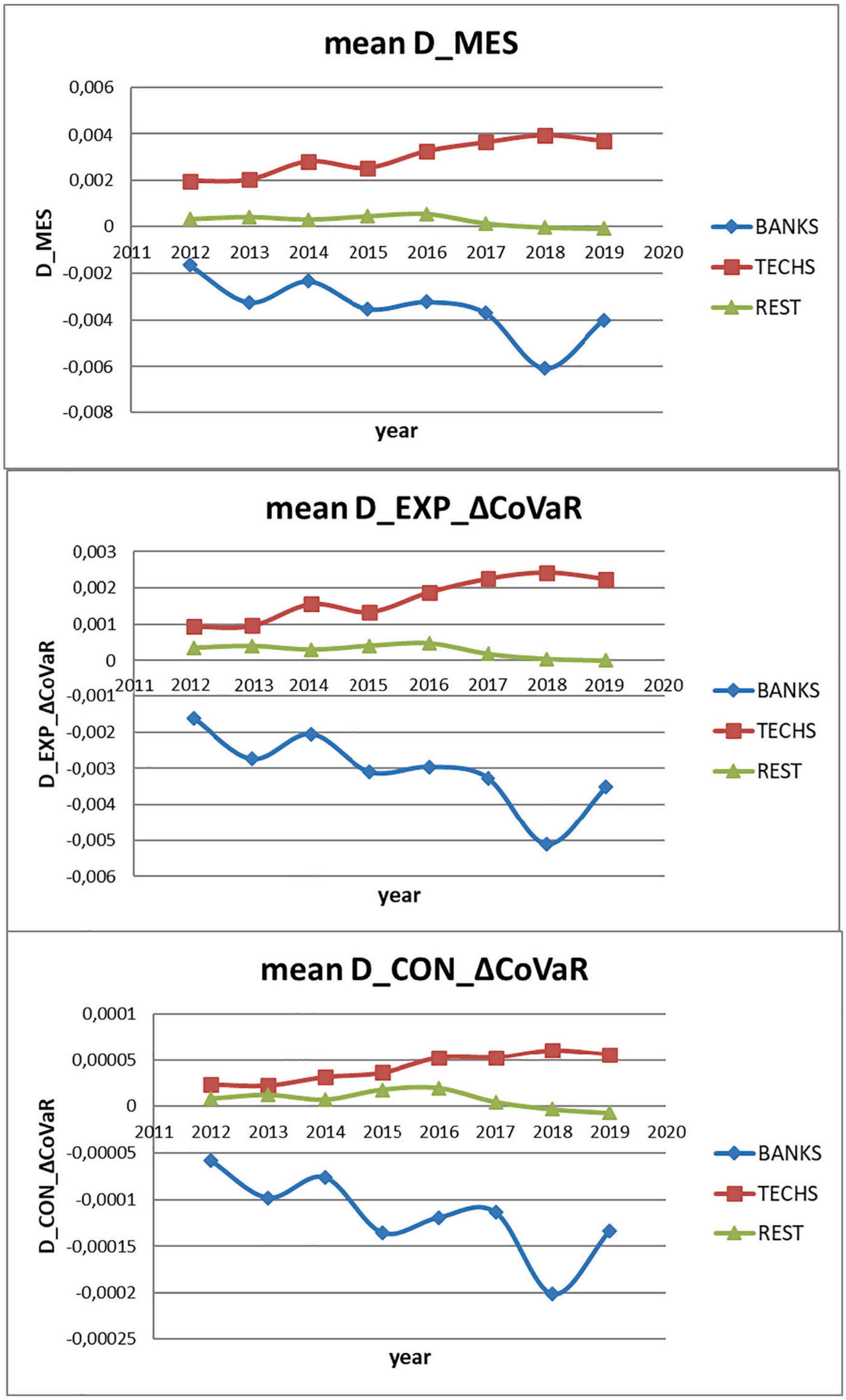

Fig. 2. Evolution over time of the various non-systematic measures of risk commonality.
This figure shows the evolution over time of the sector-specific cross-sectional means of the various measures of non-systematic risk commonality between 2012 and 2019. These measures are calculated using the residual equity returns $\varepsilon_{i,t} = r_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i \cdot R_{m,t}$ of a market model. The employed system index is the market capitalization-weighted residual return index.

in Section 4.1.2) as dependent variables. With this specification, we want to check whether tech firms exhibit a larger level of risk commonality due to non-systematic risk factors (such as direct interactions across technology companies or between technology companies and other companies in the sample, for example, due to business relationships) than non-tech firms/non-banks.

As the results in Table 8 show this indeed is the case. The regression coefficients of the dummy TECHS are all positive and highly significant, and they are even larger than those for the dummy BANKS.[44] These results align with the visual and descriptive results shown in Fig. 2 and Table 9.

[44] In contrast to the baseline results, here we observe that the regression based on the contribution measure has only slightly higher R^2 than the regressions based on the exposure measures.

Table 9
Means of the various measures of non-systematic risk commonality per sector.
This table shows the sector-specific means and medians of the various measures of non-systematic risk commonality (D_MES: non-systematic Marginal expected shortfall, D_EXP_ΔCoVaR: non-systematic exposure ΔCoVaR, D_CON_ΔCoVaR: non-systematic contribution ΔCoVaR) across firms and time between 2012 and 2019. Unreported *t*-tests confirm a significant difference in the mean/median values between all sectors at the 1 %-significance level (results can be found in the supplementary data). Furthermore, all means and medians are statistically different from zero, except for the median D_MES of non-tech firms/non-banks.

Measure of non-systematic risk commonality	Banks	Tech firms	Non-tech firms/ non-banks
Mean D_MES	−0.00337	0.00299	0.000251
Median D_MES	−0.00324	0.00228	0.000128
Mean D_EXP_ΔCoVaR	−0.00300	0.00176	0.000285
Median D_EXP_ΔCoVaR	−0.00281	0.00126	0.000299
Mean D_CON_ΔCoVaR	−0.000114	0.000042	0.000007
Median D_CON_ΔCoVaR	−0.000110	0.000035	0.000009
Observations	253	689	2651

Comparing the results shown in Tables 3 and 9, it can be seen that the level of risk commonality considerably decreases when switching from measures for total risk commonality (see Section 5.1) to measures for non-systematic risk commonality. This is true for the sector TECHS as well as for the sector BANKS and is an expected result because for non-systematic risk commonality, exposure to systematic risk factors that could contribute to risk commonality is excluded.

Comparing Figs. 1 and 2, it is remarkable that for the measures of non-systematic risk commonality, there is no longer a common trend over time for the three sectors (TECHS, BANKS, and REST). Instead, we can see that the measures of non-systematic risk commonality for the sectors BANKS and REST tend to decrease in recent years, whereas those of the TECH sector tend to increase.

5.4. Intra-group risk commonality of tech firms

The results for tech firms' risk commonality presented in Sections 5.1 and 5.3 are potentially subject to the concern that these are mainly driven by the high proportion of tech companies in the S&P 500 index. As this index serves as a ‘system’ for the computation of the measures of risk commonality, a large fraction of tech firms in the S&P 500 index automatically generates a large level of risk commonality for tech firms.

To address this issue, in this section, we investigate to what extent the risk commonality of tech companies is due to intra-group (within the sector of tech firms) risk commonality and whether this share is larger than that one of banks. Furthermore, we analyze whether the intra-group risk commonality of tech firms is more strongly driven either by systematic or non-systematic risk factors than this is the case for banks.

We address the first question in two ways. First, following an indirect approach, we calculate for each firm i in sector $g(i)$ the relative variation (hereafter generally referred to as variation in measures; ViM) between the measures of total risk commonality in the default setting and in the case that all firms in the S&P 500 which do not belong to a specific sector $g(i)$ serve as a system (see the definitions and notation in Section 4.1.3):

$$ViM^{\%}_{i,g(i),t} = \left[\frac{RCM\left(r_{i,t}; R_{S\&P\ 500\ without\ sector\ g(i),t}\right) - RCM\left(r_{i,t}; R_{S\&P\ 500,t}\right)}{RCM\left(r_{i,t}; R_{S\&P\ 500,t}\right)}\right]. \tag{9}$$

If we see a decline here, this indicates that, on average, the risk commonality of firms within the sector is larger than that one of firms across sectors. As Table 10 (Panel A) shows, this is indeed the case for both sectors $g \in \{TECHS, BANKS\}$. Second, following a direct approach, we calculate for each firm i in sector $g(i)$ the relative variation between the measures of total risk commonality in the default setting and in the case that all firms in the S&P 500 which belong to a specific sector $g(i)$ serve as a system (see Section 4.1.3):

Table 10
Mean variations in measures (ViM).
The table shows the mean variations in measures (ViM) for the sectors TECHS and BANKS for different measures of risk commonality. MES_$ViM^{\%}_{i,g(i)}$: relative variation in the marginal expected shortfall, EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$: relative variation in the exposure ΔCoVaR, CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$: relative variation in the contribution ΔCoVaR.

	(1) TECHS	(2) BANKS
Panel A: relative variation between the measures of total risk commonality in the default setting and in the case that all firms in the S&P 500 which do not belong to a specific sector $g(i)$ serve as system		
MES_$ViM^{\%}_{i,g(i)}$	−0.456	−0.0471
EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	−0.567	−0.0818
CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	−0.901	−0.121
Panel B: relative variation between the measures of total risk commonality in the default setting and in the case that all firms in the S&P 500 which do belong to a specific sector $g(i)$ serve as system		
MES_$ViM^{\%}_{i,g(i)}$	0.0183	0.0796
EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	0.0485	0.113
CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	0.251	0.984
Panel C: relative variation between the measures of risk commonality based on a system index with all firms in the S&P 500 that belong to a specific sector $g(i)$ when switching from equity returns to residual equity returns		
MES_$ViM^{\%}_{i,g(i)}$	−0.773	−0.493
EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	−0.812	−0.491
CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	−0.773	−0.589
Panel D: relative variation between the measures of risk commonality based on a system index with all firms in the S&P 500 that do not belong to a specific sector $g(i)$ when switching from equity returns to residual equity returns		
MES_$ViM^{\%}_{i,g(i)}$	−1.283	−1.045
EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	−0.578	−1.117
CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	−0.378	−1.152

$$ViM^{\%}_{i,g(i),t} = \left[\frac{RCM\left(r_{i,t}; R_{S\&P\ 500\ only\ sector\ g(i),t}\right) - RCM\left(r_{i,t}; R_{S\&P\ 500,t}\right)}{RCM\left(r_{i,t}; R_{S\&P\ 500,t}\right)}\right]. \tag{10}$$

In this case, a strong intra-group risk commonality would lead to a positive relative variation. As Table 10 (Panel B) shows, this is also the case for both sectors $g \in \{TECHS, BANKS\}$.

In order to evaluate whether the above relative variations are large or small, we need a reference point. That is why we compute the relative variations (9) and (10) for the sectors $g \in \{TECHS, BANKS\}$ and run the following random-effects panel regression:

$$ViM^{\%}_{i,g(i),t} = \alpha + \lambda_t + \gamma \cdot TECHS + \delta \cdot CONNECT_{i,t-1} + \sum_{k=1}^{M} \beta_k \cdot CONTROLS_{k,i,t-1} + u_{i,t} \tag{11}$$

where TECHS is equal to 1 if firm i belongs to the sector TECHS, and 0 if firm i belongs to the sector BANKS.

For the indirect approach, a negative regression coefficient γ for the dummy variable TECHS implies that the relative reduction of risk commonality (see Table 10, Panel A) by excluding the own sector from the system index is higher for tech companies than for banks. As can be seen in Table 11 (Panel A), this indeed is the case suggesting that the

Table 11
Intra-group risk commonality.
The table shows the results of the modified random-effects panel regressions for the analysis of intra-group risk commonality. For Panel A, dependent variables are the relative variations of firm i between the measures of total risk commonality in the default setting and in the case that all firms in the S&P 500 which do not belong to a specific sector $g(i)$ serve as system. For Panel B, dependent variables are the relative variations of firm i between the measures of total risk commonality in the default setting and in the case that all firms in the S&P 500 which belong to a specific sector $g(i)$ serve as system. MES_$ViM^{\%}_{i,g(i)}$: relative variation in the marginal expected shortfall, EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$: relative variation in the exposure ΔCoVaR, CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$: relative variation in the contribution ΔCoVaR. The variable of interest is the dummy variable TECHS, which is 1 when a firm belongs to the sector TECH and 0 when a firm belongs to the sector BANKS. CONTROLS encompass: CONNECT as Granger-based measures for interconnectedness, SIZE measured by ln(total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, and SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket. Further, we control for year-fixed effects. Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	(1)	(2)	(3)
	MES_$ViM^{\%}_{i,g(i)}$	EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$
Panel A: Indirect			
TECHS	−0.361***	−0.413***	−0.773***
	(0.0449)	(0.0509)	(0.0147)
Constant	−0.112	−0.211	−0.0897
	(0.247)	(0.277)	(0.0787)
Observations	917	917	917
Number of firms	119	119	119
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.511	0.567	0.975
Panel B: Direct			
TECHS	−0.00367**	−0.00299***	−0.00725***
	(0.00148)	(0.00105)	(0.000421)
Constant	0.0314***	0.0196***	0.0135***
	(0.00693)	(0.00519)	(0.00207)
Observations	917	917	917
Number of firms	119	119	119
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.189	0.233	0.810

share of total risk commonality that is explained by intra-group risk commonality is higher for tech firms than for banks.[45]

For the direct approach, a positive regression coefficient γ for the dummy variable TECHS would imply that the relative increase of risk commonality by focusing on the own sector in the system index is higher for tech companies than for banks. This would further indicate that the share of total risk commonality explained by intra-group risk commonality is higher for tech firms than for banks. However, as the results in Table 11 (Panel B) show, we find the opposite because the regression coefficient for the dummy variable TECHS is significantly negative in all regressions. Thus, we have conflicting results based the indirect and the direct approach: while the indirect approach indicates that the share of total risk commonality explained by intra-group risk commonality is higher for tech firms than for banks, the direct approach indicates that the opposite is true. However, it should be noted that also for tech firms, on average, the relative variation (10) is positive (see Table 10, Panel B)

[45] Note that since STRUCTURE is an industry-level variable, we have to drop it from the vector of control variables in the analysis based only on industry-level variation.

Table 12
Non-systematic intra-group risk commonality.
The table shows the results of the modified random-effects panel regressions for the analysis of non-systematic intra-group risk commonality. Dependent variables are the relative variations of firm i between the measures of risk commonality based on a system index with all firms in the S&P 500 that belong to a specific sector $g(i)$ when switching from equity returns to residual equity returns for computing the measures. MES_$ViM^{\%}_{i,g(i)}$: relative variation in the marginal expected shortfall, EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$: relative variation in the exposure ΔCoVaR, CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$: relative variation in the contribution ΔCoVaR. The variable of interest is the dummy variable TECHS, which is 1 when a firm belongs to the sector TECH and 0 when a firm belongs to the sector BANKS. CONTROLS encompass: CONNECT as Granger-based measures for interconnectedness, SIZE measured by ln(total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, and SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket. Further, we control for year-fixed effects. Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	(1)	(2)	(3)
	MES_$ViM^{\%}_{i,g(i)}$	EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$
TECHS	−0.210***	−0.232***	−0.282***
	(0.0433)	(0.0440)	(0.0309)
Constant	−0.517***	−0.431**	−0.506***
	(0.183)	(0.211)	(0.126)
Observations	917	917	917
Number of firms	119	119	119
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.353	0.375	0.671

which means that the measures of risk commonality $RCM(r_i; R_{S\&P\ 500\ only\ sector\ TECHS})$ tend to be larger than $RCM(r_i; R_{S\&P\ 500})$. Thus, on average, the risk commonality within the sector of tech firms is larger than across the sectors, which, of course, is not too surprising.

Next, we analyze whether the intra-group risk commonality of tech firms is more strongly driven either by systematic or non-systematic risk factors than this is the case for banks. For this purpose, we calculate for each firm i in sector $g(i)$ the following relative variation (see Section 4.1.3):

$$ViM^{\%}_{i,g(i),t} = \left[\frac{RCM\left(\varepsilon_{i,t}; R_{\varepsilon_{i,t}(S\&P500\,only\,sector\,g(i))}\right) - RCM\left(r_{i,t}; R_{S\&P500\,only\,sector\,g(i),t}\right)}{RCM\left(r_{i,t}; R_{S\&P500\,only\,sector\,g(i),t}\right)}\right]. \tag{12}$$

Thus, we compute how large the relative variation in the measures of risk commonality based on a system index with all firms in the S&P 500 that belong to a specific sector $g(i)$ is when we switch from equity returns to residual equity returns for computing the RCM. As explained in Section 4.1.2, when using residual equity returns, the firms' exposure to systematic risk factors does no longer influence the calculated values for the measures of risk commonality. We termed these RCM as measures of non-systematic risk commonality. Then, we re-run the regression (11) for the values computed in Eq. (12) as dependent variable.

As seen in Table 10 (Panel C), the relative variation is negative on average. This is true for the TECHS sector as well as for BANKS. This result was expected because when computing non-systematic risk commonality based on residual equity returns, exposure to systematic risk factors that could contribute to risk commonality is missing. It is in line with the result discussed in Section 5.3.

When re-running the regression (11) for the values computed in Eq. (12) as the dependent variable, a negative regression coefficient γ for the dummy variable TECHS would imply that the relative reduction of intra-group risk commonality resulting from focusing on non-systematic reasons for risk commonality is higher for tech companies than for banks. As can be seen in Table 12, this indeed is the case. The regression coefficients of the dummy variable TECHS are significantly negative in all cases. This result suggests that the intra-group risk commonality of tech firms is driven to a larger extent by systematic risk factors than this is the case for banks.[46]

5.5. Inter-group risk commonality of tech firms

Next, we repeat the last step of the analysis in the previous section and investigate whether the inter-group (across sectors) risk commonality of tech firms is more strongly driven either by systematic or non-systematic risk factors than this is the case for banks. For this purpose, we calculate for each firm i in sector $g(i)$ the following relative variation (see Section 4.1.3):

$$ViM^{\%}_{i,g(i),t} = \left[\frac{RCM\left(\varepsilon_{i,t}; R_{\varepsilon_{i,t}(S\&P\ 500\ without\ sector\ g(i))}\right) - RCM\left(r_{i,t}; R_{S\&P\ 500\ without\ sector\ g(i),t}\right)}{RCM\left(r_{i,t}; R_{S\&P\ 500\ without\ sector\ g(i),t}\right)}\right]. \tag{13}$$

Thus, we compute how large the relative variation (in fact, again a reduction; see Table 10 (Panel D)) in the measures of risk commonality based on a system index with all firms in the S&P 500 that do not belong to a specific sector $g(i)$ is when we switch from equity returns to residual equity returns for computing the RCM. By eliminating a sector $g(i)$ from the system index used for calculating RCM, only risk commonality with firms outside this sector is measured by the RCM. This is what we call inter-group risk commonality. Then, again, we re-run the regression (11) for the values computed in Eq. (13) as dependent variable.

As shown in Table 13, the regression coefficients for the dummy variable TECHS are positive, but only in case of CON_ΔCoVaR as dependent variable, it is significantly different from zero. These results are a weak indication that the relative reduction of inter-group risk communality resulting from focusing on non-systematic reasons for risk commonality is smaller for tech companies than for banks. Analogously to the argumentation in the previous section, this suggests that tech firms' inter-group risk commonality is driven to a larger extent by non-systematic risk factors (such as direct interactions due to business relationships) than this is the case for banks.

Table 13
Non-systematic inter-group risk commonality.
The table shows the results of the modified random-effects panel regressions for the analysis of non-systematic inter-group risk commonality. Dependent variables are the relative variations of firm i between the measures of risk commonality based on a system index with all firms in the S&P 500 that do not belong to a specific sector $g(i)$ when switching from equity returns to residual equity returns for computing the measures. MES_$ViM^{\%}_{i,g(i)}$: relative variation in the marginal expected shortfall, EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$: relative variation in the exposure ΔCoVaR, CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$: relative variation in the contribution ΔCoVaR. The variable of interest is the dummy variable TECHS, which is 1 when a firm belongs to the sector TECH and 0 when a firm belongs to the sector BANKS. CONTROLS encompass: CONNECT as Granger-based measures for interconnectedness, SIZE measured by ln(total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, and SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket. Further, we control for year-fixed effects. Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	(1)	(2)	(3)
	MES_$ViM^{\%}_{i,g(i)}$	EXP_ΔCoVaR_$ViM^{\%}_{i,g(i)}$	CON_ΔCoVaR_$ViM^{\%}_{i,g(i)}$
TECHS	0.133	0.519	0.900***
	(0.342)	(0.512)	(0.335)
Constant	2.400	0.486	−1.567
	(2.239)	(4.048)	(2.132)
Observations	917	917	917
Number of firms	119	119	119
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.0119	0.0121	0.0222

5.6. Explanatory factors for tech firms' level of total risk commonality

In Sections 5.1 and 5.3, we demonstrate that tech firms' total risk commonality is, on average, significantly higher than that one of non-tech firms/non-banks. In this section, we focus on exploring which firm-level factors of tech firms are associated with higher levels of risk commonality. Thus, we have to omit our industry-level variable STRUCTURE once again. Following the banking literature on systemic risk, we mainly focus on firm-specific balance sheet variables as potentially relevant firm-level factors. The analysis is done for all types of risk commonality that we have considered so far, i.e., total risk commonality (see Section 5.1), non-systematic risk commonality (see Section 5.3), intra-group risk commonality based on a system index consisting of all firms in the S&P 500 that belong to a specific sector (see Section 5.4), and inter-group risk commonality based on a system index consisting of all firms in the S&P 500 that do not belong to a specific sector (see Section 5.5). Uncovering balance sheet variables with a strong association with large risk commonality could provide regulators with a fast and reliable strategy for the identification of entities on which regulatory attention should be focused.

There is a large body of related literature exploring the relation between balance sheet variables and risk commonality measures of financial institutions (see, e.g., Bierth et al. (2015), Bostandzic et al. (2014), Girardi and Ergün (2013), López-Espinosa et al. (2012), Weiß et al. (2014a, 2014b)). However, many of the bank-specific variables used in these studies do not exist for non-banks (e.g., the ratio of interbank loans to total assets, the ratio of total deposits to total loans, loan loss provisions, or the ratio of non-interest income to total income). In the following, we consider only those variables that can be calculated for banks as well as for non-banks and that we expect to be associated with the level of risk commonality of tech firms. Furthermore, we briefly argue which direction of association between the variables and the level of risk commonality we expect.

On the one hand, we consider those variables that we employed in the previous sections as controls, i.e., SIZE, INT-ASSET-RATIO, EQUITY-RATIO, MARKET-TO-BOOK-RATIO, and, as non-balance sheet variables, SHARE and CONNECT (GIN and GOUT, respectively). The expected sign of the regression coefficients of these variables was already

[46] In the extreme case, when the intra-group risk commonality is completely driven by systematic risk factors, the relative variation computed in Eq. (12) would be equal to −100 %, i.e., the lowest possible value would be reached. Thus, the larger the relative reduction (12) is, the larger the contribution of systematic risk factors to intra-group risk commonality is.

Table 14
Explanatory factors for the risk commonality of tech firms.
The table shows the results of firm-/year-fixed-effects panel regressions. Dependent variables are the various firm-specific measures of total risk commonality and non-systematic risk commonality of tech firms (MES: Marginal expected shortfall, EXP_ΔCoVaR: exposure ΔCoVaR, CON_ΔCoVaR: contribution ΔCoVaR, D_MES: non-systematic Marginal expected shortfall, D_EXP_ΔCoVaR: non-systematic exposure ΔCoVaR, D_CON_ΔCoVaR: non-systematic contribution ΔCoVaR). The set of potential explanatory variables encompasses: SIZE measured by ln(total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, RD-RATIO measured by research and development costs divided by total assets, BUP-RATIO measured by the gross value of brands, patents, and trademarks divided by total assets, WC-RATIO measured by working capital divided by total assets, GIN as a measure of interconnectedness counting the number of firms that Granger cause the equity return of a firm, GOUT as a measure of interconnectedness counting the number of firms that are Granger caused by the equity return of a firm, and SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket. The regression coefficients and standard errors are multiplied by 100 for readability (°). Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	Total risk commonality			Non-systematic risk commonality		
	(1)	(2)	(3)	(1)	(2)	(3)
	MES (°)	EXP_ΔCoVaR (°)	CON_ΔCoVaR (°)	D_MES (°)	D_EXP_ΔCoVaR (°)	D_CON_ΔCoVaR (°)
SIZE	0.0051	−0.0138	−0.0141	0.0298	0.0212	0.0003
	(0.0817)	(0.0550)	(0.0117)	(0.0652)	(0.0504)	(0.0011)
INT-ASSET-RATIO	−0.106	−0.0938	−0.0747	0.0157	0.0259	0.0027
	(0.281)	(0.207)	(0.0583)	(0.182)	(0.132)	(0.0034)
EQUITY-RATIO	0.0008	0.0012	0.0009**	−0.0010	−0.0007	0.00001
	(0.0019)	(0.0013)	(0.0004)	(0.0010)	(0.0007)	(0.00001)
MARKET-TO-BOOK-RATIO	−0.0003	−0.0004	−0.0002	0.0006	0.0001	0.00001
	(0.0009)	(0.0006)	(0.0002)	(0.0007)	(0.0006)	(0.00001)
RD-RATIO	−0.995	−0.810	−0.123	−0.677	−0.551	−0.0160
	(1.180)	(0.943)	(0.196)	(0.515)	(0.399)	(0.0099)
BUP-RATIO	−2.210	−1.95	−0.705***	−1.43	−1.21	−0.0472*
	(2.050)	(1.47)	(0.258)	(1.71)	(1.27)	(0.0242)
WC-RATIO	−0.415	−0.341*	−0.103*	0.271	0.212	0.0045
	(0.249)	(0.191)	(0.0525)	(0.182)	(0.137)	(0.0031)
GIN	−0.209	−0.139		−0.157*	−0.128*	
	(0.198)	(0.136)		(0.0854)	(0.0645)	
GOUT			0.0390			0.0003
			(0.0323)			(0.0041)
SHARE	1.65	1.84	1.26*	0.0449	0.0357	0.122***
	(2.78)	(1.76)	(0.669)	(0.0291)	(0.0218)	(0.0452)
Constant	2.69*	1.96**	0.848***	−0.183	−0.185	−0.0020
	(1.36)	(0.933)	(0.184)	(1.09)	(0.841)	(0.0187)
Observations	326	326	326	326	326	326
Number of firms	53	53	53	53	53	53
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0450	0.0410	0.403	0.011	0.041	0.110

discussed in Section 5.1. On the other hand, some new balance sheet variables are considered that we expect to be particularly relevant for the risk commonality of tech firms. First, this is RD-RATIO, which is measured as the ratio of research and development expenditures to total assets. This variable is used as a proxy for the innovation potential of a firm. We hypothesize that the larger this innovation potential is, the larger the probability that the firm offers goods or services that are non-substitutable for other firms. Thus, we expect larger values of RD-RATIO to be associated with larger levels of the measures of risk commonality. Second, we consider BUP-RATIO defined as the ratio of the gross value of brands, patents and trademarks to total assets. For the same reason as for RD-RATIO, we expect a positive association between this variable and the level of risk commonality. Third, we use WC-RATIO which is the ratio of the working capital of a firm to its total assets and, hence, reflects a firm's liquidity. As there are arguments in the banking literature that low liquidity can lead to an increased risk commonality (see Acharya and Thakor (2016)), we also consider this variable.

Panel regressions of the following type are run for the sector TECHS (with firm−/time-fixed effects to account for unobserved heterogeneity):

$$RCM_{i,t} = \alpha_i + \lambda_t + \delta \cdot CONNECT_{i,t-1} + \sum_{m=1}^{M} \beta_m \cdot VARIABLES_{m,i,t-1} + \varepsilon_{i,t} \quad (14)$$

where $RCM_{i,t}$ denotes the average value in year t of some measure of risk commonality of firm i.

Table 14 shows that only a few variables are significantly associated with the total or non-systematic risk commonality of tech firms. The measure CON_ΔCoVaR is most often significantly associated with one of the variables. In the case of SHARE and WC-RATIO, the signs of the significant regression coefficients are in line with our expectations. However, in the case of BUP-RATIO and GIN the signs of the significant regression coefficients are contrary to our expectations.

In Table 15 it can be seen that the inter-group risk commonality is most strongly associated with firm-specific variables. For all measures of inter-group risk commonality, SIZE, INT-ASSET-RATIO, MARKET-TO-BOOK-RATIO and SHARE enter the regressions with significant coefficients whose signs are broadly in line with our expectations, except for INT-ASSET-RATIO. For all measures of intra-group risk commonality, WC-RATIO and SHARE have significant regression coefficients with the expected sign.

In summary, the number of significant explanatory factors is quite small, especially for total and non-systematic risk commonality of tech firms. This result might indicate that the employed firm-specific variables are too coarse proxies for the real underlying factors driving the level of risk commonality of tech firms. For these firms, potential explanatory variables are likely to be quite specific for the respective business model. For example, the number of users may be relevant for platforms, while marketing revenues may be important for others. Thus, there is likely to be a large within-group variation in relevant firm-specific variables for tech firms, which we do not take into account when using identical variables for all firms. However, using specific

Table 15
Explanatory factors for the intra-group and inter-group risk commonality of tech firms.
The table shows the results of firm-/year-fixed-effects panel regressions. Dependent variables are the various firm-specific measures of intra-group risk commonality (based on a system index consisting of all firms in the S&P 500 that belong to a specific sector) and inter-group risk commonality (based on a system index consisting of all firms in the S&P 500 that do not belong to a specific sector) of tech firms (MES: Marginal expected shortfall, EXP_ΔCoVaR: exposure ΔCoVaR, CON_ΔCoVaR: contribution ΔCoVaR). The set of potential explanatory variables encompasses: SIZE measured by ln(total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, RD-RATIO measured by research and development costs divided by total assets, BUP-RATIO measured by the gross value of brands, patents, and trademarks divided by total assets, WC-RATIO measured by working capital divided by total assets, GIN as a measure of interconnectedness counting the number of firms that Granger cause the equity return of a firm, GOUT as a measure of interconnectedness counting the number of firms that are Granger caused by the equity return of a firm, and SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket. The regression coefficients and standard errors are multiplied by 100 for readability (°). Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	Intra-group risk commonality			Inter-group risk commonality		
	(1)	(2)	(3)	(1)	(2)	(3)
	MES (°)	EXP_ΔCoVaR (°)	CON_ΔCoVaR (°)	MES (°)	EXP_ΔCoVaR (°)	CON_ΔCoVaR (°)
SIZE	−0.0115	−0.0219	−0.0146	0.247***	0.192***	0.0189**
	(0.0854)	(0.0593)	(0.0214)	(0.0811)	(0.0575)	(0.0074)
INT-ASSET-RATIO	−0.365	−0.335	−0.197***	−0.915***	−0.735***	−0.0779***
	(0.298)	(0.213)	(0.0687)	(0.287)	(0.199)	(0.0191)
EQUITY-RATIO	0.0007	0.00142	0.0011*	0.0008	0.0012	0.0001
	(0.0021)	(0.0015)	(0.0005)	(0.0020)	(0.0013)	(0.0001)
MARKET-TO-BOOK-RATIO	0.0002	0.0001	0.0001	0.0015*	0.0012*	0.0001*
	(0.0009)	(0.0006)	(0.0002)	(0.0008)	(0.0006)	(0.00001)
RD-RATIO	−1.32	−1.12	−0.138	0.808	0.572	0.187**
	(1.20)	(0.991)	(0.209)	(1.23)	(0.920)	(0.0794)
BUP-RATIO	−2.63	−2.40	−1.10***	−2.55	−2.24	−0.339***
	(2.50)	(1.83)	(0.281)	(2.11)	(1.41)	(0.123)
WC-RATIO	−0.517**	−0.441**	−0.160***	−0.529*	−0.426*	−0.0328
	(0.253)	(0.197)	(0.0597)	(0.312)	(0.229)	(0.0200)
GIN	−0.289	−0.218		−0.316**	−0.228**	
	(0.190)	(0.137)		(0.155)	(0.104)	
GOUT			−0.0110			−0.0110
			(0.0167)			(0.0167)
SHARE	5.80*	5.41***	4.09***	11.0***	9.00***	1.05***
	(3.09)	(1.99)	(0.886)	(3.86)	(2.61)	(0.339)
Constant	2.97**	2.28**	0.991***	−2.49*	−2.32**	−0.261**
	(1.44)	(1.02)	(0.338)	(1.38)	(0.975)	(0.121)
Observations	326	326	326	326	326	326
Number of firms	53	53	53	53	53	53
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0180	0.0310	0.413	0.0514	0.112	0.367

variables for subgroups of tech firms would lead to statistical problems, as the number of data points available for each model estimation would shrink considerably.

6. Robustness checks

In this section, we report the results of several robustness checks for our main finding that tech companies exhibit a higher total risk commonality than non-tech firms/non-banks and that the difference between the total risk commonality of tech firms and non-tech firms/non-banks is even increasing over time.

First, we address some identification concerns in more detail. As mentioned in Section 5.1, we confront the concerns about potential omitted variable biases and confounding effects by including a broad set of control variables. Some of these control variables, however, can be endogenous with respect to risk commonality so that their inclusion can bias the results. In our baseline specifications, we control for potential reverse causality with regard to these control variables by using their lagged values (by one period). To address some remaining concerns about the exogeneity of these control variables, in unreported tests (results can be found in the supplementary data), we omit all CONTROLS as well as the variable CONNECT. The results for the regression coefficients of the dummy variables TECHS and BANKS qualitatively do not change. In addition, we also perform the analysis with contemporaneous control variables. Again, the results for the regression coefficients for the dummy variables TECHS and BANKS qualitatively do not change (results can be found in the supplementary data).

Furthermore, we demonstrate that our results are also mostly robust to the application of the alternative identification approach proposed by Lewbel (2012). This approach uses a vector of variables generated from the regressors and the heteroscedastic error terms as instruments for the potentially endogenous regressors.[47] Again, the results for the regression coefficients for the dummy variables TECHS and BANKS remain qualitatively the same, except that we no longer have any significance of TECHS for the contribution measure CON_ΔCoVaR (results can be found in the supplementary data).

Next, we investigate the robustness of our finding that an increasing time trend for the difference between the total risk commonality of tech firms and non-tech firms/non-banks exists (see Section 5.1 and Table 4). For this, on the one hand, we carry out independent cross-sectional regressions for the different years in our sample period ($Y = 2012, \ldots, 2019$):

$$RCM_i^Y = \alpha_i^Y + \gamma_1^Y \cdot BANKS + \gamma_2^Y \cdot TECHS + \delta^Y \cdot CONNECT_i^{Y-1} + \sum_{m=1}^{M} \beta_m^Y \cdot CONTROLS_{m,i}^{Y-1} + \varepsilon_i^Y. \tag{15}$$

By doing this, we can explore how the significance of belonging to the sector of tech firms for the level of risk commonality has changed in

[47] For the estimation, we use the pre-implemented STATA routine *ivreg2h*.

Table 16
Results of the baseline panel regressions with time-dummy-interaction terms.
The table shows the results of the baseline fixed-effects panel regressions with time-dummy-interaction terms. Dependent variables are the various firm-specific measures of total risk commonality (MES: Marginal expected shortfall, EXP_ΔCoVaR: exposure ΔCoVaR, CON_ΔCoVaR: contribution ΔCoVaR). The variable TIME consists of year-fixed effects (1, …, 8). Thus, the interaction term TIME x TECHS equals 1, …, 8 for TECH firms and 0 otherwise, and analogously, TIME x BANKS equals 1, …, 8 for BANKS and 0 otherwise. The variables of interest are the interaction terms TIME x TECHS and TIME x BANKS. CONTROL variables are: SIZE measured by ln(total assets), INT-ASSET-RATIO measured by intangible assets divided by total assets, EQUITY-RATIO measured by the book value of equity divided by total assets, MARKET-TO-BOOK-RATIO measured by the market value of equity divided by book value of equity, GIN as a measure of interconnectedness counting the number of firms that Granger cause the equity return of a firm, GOUT as a measure of interconnectedness counting the number of firms that are Granger caused by the equity return of a firm, SHARE measured by the ratio of a company's market capitalization to the market capitalization of the (corresponding) total submarket, and STRUCTURE measured by the ratio of the sum of the market capitalization of the three largest companies (by market capitalization) in a submarket to the market capitalization of the (corresponding) total submarket. Further, we control for year- and firm-fixed effects. The regression coefficients and standard errors are multiplied by 100 for readability (°). Robust standard errors clustered at the firm level are reported in parentheses, and *** (**;*) indicates significance at 1 % (5 %; 10 %).

Variables	(1)	(2)	(3)
	MES (°)	EXP_ΔCoVaR (°)	CON_ΔCoVaR (°)
TIME × TECHS	0.0283***	0.0268***	0.0165***
	(0.0068)	(0.0047)	(0.0015)
TIME × BANKS	0.0074	0.006	0.008***
	(0.0087)	(0.0061)	(0.0018)
Constant	1.98***	1.23***	0.502***
	(0.403)	(0.291)	(0.106)
Observations	3505	3505	3505
Number of firms	454	454	454
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
R^2	0.086	0.087	0.349

each of the sample years. For the sake of brevity, we do not report the regression results here in detail (results can be found in the supplementary data). The result for the contribution measure CON_ΔCoVaR is remarkable. The TECH dummy becomes significant for this measure only in the years 2017 and 2019. Thus, only in the most recent years, the distress of individual tech firms seems to be more strongly associated with market-wide distress than this is the case for non-tech firms/non-banks. Furthermore, the size of the significant regression coefficients of the dummy variable TECHS with respect to the exposure measures MES and EXP_ΔCoVaR tends to increase in the most recent years.

To further zoom into the dynamics of the total risk commonality of tech firms, on the other hand, we re-estimate the panel models of Section 5.1 by interacting TIME (measured in year-fixed effects 1, …, 8) and the sector dummy variables TECHS and BANKS, respectively, in our baseline regressions:

$$RCM_{i,t} = \alpha_i + \lambda_t + \gamma_1 \cdot TIME_t \cdot BANKS + \gamma_2 \cdot TIME_t \cdot TECHS + \delta \cdot CONNECT_{i,t-1} + \sum_{m=1}^{M} \beta_m \cdot CONTROLS_{m,i,t-1} + \varepsilon_{i,t}. \tag{16}$$

A positive regression coefficient γ_2 and γ_1, respectively, would indicate a growing level of risk commonality of the respective sector over time (in comparison to the sector REST). An advantage of the approach shown in Eq. (16) is that we can now estimate time-fixed effects as well as firm-fixed effects in our panel regressions. As Table 16 shows, we find positive and highly significant regression coefficients for the time-interacted dummy variable TECHS for all measures of total risk commonality. This is even true for the measure CON_ΔCoVaR, for which only a weak significance could be observed in the baseline panel regressions without TIME x TECHS interaction terms (see Table 6 in Section 5.1). These results coincide with our previous findings in Section 5.1 and strengthen our claim that the digital economy is currently building up risk commonality compared to non-tech firms/non-banks.

Next, in order to reduce the effect of outliers, we re-estimate the baseline panel regressions in Section 5.1 using variables (except the dummies) that are winsorized and trimmed, respectively, at the 1 %/99 %-percentile.[48] Again, we do not observe any qualitative differences in the results for the sector of tech firms (results can be found in the supplementary data). The only difference compared to our baseline regressions is that being a tech firm is no longer significant for CON_ΔCoVaR in the case of trimmed variables. In contrast, this exception does not apply for the results obtained with winsorized variables.

In further unreported tests (results can be found in the supplementary data), we show that our ΔCoVaR results are robust with respect to the estimation method. For this, we use a quantile regression without state variables (for a quantile $\alpha = 5\%$) as proposed by Adrian and Brunnermeier (2016) for the computation of CON_ΔCoVaR and EXP_ΔCoVaR. Estimating ΔCoVaR this way yields a single value of this measure for each year of our sample. The results we obtain when we use these values in our baseline regressions qualitatively do not differ from those we obtain when employing ΔCoVaR values computed with the time series approach.

In our baseline panel regressions of Section 5.1, we investigate whether the level of total risk commonality of tech firms and banks on average differs from that of non-tech firms/non-banks. For this, we do not necessarily need the panel structure of our data set. Therefore, we have performed pooled OLS regressions as an additional robustness check. We carried out these pooled OLS regressions, once with firm-fixed effects and time-clustered standard errors and once with time-fixed effects and firm-level clustered standard errors (results can be found in the supplementary data). The results of the pooled regressions with time-fixed effects indicate that we only lose the weak significance of the dummy TECHS with respect to CON_ΔCoVaR. For all other measures of risk commonality, the results do qualitatively not differ from those of our baseline panel regressions. For the pooled OLS regressions with firm-fixed effects, we find similar signs for the regression coefficients of the dummy variables as in the baseline regressions but hardly any significance. This lacking significance may be due to the high number of firm-fixed effects.

7. Implications and further research

Our results indicate some important policy implications. First, they suggest that regulators must also look for risk accumulation outside the traditional financial world. Therefore, intensified monitoring, and eventually, regulation might be necessary. Second, our results also suggest that the framework of monitoring systemic risk of financial institutions might provide a valuable point of departure when designing regulatory tools for monitoring the risk commonality of tech firms. Third, our results indicate that the driving forces for intra-group and inter-group risk commonality can be quite different for banks and tech firms (systematic risk factors vs. direct business relationships). This may be a relevant finding for national supervisors when deciding on appropriate regulatory measures to limit the risk commonality of tech firms.

We find that tech firms show, at least on average, a larger risk commonality with the whole US economy than non-tech firms/non-banks and that this effect seems to increase over time, but we cannot say

[48] We follow this common approach of treating outliers, see, e.g., Adams et al. (2019, p. 352). We further did this analysis at the 5 %/95 % level. Our results remain qualitatively the same with the exception that at this level CON_ΔCoVaR is insignificant for both approaches (results can be found in the supplementary data).

what threshold is harmful. Thus, future research could address the question of what level of risk commonality is indeed too high (i.e., destabilizing for the whole economy) and thus requires a stricter regulation of tech companies. To this end, appropriate indicators have to be developed that operationalize the notion of 'destabilizing'. Furthermore, it would be helpful for regulators if simple firm-specific factors could be identified that are statistically and economically significantly associated with a high degree of risk commonality of a firm. Additionally, as we have observed an increasing risk commonality of tech firms over time, it would be interesting to include the time period from Covid-19 onwards to check whether this trend has continued. Further, we have focused on a limited number of subgroups of tech companies that are most likely to have an impact on the stability of the US economy. In particular, we have considered only one international tech subsample. Of course, it is conceivable that other international tech subgroups may have an impact on the US economy. Thus, future research could extend the analysis to more international tech subsamples. Finally, alternative techniques for measuring risk commonality should also be considered in future research. Under the assumption of sufficiently informationally efficient stock markets, the measures of risk commonality used in this paper presume that risk commonality is always reflected in stock prices. The usage of alternative measures that do not rely on broad assumptions about the functioning of financial markets would be desirable.

8. Conclusion

Motivated by the public discussion about the negative and the positive consequences of a growing sector of digitally-oriented tech companies, we analyze the risk commonality of tech firms as reflected in stock prices. For this purpose, we focus on tech firms in the S&P 500 index and employ well-established systemic risk measures from the literature on financial institutions. We interpret these measures as measures of risk commonality.

We find that, on average, the level of total risk commonality of tech firms is larger than that one of non-tech firms/non-banks. The difference between the level of risk commonality of tech firms and non-tech firms/non-banks increases over time. Furthermore, we observe a high intra-group risk commonality for tech firms. We find that the intra-group risk commonality of tech firms is driven to a larger extent by exposure to systematic risk factors than this is the case for banks. In contrast, there is weak evidence that the inter-group risk commonality of tech firms is driven to a larger extent by non-systematic risk factors (e.g., direct business relationships) than this is the case for banks. Finally, we find few balance sheet or other firm-specific variables that are significantly associated with the level of total risk commonality. Some more significant firm-specific variables are found when we look at the level of inter- and intra-group risk commonality.

As discussed in the previous Section 7, our results point to some important policy implications. However, it is also clear that these results can only be a starting point for exploring the relevance and determinants of risk spillovers outside the financial world, which up to now is a highly underexamined area of research.

CRediT authorship contribution statement

Valeriya Dinger: Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Peter Grundke:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Kai Rohde:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis.

Acknowledgments

We express our gratitude to two anonymous reviewers for their valuable comments to improve the paper. We are also grateful for the feedback from the participants of various events, including the Unicredit/HVB doctoral seminar 2021 in Bremen, Germany; the IFABS 2021 in Oxford, Great Britain; the International Conference on Operations Research 2021 in Bern, Switzerland; and the 27th Annual Meeting of the German Finance Association (DGF) 2021 in Innsbruck, Austria. Special thanks also go to the Universitätsgesellschaft Osnabrück e.V. (Osnabrück University Society) for its financial support for conference participation.

Appendix A. Statistical methodology

We strictly follow Benoît et al. (2013) with respect to the computation of the three measures of risk commonality: MES, EXP_ΔCoVaR, and CON_ΔCoVaR. We refer to their work and the references therein for more details of the statistical and econometric issues involved.[49] We use the MATLAB code that Benoît et al. (2013) kindly provide via their own open source project runmycode.org and that is also employed in Abendschein and Grundke (2022).

Benoît et al. (2013) note that there is no unique way to compute the respective measures. More precisely, in the original papers, different econometric methods are outlined, which could lead to problems when the measures of risk commonality are jointly analyzed since results might be distorted by model risk. Benoît et al. (2013) propose a unified multivariate DCC-GARCH framework in which the major measures of risk commonality can be computed based on some few common parameters.

We compute the measures of risk commonality based on ten years of data. Following Kabaila and Mainzer (2018, p. 32), the first 500 observations are required to estimate the tail behavior of MES with a kernel approach. Additionally, the first 500 observations account for the burn-in-phase of the GARCH framework. We then use the average of the daily measures for every calendar year 2010, …, 2019. The period of interest is defined as January 1, 2012 to December 31, 2019.

Benoît et al. (2013) build upon work of Brownlees and Engle (2012) where the two-dimensional vector r_t made of the demeaned market equity return $R_{m,t}$ and the demeaned bank equity return $r_{i,t}$ is defined as (see Brownlees and Engle (2012, p. 12) and Benoît et al. (2013, pp. 8))

$$r_t = H_t^{1/2} \nu_t \tag{C1}$$

where $H_t^{1/2}$ is the Cholesky factor of the conditional variance-covariance matrix H_t being defined as (see Benoît et al. (2013, p. 9))

$$H_t = \begin{pmatrix} \sigma_{m,t}^2 & \sigma_{i,t}\sigma_{m,t}\rho_{i,t} \\ \sigma_{i,t}\sigma_{m,t}\rho_{i,t} & \sigma_{i,t}^2 \end{pmatrix}. \tag{C2}$$

[49] See mainly Appendix A in Abendschein (2020) for this brief description of the statistical methodology.

The vector $\nu_t' = (\varepsilon_{m,t}, \ \xi_{i,t})$ is supposed to be i. i. d. and standard normally distributed with $E(\nu_t) = 0$ and $E(\nu_t \nu_t') = I_2$. Estimates for the conditional market equity return variance $\sigma^2_{m,t}$, the conditional bank equity return variance $\sigma^2_{i,t}$ as well as the conditional correlation between market and bank equity returns $\rho_{i,t}$ are employed in the following as main ingredients for the computation of the measures of risk commonality.

Marginal expected shortfall (MES)

In Eq. (1) in the main text, MES is defined as

$$MES_\alpha^{i,t} = -\mathbb{E}_{t-1}\left(r_{i,t} | R_{m,t} < C\right). \tag{C3}$$

MES is multiplied with (-1) so that larger values represent a larger risk commonality. C is an unconditional threshold equal to the unconditional Value-at-Risk (VaR) of the system.[50] Benoît et al. (2013, p. 9) show that in the presence of the realistic assumption of non-linear dependencies between market and bank equity returns, MES can be estimated as

$$\widehat{MES}_\alpha^{i,t} = -\widehat{\sigma}_{i,t} \cdot \widehat{\rho}_{i,t} \cdot \mathbb{E}_{t-1}\left(\varepsilon_{m,t} | \varepsilon_{m,t} < \kappa\right) - \widehat{\sigma}_{i,t} \cdot \sqrt{1 - \widehat{\rho}_{i,t}^{\,2}} \cdot \mathbb{E}_{t-1}\left(\xi_{i,t} | \varepsilon_{m,t} < \kappa\right). \tag{C4}$$

The conditional variance $\sigma^2_{i,t}$ is estimated in the framework of a GJR-GARCH (1,1) specification with a pseudo maximum likelihood approach, similar to the conditional correlation $\rho_{i,t}$ which is estimated in a dynamic conditional correlations model based on the work of Engle (2002). Eq. (C4) explicitly takes into account non-linear dependencies between market and bank equity returns that are not captured by the (linear) correlation $\rho_{i,t}$. This requires to estimate the conditional tail expectation according to (see Benoît et al. (2013, p. 42))

$$\mathbb{E}_{t-1}\left(\xi_{i,t} | \varepsilon_{m,t} < \kappa\right) = \frac{\sum_{s=1}^{T} K\left(\frac{\kappa - \varepsilon_{m,s}}{h}\right) \cdot \xi_{i,s}}{\sum_{s=1}^{T} K\left(\frac{\kappa - \varepsilon_{m,s}}{h}\right)} \tag{C5}$$

and

$$\mathbb{E}_{t-1}\left(\varepsilon_{m,t} | \varepsilon_{m,t} < \kappa\right) = \frac{\sum_{s=1}^{T} K\left(\frac{\kappa - \varepsilon_{m,s}}{h}\right) \cdot \varepsilon_{m,s}}{\sum_{s=1}^{T} K\left(\frac{\kappa - \varepsilon_{m,s}}{h}\right)}. \tag{C6}$$

Brownlees and Engle (2012) suggest to use a non-parametric kernel density approach to estimate tail dependencies in the presence of the unknown marginal distribution of $\varepsilon_{m,t}$ and $\xi_{i,t}$. The threshold C in Eq. (C3) is chosen as the unconditional Value-at-Risk $VaR_m(\alpha)$ of the market equity return, κ in Eq. (C4) is defined as $\kappa = \frac{VaR_m(\alpha)}{\sigma_{m,t}}$, $K(\cdot)$ is the integral over the Gaussian kernel function, and h is a bandwidth parameter. For further references with respect to the estimation of the kernel function, we refer to Scaillet (2005).

The unconditional $VaR_m(\alpha)$, used to define the conditioning event in the MES and in the numerator of kappa, is in a straightforward manner estimated based on the ex-post realized market equity returns $R_{m,t}$, that is (see Benoît et al. (2013, p. 43))

$$\widehat{VaR}_m(\alpha) = percentile\left(\left\{R_{m,t}\right\}_{t=1}^{T}, \alpha\right) \tag{C7}$$

with α equal to 5%.

ΔCoVaR

CoVaR and ΔCoVaR are defined as

$$P\left(r_{i,t} \le CoVaR_t^{i|R_{m,t} = VaR_{m,t}(\alpha)} | R_{m,t} = VaR_{m,t}(\alpha)\right) = \alpha \tag{C8}$$

and

$$\Delta CoVaR_t^{i|R_{m,t}}(\alpha) = -\left(CoVaR_t^{i|R_{m,t} = VaR_{m,t}(\alpha)} - CoVaR^{i|R_{m,t} = VaR_{m,t}(0.5)}\right). \tag{C9}$$

Once again, ΔCoVaR is multiplied with (-1) so that larger values represent a larger risk commonality. In our DCC-GARCH framework, this leads to the estimation of ΔCoVaR as (see Benoît et al. (2013, p. 44))

$$\Delta\widehat{CoVaR}_t^{i|R_{m,t}}(\alpha) = -\widehat{\gamma}_{m,t} \cdot \left(\widehat{VaR}_{m,t}(\alpha) - \widehat{VaR}_m(0.5)\right). \tag{C10}$$

While α is set to equal 0.05, an estimate for $\gamma_{m,t}$ can be computed with the help of the previously estimated parameters for the conditional variance and correlation, respectively, that is (see Benoît et al. (2013, p. 44))

$$\widehat{\gamma}_{m,t} = \frac{\widehat{\rho}_{i,t} \cdot \widehat{\sigma}_{i,t}}{\widehat{\sigma}_{m,t}}. \tag{C11}$$

[50] See Benoît et al. (2013, p. 42).

The conditional market Value-at-Risk $VaR_{m,t}$ is computed with the help of the estimate of the conditional variance $\widehat{\sigma}_{m,t}$. Under some general assumptions, Benoît et al. (2013, p. 43) show that

$$\widehat{VaR}_{m,t}(\alpha) = F_m^{-1}(\alpha)\cdot\widehat{\sigma}_{m,t} \tag{C12}$$

with F_m being the empirical distribution of the (unknown) true distribution of the standardized market equity returns $\left(\frac{R_{m,t}}{\sigma_{m,t}}\right)$. The ΔCoVaR defined in Eq. (C9) we refer to as EXP_ΔCoVaR in the main text. For computing CON_ΔCoVaR, i and m have to be switched in the calculations.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.techfore.2024.123968.

Data availability

The authors do not have permission to share data.

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