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Understanding the impact of the financial technology revolution on systemic risk: Evidence from US and EU diversified financials[☆]

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ABSTRACT

In this paper we first detect the impact of tech-driven downturns on US and EU diversified financials' systemic risk measures (SRMs). Then, we study the relationship between these latter and the performance of BigTechs, FinTechs and cryptoassets, as proxied by the performance of specifically built market indexes. We find that equity related tech-driven downturns exacerbate systemic risk more than crypto ones. A better performance of BigTechs reduces financial systemic risk, with an increasing magnitude under tail conditions. The interconnectedness between FinTechs and traditional financial intermediaries might end up with an increase in systemic risk even under bullish circumstances. We provide useful insights in the perspective of financial institutions' and supervisors' integration of technology-driven risk analysis into their risk management procedures and prudential supervisory practices.

1. Introduction

By changing the structure of financial intermediation, FinTech companies ("FinTechs") pose a serious threat to the sustainability of financial intermediaries' business model (Frost et al., 2019; Boot et al., 2021). The way mainstream financial intermediaries create value is significantly affected by the development of digital innovation and new technologies, which might either provide new business opportunities or trigger a disintermediation process. Technology applications to financial intermediation can foster efficiency, competition and easier consumers' access to financial products and services, but can also raise pressure on incumbents by new competitors. The implications in terms of changes in financial intermediaries' behavior, financial system stability, and supervisory standards and practices, are far from clear yet.

Due to the large stock of their users' data, BigTech companies ("BigTechs") can offer an extremely wide range of services (Chaudhry et al., 2022). Based on the so-called Data-Network-Activities loop, by taking advantage of the intrinsic network effects in digital services, BigTechs can employ their users' data to grow at a pace which raises with the volume of data generated by users' activity (Bank for International Settlements, 2019; Frost et al., 2019). This makes it easy for them to reach a systemic

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relevance within the financial sector. The growth of both BigTechs and FinTechs is based on a list of common drivers, such as access to multiple data sources, technological advances, absence of regulation, high concentration, and low competition. The interactions between these companies and the traditional financial system make this growth not free of potential systemic risks (Carstens, 2019).

The capitalization of crypto markets grew from USD 1.2 billion in 2013 to USD 1.5 trillion in mid-2023, with a peak of almost USD 3 trillion at the end of 2021, an unmatched growth rate in history (Rubbaniy et al., 2021), which is driven by investor' sentiment and perception of this new asset more than by its economic fundamentals (Burggraf et al., 2021; Acharya et al., 2012; Akyildirim et al., 2021). According to Financial Stability Board (2022), direct linkages between crypto-assets and mainstream financial system are still limited, and episodes of price volatility have not spilled over to core financial markets and to financial institutions. Nevertheless, given the rapid evolution of crypto-assets markets, as well as the raising interconnectedness of crypto-assets to financial institutions, concerns arise about the financial system stability in the future.[1] As for BigTechs and FinTechs, a complete assessment and an effective monitoring of the potential risks stemming from crypto markets are challenging, mainly due to the scant information about some of their characteristics, namely their liquidity and the extent of the use of leverage, and about the nature and size of financial intermediaries' exposure (Financial Stability Board, 2018). European Central Bank (2019) warns that the lack of hard data on exposures of supervised entities to crypto-assets is a limitation in the assessment of systemic risk.

From this paper perspective, prior works about the link between the technological revolution and financial system performance and stability typically belong to two main research areas. On the one hand, there is a group of studies that examine the return and volatility transmission across cryptocurrencies and other financial assets, the risk spillover pattern between the former and the latter (see e.g., Corbet et al., 2018; Diebold and Yilmaz, 2012; Li and Huang, 2020). Some scholars also test for the hedging and "safe heaven" properties of cryptocurrencies (see e.g., Dyhrberg, 2016; Bouri et al., 2017; Klein et al., 2018), and study the speculative bubbles that cryptocurrencies seem to be prone to (see e.g., Cheah and Fry, 2015), as well as the possibility that these bubbles may spread contagion and weaken financial stability (Yarovaya et al., 2016).

On the other hand, there is a bunch of papers specifically dealing with how technological innovation and competition by tech-driven companies can affect the structure of the banking industry and banks' provision of liquidity and loans. Works in this area deal with a series of different subjects. Some of them study the potential growth of transaction-oriented banking activities at the expense of relationship ones (Boot and Ratnovski, 2016), or examine the extent to which innovation can lower the cost of financial services (Welltrado, 2018; Fuster et al., 2019).

Many papers tackle, from both an empirical and a theoretical point of view, lending-related issues. Thakor and Merton (2018) provide a theory suggesting that, because of their access to low-cost deposit funding, banks have an advantage in developing investor trust, even if incentive problems may be more numerous and complex than those of P2P platforms. Banks appear to be more competitive than fintech lenders in relationship-based activities (Balyuk et al., 2022). Empirical evidence also shows that, by serving both marginal and infra-marginal borrowers, non-bank lenders, namely P2P platforms, compete with banks, but tend to have a competitive advantage when credit institutions experience a shock that limits their credit supply (Tang, 2019). A model of competition between banks and P2P platforms developed by De Roure et al. (2022) predicts that lending by P2P platforms is negatively correlated with bank lending and that P2P platforms can capture the riskiest and least profitable bank customers. By comparing fintech lenders with other non-bank lenders active in the mortgage credit market, Jagtiani et al. (2021) show that the former are expanding credit availability for consumers and that their market share is larger in areas characterized by lower borrowers' quality and higher denial rates. Finally, a stream of research delves into the advantages of using big data to assess credit risk (Berg et al., 2020; Bartlett et al., 2022; Fuster et al., 2022).

As for the potential threats to the financial system stemming from the three players of the tech revolution we are interested in, namely BigTechs, FinTechs and crypto-assets, Li et al. (2020) argue that FinTechs are intrinsically linked to financial institutions because: (i) they compete in similar market segments and businesses (Dorfleitner et al., 2017; Kommel et al., 2019; Yao et al., 2017);, offering financial services with digital technology (Carstens, 2019) (ii) they cooperate closely (Romānova and Kudinska, 2016); and (iii) traditional financial institutions are increasingly investing into FinTech companies (Lee and Shin, 2018). As a result, the risks inherent to FinTechs could spill over to traditional financial intermediaries, being a potential source of systemic risk (Financial Stability Board, 2017; He et al., 2017). BigTech companies act as new competitors of traditional financial intermediaries, being involved in key financial services. This competition may lead to a decrease in the market share of mainstream financial companies, implying the disruption of the classic approach to financial intermediation. Finally, as for crypto-assets, Li and Huang (2020) argue that, even if their overall penetration into financial markets is not yet deep, they have the potential to significantly increase systemic risk of traditional financial markets.

Up to date, it is not altogether clear whether the tech revolution will completely disrupt traditional financial services and activities or if it will strengthen the quality and performance of banks', insurers' and financial firms' asset portfolios (Murinde et al., 2022). Therefore, since it is reasonable to assume that there will be a future stronger interaction between tech-related companies and assets and traditional financial system, as well as that financial institutions' asset portfolios will be increasingly exposed towards technology-driven firms and assets, it becomes critical to understand the risks, in terms of financial system stability, coming from FinTechs, BigTechs and crypto-assets. We empirically tackle this issue by studying whether and how the performance of BigTechs, FinTechs and crypto-assets affects mainstream financial systemic risk. Based on what argued before about the potential transmission

[1] The channels through which vulnerabilities in crypto-assets might have systemic implications for financial stability can be summed up as follows: (i) financial sector (direct) exposures to crypto-assets; (ii) knock-on effects on the financial system stemming from impact of changes in the value of crypto-assets on their investors (wealth effect); (iii) investor confidence in crypto-asset markets; (iv) extent of crypto-assets' use in payments and settlements. For a detailed analysis, see Financial Stability Board (2018).

channels through which this might happen, from a methodological standpoint, adopting a systemic perspective is deemed necessary when studying the way how the tech revolution will change the financial system.

Even though there is a consensus about its systemic implications, to the best of our knowledge, very few papers have tried to empirically assess the effects of tech revolution on financial systemic risk (see e.g., Li et al., 2020); the rest of the extant literature investigates the relationship between tech-driven firms and assets and traditional financial system using a qualitative approach (see e.g., Romānova and Kudinska, 2016; Drasch et al., 2018; Lee and Shin, 2018). Given the lack of reliable data to directly observe the above discussed interaction channels (European Central Bank, 2019), we follow an indirect approach and make recourse to market data. We first study the reaction of US and EU financial systemic risk to downturns of BigTechs, FinTechs and crypto-assets. Then, we indirectly capture the impact of the technology revolution on financial systemic risk by observing the relationship between this risk and the level and risk of some representative BigTech, FinTech and crypto-assets indexes.

We focus our analysis on a group of financial companies, which we refer to in the rest of the paper as "diversified financial companies", or even "diversified financials" in short, which is by far less investigated than the banking sector, and includes: (i) companies active in a range of financial services and/or with some interest in different financial services including banking, insurance and capital markets, with no dominant business line; (ii) companies with significantly diversified holdings, predominantly of a non-controlling nature, across three or more sectors, none of which contributes a majority of profit and/or sales; (iii) companies providing specialized financial services, deriving a majority of revenue from one specialized line of business, such as commercial financing companies, leasing institutions, factoring services, and specialty boutiques; and, (iv) companies active in the consumer finance services, including personal credit, credit cards, lease financing, travel-related money services and pawn shops. The choice to specifically account for this type of financial intermediaries complements the extant studies in this area which are mainly bank-focused.

"Diversified financials" is a specific industry group of the Global Industry Classification Standard (GICS) that contains a range of consumer and commercially oriented companies offering a wide variety of financial products and services, including various lending products (such as home equity loans and credit cards), insurance, and securities and investment products. Most of these firms are non-banking financial companies, which, in turn, are less regulated compared to banks and insurers, and, according to Bloomberg database, account for around 55% and 25% of the market capitalization of the entire financial sector in the United States and European Union, respectively. The fundamental interconnections that such intermediaries have with FinTechs, BigTechs and crypto-assets, on one hand, and with the banking and insurance industries, as well as with the wider economy, on the other, strongly motivates us to examine how the financial technology revolution affects the systemic risk of this group of financial firms.

As far as the first part of our empirical analysis is concerned, we detect whether, to what extent and how quickly a market-based systemic risk measure (SRM) of the US and EU diversified financials, namely the delta conditional Value at Risk ($\Delta CoVaR$) developed by Adrian and Brunnermeier (2016), is sensitive to downturns related to technology-driven firms and assets. In the section of robustness tests, we replace the $\Delta CoVaR$ with the marginal expected shortfall (MES) of Acharya et al. (2017) and the $SRISK$ introduced by Brownlees and Engle (2017).[2] Overall, our results show that BigTechs, and, with an even stronger impact, FinTechs exacerbate financial systemic risk more than crypto-assets, for moderate downturn events (up to −10%). In contrast, crypto-assets are the only able to increase systemic risk for more severe downturn episodes (−15% and −20%). We also find that the BigTechs, FinTechs and crypto-assets downturns affect in a different way diversified financial companies in US and EU, with US companies' systemic risk appearing to be more sensitive to declines in the value of the Bitcoin than EU ones.

Regarding the second section of the empirical part, assessing the impact of the technology revolution on financial systemic risk, we focus on the potential effect of FinTechs, BigTechs and crypto-assets performance on the systemic risk of US and EU diversified financials. We examine the relationship between the $\Delta CoVaR$, on the one hand, and the performance of some representative FinTechs, BigTechs and crypto-assets market indexes, on the other. The BigTech sector seems to be the major source of systemic risk mitigation, since increases in the level of BigTech indexes reduce $\Delta CoVaR$, especially in tail market conditions. This effect is more pronounced in the United States than in the European Union. In contrast, financial systemic risk is positively related to the VaR and ES of BigTech companies' indexes, with generally much higher regression coefficients in tail conditions.

As for the relationship between the level of FinTech indexes and $\Delta CoVaR$, our evidence shows that it is affected by the location of the companies included in the indexes. Consistently with Li and Huang (2020), when considering the US FinTech Index we observe that a raise in its level determines an increase of US diversified financials' systemic risk. This entails a risk spillover from FinTech to financial institutions not only under a bearish situation, but also under bullish conditions, proving a high interrelationship between US FinTechs and the US financial systemic risk, with a magnitude that increases in tail conditions. Surprisingly, a better performance of US FinTechs seems to mitigate systemic risk of the EU sector of diversified financial companies, probably because of the lower penetration of this market by EU financial sectors. Furthermore, a raise in the level of the Global FinTech Index reduces systemic risk of diversified financials in both US and EU, thus confirming that the risk mitigation effect prevails when there is not a perfect correspondence between the geographical area of origin of the companies included into the index and that of the diversified financials.

Finally, we introduce into the analysis a series of dummy variables capturing downturns of different magnitude in the FinTechs, BigTechs and crypto-assets indexes, and study the interaction of the performance and risk measures of these indexes with financial systemic risk under such different conditions. We observe a mitigation of the effects of FinTech and BigTech indexes on systemic

[2] For the sake of space, in the paper we report only the results based on the $\Delta CoVaR$ and do not show the results for MES and $SRISK$, which are discussed in the online Appendix A.

risk, while crypto-assets increase systemic risk when considering both performance and risk measures during extreme outlier events. We argue that this is due to a lack in regulation for these new technology-driven assets, which, being extremely volatile, are subject to potential bubbles, with daily drops that can also exceed −20%. This is prevented in equity markets where most stock exchange regulators around the world would react to such events with market interventions – e.g., by banning or restricting short sales.

Compared to the existing studies (see, among others Li and Huang, 2020; Li et al., 2020; Murinde et al., 2022; Chaudhry et al., 2022), which alternatively focus on FinTechs, BigTechs or cryptocurrencies, our paper provides a significant contribution by comprehensively investigating how risks arising from each of these three technological-driven sectors affect financial stability assessed through market-based SRMs. The use of these SRMs allows to overcome the issues associated with the lack of data regarding the direct exposure of financial companies towards tech-driven firms and assets, and to adequately account for the interconnectedness within the financial system (Cai et al., 2018). Furthermore, investigating the impact of the technology revolution on the stability of the diversified financial companies in the United States and European Union allows to further deepening financial systemic risk and shedding more light on its determinants within a unique setting, providing useful insights to prove the link between the tech-driven world and traditional financial system, and to prevent potential episodes of financial instability.

The remainder of the paper is organized as follows. In Section 2 we outline the systemic risk models focusing on the estimation of $\Delta CoVaR$, the main hypotheses and the methodologies we use to test them. Section 3 describes the data used for the empirical analysis. Results are discussed in Section 4, whereas Section 5 provides concluding remarks and discusses some policy implications.

2. Methodology and hypotheses

In Section 2.1, we present the methodology used to estimate the systemic risk of US and EU diversified financial companies. We use the $\Delta CoVaR$ as proposed by Adrian and Brunnermeier (2016). As discussed in Section 2.2, we perform a formal test to investigate whether, to what extent and how quickly this market-based systemic risk measure incorporates the information deriving from a downturn of: (i) US and EU BigTech sector; (ii) Global and US FinTech sector; and, (iii) a composite crypto index and the Bitcoin, which is the largest crypto-asset by market cap. In Section 2.3, we describe the quantile regression method through which we investigate the impact of technology and digital finance on the stability of the diversified financials in US and EU. We indirectly capture the impact of the technology development on financial systemic risk by observing the relationship between this risk and the level and risk, measured in terms of VaR and ES, of the BigTech, FinTech and crypto-assets indexes.

2.1. Measuring systemic risk

Adrian and Brunnermeier (2016) introduced the $\Delta CoVaR$ as a measure for market-based systemic risk, which is based on the most common risk measure used by financial institutions, namely the VaR.[3] The VaR focuses on the risk of an individual institution in isolation, which does not necessarily represent its contribution to the overall systemic risk. To emphasize the systemic nature of this risk measure, Adrian and Brunnermeier (2016) added the prefix "Co", which stands for "conditional".

We define the $\Delta CoVaR^i$ as the conditional VaR of the US and EU sector of diversified financial companies (i) that is conditional on the financial system being in a tail condition. We estimate $\Delta CoVaR^i$ as the difference between the $CoVaR$ of our financial sector i conditioned on the distress of the financial system and its $CoVaR$ conditioned on the median state. We denote the q% VaR quantile by $VaR_{q,Market}$:

$$Pr(X_{Market} \leq VaR_{q,Market}) = q\% \tag{1}$$

where X_{Market} is the US or the EU financial system's *"return loss"* for which $VaR_{q,Market}$ is defined. $CoVaR_q^{i|C(X_{Market})}$ is the VaR of sector i that is conditional on some event $C(X_{Market})$ in that financial system. Event C is an event equally likely across institutions, such as the financial system's loss at or above its $VaR_{q,Market}$. $CoVaR_q^{i|C(X_{Market})}$ is implicitly defined by the q%-quantile of the conditional probability distribution:

$$Pr(X^{i|C(X_{Market})} \leq CoVaR_q^{i|C(X_{Market})}) = q\% \tag{2}$$

The $\Delta CoVaR$ of sector i that is conditional on the entire financial system being under distress is computed as follows:

$$\Delta CoVaR_q^i = CoVaR_q^{i|X_{Market}=VaR_{q,Market}} - CoVaR_q^{i|X_{Market}=VaR_{50\text{th},Market}} \tag{3}$$

We use a quantile regression to estimate $\Delta CoVaR$. In particular, following Adrian and Brunnermeier (2016), we estimate the following[4]:

$$X_{q,i} = \alpha_q + \beta_q X_{q,Market} \tag{4}$$

where $X_{q,i}$ and $X_{q,Market}$ denote sector i and the financial system return loss, respectively. Using the predicted value of $X_{Market} = VaR_{q,Market}$, we yield the $CoVaR_{q,i}$ measure as follows:

$$CoVaR_q^i = VaR_q^{i|X_{Market}=VaR_{q,Market}} = \hat{\alpha}_q + \hat{\beta}_q VaR_{q,Market} \tag{5}$$

[3] For several studies providing extensions of the $\Delta CoVaR$ estimation method see among others Girardi and Ergün (2013), López-Espinosa et al. (2012), Reboredo and Ugolini (2015) and Sedunov (2016).

[4] For simplicity of exposition we drop the index notation and the error term from the regression equation.

where $VaR_{q,Market}$ is the q%-quantile of the financial system losses. Based on Eq. (3), we estimate $\Delta CoVaR_q^i$ as:

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_q^{i|X_{Market}=VaR_{50\text{th},Market}} = \hat{\beta}_q(VaR_{q,Market} - VaR_{50\text{th},Market}) \tag{6}$$

Based on Eq. (6), we estimate $\Delta CoVaR_{95\text{th}}^i$ as the difference between the predicted $CoVaR$ at the 95th quantile and the one at the 50th quantile.

Our study considers an equity loss with positive values. For this reason, in the empirical results, we consider only positive values for $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$, because a negative capital shortfall indicates a capital surplus.[5]

2.2. Testing systemic risk during technology driven market downturns

As in Morelli and Vioto (2020) and Curcio et al. (2023), to analyze the impact of a market downturn driven by BigTechs, FinTechs and crypto-assets, we use the Wilcoxon signed rank sum test for paired data, which allows to test whether, to what extent and how quickly SRMs of US and EU sectors of diversified financial companies react to drops ranging from −2.5% to −20% of market indexes built on technology-driven firms and assets. By using different thresholds to define a downturn episode, namely a decrease of at least −2.5%, −5%, −7.5%, −10%, −15% or −20%, we investigate whether the level of systemic risk of the US and EU diversified financials observed during the five days after a downturn is greater than that recorded five days before, thus applying the Wilcoxon signed rank sum test to the following null hypothesis:

$$H_0 : SRM_{t:t+4}^i \leq SRM_{t-5:t-1}^i \tag{7}$$

$$H_1 : SRM_{t:t+4}^i > SRM_{t-5:t-1}^i \tag{8}$$

where i indicates the US or EU sector of diversified financial companies and t is the day when the FinTech, BigTech or crypto-assets index falls under the six considered thresholds defined above. The failure to reject the null hypothesis (7) implies that the market does not perceive an increase in systemic risk due to a fall of a tech-driven index.

2.3. Investigating the relationship between systemic risk and the financial-technology revolution

To detect the potential impact of technology developments on financial systemic risk, we adopt an indirect approach and argue that: (i) BigTech and FinTech companies' performance gets better as the transition to a more technologically driven economy goes on; (ii) crypto-assets performance is not necessarily related to the transition to a more technologically driven economy, being affected by investors' sentiment more than economic fundamentals (Burggraf et al., 2021; Acharya et al., 2012; Akyildirim et al., 2021); (iii) the performance of BigTechs, FinTechs and crypto-assets does reflect in the performance measures, in terms of level and risk, of BigTech, FinTech and crypto-assets market indexes specifically built by market data providers. Therefore, we investigate the impact of the technological revolution on the financial system stability by assessing the relationship between the level and risk of some representative BigTech, FinTech and crypto-assets indexes and the $\Delta CoVaR$ of US and EU diversified financials.

To do that, we use the quantile regression method (Koenker and Bassett, 1978; Koenker, 2005), which allows to account for the information in the tails of the distribution and permits to alleviate some of the statistical issues due to outliers, which can significantly affect the tail values of a distribution, and distort the estimated relationship coefficients, when studying systemic risk dynamics (Härdle and Song, 2010). Therefore, we use quantile regressions to test whether the dynamics of indirect systemic contagion from BigTechs, FinTechs and crypto-assets to diversified financials are sensitive to different quantiles. To this end, we examine the relationship between diversified financials' $\Delta CoVaR$, on the one hand, and the level and risk of BigTech, FinTech and crypto-assets indexes, on the other.

In the simplest terms, we run the following quantile regression:

$$y_i = \alpha_\tau + \beta_\tau x_i' + \varepsilon_{\tau,i} \tag{9}$$

where y_i is the $\Delta CoVaR$; x_i' is the independent variable represented by performance and risk measures of FinTech, BigTech or crypto-assets indexes; α_τ is the constant; β_τ is the vector of the estimated relationship coefficients, and ε_τ is the error term. The subscript $\tau \in (0,1)$ represents the quantile. We write the τth conditional quantile function as $Q_\tau(y|x) = \beta_\tau x'$.

The estimator $\hat{\beta}_\tau$ is computed by minimizing the weighted sum of the absolute errors, where the weights are dependent on the quantile values:

$$\hat{\beta}_\tau = arg\ min\left(\sum_{i=y_i>x_i'\beta_\tau} \tau\left|y_i - x_i\beta_\tau\right| \quad + \sum_{i=y_i<x_i'\beta_\tau} (1 - -\tau)\left|y_i - x_i\beta_\tau\right| \right) \tag{10}$$

When distressful conditions are technologically driven, financial stability may be threatened by disinvestment in such type of assets or by the deterioration of their value. This may exacerbate systemic risk due to the losses that some financial companies have

[5] We estimate negative values for $VaR_{q,t}^i$ and $CoVaR_{q,t}^i$ only at the 50th quantile, which represents the median state, so the absence of a distress for sector i.

to recognize for being directly exposed towards tech-driven firms or assets, for example due to direct investments in the form of equity stakes or loans issued. Then, due to the interconnectedness characterizing the overall financial system, instability spills from these directly exposed financial companies over other financial institutions, which, even with no direct exposure towards tech-driven assets or firms, are exposed to a contagion risk. Thus, we use Eq. (11) to investigate the interaction between a technologically driven downturn due by BigTechs, FinTechs or crypto-assets and systemic risk as follows:

$$y_i = \alpha_\tau + \beta_\tau D^{Down} x_i' + \varepsilon_{\tau,i} \tag{11}$$

where D^{Down} is a dummy variable that equals 1 if the variable used to measure the downturn of BigTechs, FinTechs or crypto-assets on day t is lower than a certain threshold and 0 otherwise.

Overall, we expect a negative (positive) association between the level (risk) of BigTech indexes and financial systemic risk because the nature of the link between financial intermediaries and BigTechs is not different from that of the relationship between the former and other companies in which they invest, irrespective of the different forms their investments can take (equity stake, loans, etc.). This means that we do expect to find a mitigation effect of the systemic risk of diversified financials following a raise in the level of BigTech indexes and a reinforcement effect of the systemic risk in the case of higher VaR or ES of the same indexes. When investigating the link between FinTechs and US and EU diversified financials, we do not expect the same as for BigTechs, because the nature of this link is different, as already found by previous studies. In particular, Li et al. (2020) find that FinTechs' risk spillover to financial institutions positively correlates with financial institutions' increase in systemic risk, with linkages in the network that are stronger in the bearish case. Thus, we expect a positive relationship between the level, but also the risk, of FinTechs and systemic risk of diversified financial companies, being FinTech sector strongly interconnected with the traditional financial sector. Finally, we expect the same relationships between the level and risk of crypto-assets indexes and financial systemic risk, mainly due to the nature of such assets, which cannot be considered a currency (Draghi, 2018) and positively correlate with downward markets (Klein et al., 2018).

The quantile regression focuses on estimating the interrelation between the dependent variables and their predictors at the median level ($\tau = 0.5 = 50$th) and at any other specific quantile. In our study, we consider estimates at the 5th, 10th, 50th, 90th and 95th quantiles. In the literature, low quantiles (e.g., up to the 50th) are considered tranquil periods in the market, while high quantiles (e.g., above the 75th) represent distress in the market (see, e.g., Adrian and Brunnermeier, 2016).

3. Data

To estimate $\Delta CoVaR$ for US and EU diversified financials, we collect data on the daily equity prices of the S&P 500 Diversified Financials Industry Group GICS Level 2 and STOXX Europe 600 Diversified Financials Industry Group GICS Level 2, respectively. GICS is a four-tiered, hierarchical industry classification system. The four tiers are: Sectors, Industry Groups, Industries and Sub-Industries. In our estimates, we condition the analysis of the Diversified Financials Industry Group on the financial sector, which is represented by the S&P 500 Financials Sector GICS Level 1 Index for the United States, and by the STOXX Europe 600 Financials Sector GICS Level 1 Index for the entire European financial system. We are strongly motivated to consider the GICS framework[6] because it has become widely recognized by market participants worldwide and enables meaningful comparisons of sectors and industries. Moreover, MSCI and Standard & Poor's review the entire framework annually to ensure an accurate representation of the marketplace. The market-based SRMs are estimated over the period from January 3, 2006 to December 31, 2021.

The BigTech related indexes we consider are the S&P 500 Technology Index and the STOXX Europe 600 Technology Index, which respectively include US and European companies that are classified as members of the GICS information technology sector. In both cases, data refer to the period ranging from January 3, 2006 to December 31, 2021. To represent the FinTech industry, we collect daily prices of the Global FinTech Index, from January 5, 2011 to December 31, 2021, which aims to benchmark the Global FinTech industry, and of the US FinTech Index, from June 30, 2015 to December 31, 2021, which is used to measure exposures towards US Fintech companies. Finally, as for the crypto-assets, we consider the Bloomberg Galaxy Crypto Index, from August 2, 2017 to December 31, 2021, to measure the performance of the largest crypto-assets traded in USD, and the Currency XBT Bitcoin, from July 19, 2010 to December 31, 2021, which is the world's largest crypto-asset by market capitalization.

All the data used in this paper are downloaded from Bloomberg, where they are readily available.

Table 1 presents descriptive statistics, in terms of mean, median, standard deviation, skewness, minimum and maximum values, of: (i) the $\Delta CoVaR$ of the US and EU diversified financials; (ii) the level, VaR and ES of BigTech, FinTech and crypto-assets indexes and Bitcoin.[7] The mean $\Delta CoVaR$ for diversified financial companies in US is slightly higher than that in EU. US diversified financials are characterized by a greater standard deviation and a larger difference between minimum and maximum values of $\Delta CoVaR$, particularly due to a much higher maximum value (16.65 vs. 10.08 for US an EU, respectively), whereas minimum respective values are very close (1.03 for US and 1.14 for EU). Finally, Bitcoin shows the greater volatility for all the performance measures, i.e., level, VaR and ES, which confirms that this crypto-asset is subject to huge fluctuations. Interestingly, the Blooomberg Galaxy Crypto Index, which includes Bitcoin together with other crypto-assets reports a much lower standard deviation than the Bitcoin stand-alone.

[6] For a detailed description of the GICS methodology, readers can refer to: "Global Industry Classification Standard (GICS) Methodology", Standard & Poor's, 2009; or, https://www.msci.com/gics.

[7] We estimate non-parametric historical VaR and ES at 5% confidence level, using a 1-year moving window. The VaR is the realized loss of the index at the 95th quantile each day t; while the ES is the average of the worst 5% realizations of the index each day t.

Table 1
Descriptive statistics of the $\Delta CoVaR$ of US and EU diversified financial companies, BigTech, FinTech and crypto-assets indexes.

	Mean	Median	Std. dev.	Skewness	Min	Max	Sample period	Obs.
$\Delta CoVaR^{Div.\ Fin.,United\ States}$	3.66	2.15	3.49	2.42	1.03	16.65	Jan. 3, 2006–Dec. 31, 2021	4028
$\Delta CoVaR^{Div.\ Fin.,European\ Union}$	3.36	2.79	1.97	1.62	1.14	10.08		4028
S&P 500 Technology Index	823.48	570.07	634.95	1.63	198.51	3107.46		4028
VaR	2.16	2	0.95	1.35	0.86	4.7		4028
ES	3.08	2.81	1.33	1.36	1.48	6.41		4028
STOXX Europe 600 Technology Index	1337.95	1189.94	635.94	1.35	486.88	3592.87		4028
VaR	2.34	2.21	0.81	1.04	1.09	4.67		4028
ES	3.27	3	1.14	1.2	1.7	6.49		4028
Global FinTech Index	265.43	224.48	134.06	0.77	86.37	587.56	Jan. 5, 2011–Dec. 31, 2021	2767
VaR	1.54	1.41	0.54	0.79	0.72	2.89	Jan. 6, 2012–Dec. 31, 2021	2515
ES	2.45	2.07	1.22	1.71	0.94	5.88		2515
US FinTech Index	2043.01	1925.8	891.16	0.67	889.53	4060.39	June 30, 2015–Dec. 31, 2021	1640
VaR	2.14	2.41	0.67	−0.23	0.99	3.13	July 1, 2016–Dec. 31, 2021	1388
ES	3.31	3.19	1.33	0.85	1.51	5.89		1388
Bloomberg Galaxy Crypto Index	950.97	486.04	918.95	1.47	197.59	3870.42	Aug. 2, 2017–Dec. 31, 2021	1113
VaR	8.5	8.16	1.34	0.23	6.45	11.06	Aug. 3, 2018–Dec. 31, 2021	861
ES	12.62	12.64	1.29	0.01	9.34	15.30		861
Currency XBT Bitcoin	6896.44	617.38	13 551.87	2.70	0.05	67 734.04	July 19, 2010–Dec. 31, 2021	2886
VaR	8.02	7.42	3.17	1.13	2.81	18.47	July 20, 2011–Dec. 31, 2021	2634
ES	13.52	11.76	5.21	1.00	6.37	27.29		2634

Notes: This table contains the descriptive statistics for the $\Delta CoVaR$ of US and EU diversified financial companies and for the BigTech, FinTech and crypto-assets indexes. As stated in Section 2, the $\Delta CoVaR$ is estimated considering an equity loss with positive values.

Table 2
Dummy variables related to downturn episodes for BigTech, FinTech and crypto-assets indexes.

	$D^{-2.5\%}$	$D^{-5\%}$	$D^{-7.5\%}$	$D^{-10\%}$	$D^{-15\%}$	$D^{-20\%}$
S&P 500 Technology Index	157	20	6	2	0	0
STOXX Europe 600 Technology Index	198	23	4	2	0	0
Global FinTech Index	49	9	4	2	0	0
US FinTech Index	72	8	4	2	0	0
Bloomberg Galaxy Crypto Index	254	125	74	42	13	5
Currency XBT Bitcoin	528	293	181	103	47	21

Notes: This table shows the frequency of downturns in BigTech, FinTech and crypto-assets indexes according to the thresholds indicated in the header of each column. D^{-x} is a dummy equal to 1 if the respective index experiences a decline equal or greater than x, with x being alternatively 2.5%, 5%, 7.5%, 10%, 15% and 20%.

We define market downturns episodes for the BigTechs, FinTechs and crypto-assets indexes by estimating six different dummy variables for each of the respective indexes. These dummies equal 1 if, on a certain day t, the index decline is lower than: (i) −2.5%, and 0 otherwise ($D^{-2.5\%}$); (ii) −5%, and 0 otherwise ($D^{-5\%}$); (iii) −7.5%, and 0 otherwise ($D^{-7.5\%}$); (iv) −10%, and 0 otherwise ($D^{-10\%}$); (v) −15%, and 0 otherwise ($D^{-15\%}$); (vi) −20%, and 0 otherwise ($D^{-20\%}$). Table 2 reports the frequency of the downturn episodes for any of the six thresholds defined above, and shows that we do not observe any event for the two worst downturn scenarios (−15% and −20%) for both BigTech and FinTech indexes, while this magnitude extreme events are found for crypto-assets related indexes, and, not surprisingly based on the comments referred to the respective volatility measures, more for the Bitcoin than for the Bloomberg Galaxy Crypto Index. We use these dummies to test the hypotheses discussed in Section 2.2 and to interact with the regression coefficients in Eq. (11).

4. Results

In Section 4.1 we discuss the results of the empirical analysis of the impact of tech-driven downturns on financial systemic risk, which we study by examining the reaction of US and EU diversified financial companies' $\Delta CoVaR$ to downturn events referred to BigTech, FinTech and crypto-assets market indexes. Section 4.2 presents the evidence resulting from the indirect analysis of the effects of the technology revolution on systemic risk, which we conduct by investigating the relationship between BigTech, FinTech and crypto-assets market indexes, on the one hand, and the $\Delta CoVaR$ of US and EU diversified financial companies, on the other. To deepen our findings, in Section 4.3 we present the results from the analysis of the effects of the technology revolution on systemic risk when interacted with dummies that reflect different severity of tech-driven downturns.

4.1. Systemic risk reaction to tech-driven downturns

Table 3 presents the results of the Wilcoxon signed rank sum test used to test the hypotheses discussed in Section 2.2. We consider a significance threshold of 5% to reject the null hypothesis. For each index and for each threshold used to define a downturn event, we calculate the success ratio, i.e., the ratio of the number of times in which the $\Delta CoVaR$ of the US or EU diversified financial

Table 3
Success ratio of the $\Delta CoVaR$ of US and EU diversified financial companies in reacting to BigTech, FinTech and crypto-assets downturns.

Panel A: United States							
	Threshold	S&P 500 Technology Index	STOXX Europe 600 Technology Index	Global FinTech Index	US FinTech Index	Bloomberg Galaxy Crypto Index	Currency XBT Bitcoin
$\Delta CoVaR$	x ≤ −2.5%	61.78%	55.56%	71.43%	52.78%	31.50%	30.11%
	x ≤ −5%	75.00%	56.52%	88.89%	87.50%	34.40%	34.13%
	x ≤ −7.5%	83.33%	50.00%	100.00%	100.00%	37.84%	34.81%
	x ≤ −10%	100.00%	50.00%	100.00%	100.00%	38.10%	34.95%
	x ≤ −15%	*NA*	*NA*	*NA*	*NA*	46.15%	34.04%
	x ≤ −20%	*NA*	*NA*	*NA*	*NA*	60.00%	52.38%
Panel B: European Union							
	Threshold	S&P 500 Technology Index	STOXX Europe 600 Technology Index	Global FinTech Index	US FinTech Index	Bloomberg Galaxy Crypto Index	Currency XBT Bitcoin
$\Delta CoVaR$	x ≤ −2.5%	62.42%	62.63%	75.51%	55.56%	38.19%	33.33%
	x ≤ −5%	90.00%	73.91%	88.89%	100.00%	35.20%	31.74%
	x ≤ −7.5%	100.00%	75.00%	75.00%	100.00%	41.89%	32.04%
	x ≤ −10%	100.00%	50.00%	100.00%	100.00%	40.48%	29.13%
	x ≤ −15%	*NA*	*NA*	*NA*	*NA*	53.85%	27.66%
	x ≤ −20%	*NA*	*NA*	*NA*	*NA*	40.00%	52.38%

Notes: This table shows the success ratio of the Wilcoxon signed rank sum test aiming to determine whether the systemic risk of the US and EU diversified financial sector during the 5 trading days after a drop of x of the related BigTech, FinTech or crypto-assets indexes, is greater than the systemic risk observed 5 days before. Rows indicate the threshold x used to test the null hypothesis ($H_0 : SRM^i_{t:t+4} \leq SRM^i_{t-5:t-1}$) of Eq. (7). The failure to reject this hypothesis means that the systemic risk level did not increase after the event. The significance threshold used for the test is set at 5% level.

companies sector referred to the five days after the event is significantly higher than that of the five days before, out of the total number of cases in which the decline in the index has been larger than the threshold. Our results show that the BigTech, FinTech and crypto-assets downturns affect in a different way diversified financial companies' systemic risk in US and EU. On average, it seems that EU diversified financials are more sensitive to downturns occurred to the BigTech and FinTech indexes, with an average success ratio larger than that observed for the US, except for the Global FinTech Index. Further, in the case of the BigTech and FinTech indexes, success ratios referred to EU diversified financials are equal to those calculated for US companies for declines of the indexes greater than or equal to −10% and nihil for the worst two thresholds, where, as already highlighted in Table 2, we do not observe any downturn event. As far as the two indexes of the crypto-assets are concerned, we do not observe a significant difference in the reaction of EU and US diversified financial companies' systemic risk to downturns in the Bloomberg Galaxy Crypto Index, whereas US companies' systemic risk appears to be more sensitive to declines in the value of the Bitcoin than EU ones. With regard to the Bloomberg Galaxy Crypto Index, the average success ratios calculated over all the thresholds are 41.33% and 41.60% for the US and EU companies, respectively; they are 36.74% for US diversified financials and 34.38% for EU ones when we examine the reaction to Bitcoin downturns. Contrary to what we observe for BigTech and FinTech indexes, success ratios referred to crypto-assets indexes never reach the value of 100%.

Diversified financials' systemic risk seems to react more to a BigTech or FinTech indexes downturn than in the case of a drop in crypto-assets indexes, both in the United States and the European Union. Interestingly, a downturn in the US BigTech sector, represented by a decline of the S&P 500 Technology Index, causes a significant increase also in the systemic risk of EU diversified financial companies, with these latter that actually react more than US ones (the average success ratio across all the thresholds is equal to 58.74% in the EU and 53.35% in the US). In terms of the speed of reaction, the success ratio reaches the maximum value of 100% for the −7.5% and −10% thresholds in the EU and only at the −10% threshold in the US. In contrast, the spillover risk effect of the EU BigTech sector to the systemic risk of US diversified financials seems to be more contained: the average success ratio is 35.35% for the US companies and 43.59% for the EU ones.

A drop in both Global FinTech and US FinTech indexes exacerbates systemic risk in the United States and the European Union. We are not dealing with huge differences across the two geographical areas, since, as for the Global FinTech Index, the average success ratio over all the thresholds is 60.05% for US and 56.57% for EU, and, as far as the US FinTech Index is concerned, average success ratios are 56.71% and 59.26%, respectively. Nevertheless, it is interesting to point out that the Global FinTech Index seems to affect the systemic risk of diversified financials in the United States more than in the European Union; EU financial intermediaries we take into account react more quickly to a drop in the US FinTech sector, reaching a 100% success ratio already at the 5% threshold.

Crypto-assets performance can determine a significant increase in the systemic risk of the diversified financial companies active in the two geographical zones, even if with success ratios by far lower than those recorded for BigTech and FinTech indexes at the −2.5%, –5%, −7.5% and −10% thresholds set to measure the intensity of their downturns. A drop in the Bloomberg Galaxy Crypto Index has quite a homogeneous effect in the United States and the European Union, with average success ratios calculated for all the thresholds accounted for equal to 41.33% and 41.60%, respectively. When the Bitcoin is considered, US diversified financials' systemic risk reacts with an average success ratio across all the thresholds that is slightly higher than EU companies, i.e., 36.74% and 34.38%, respectively. Overall, the differences between US and EU diversified financials are not so relevant to entail a different

Table 4
$\Delta CoVaR$ of US and EU diversified financial companies and BigTech, FinTech and crypto-assets indexes.

Panel A: US diversified financials

	S&P 500 Technology Index			STOXX Europe 600 Technology Index			Global FinTech Index			US FinTech Index			Bloomberg Galaxy Crypto Index			Currency XBT Bitcoin		
	Index	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*
OLS	−0.137***	1.826***	2.901***	−0.207***	2.482***	3.611***	−0.057***	0.783***	1.731***	0.042***	0.750***	1.147***	−0.005	0.268***	0.567***	0.001	0.055***	0.088***
$adj.R^2$	6.16%	48.44%	61.76%	14.13%	65.59%	69.33%	0.43%	73.42%	71.64%	13.68%	87.34%	50.94%	2.08%	8.15%	39.99%	2.00%	6.25%	6.02%
Quantile																		
τ = 5th	0.029***	0.531***	0.933***	0.031***	1.211***	1.781***	−0.062***	0.523***	0.686***	0.020***	0.360***	0.393***	−0.005	−0.139	−0.149	−0.003	0.012***	0.005**
$adj.R^2$	4.50%	20.47%	21.05%	1.25%	24.92%	27.26%	69.16%	83.52%	80.42%	83.82%	90.37%	88.70%	86.83%	90.76%	90.56%	65.78%	71.54%	71.09%
τ = 10th	0.030***	0.601***	1.000***	0.024***	1.336***	2.052***	−0.035**	0.685***	0.771***	0.016***	0.410***	0.349***	0.012***	−0.115	−0.109	0.005***	0.008***	−0.008***
$adj.R^2$	3.28%	20.38%	21.35%	0.60%	25.90%	29.41%	69.86%	84.80%	80.50%	84.47%	90.69%	88.71%	87.53%	90.77%	90.79%	66.82%	72.07%	71.91%
τ = 50th	−0.018***	1.169***	2.478***	−0.065***	1.704***	2.162***	−0.047***	0.698***	1.663***	0.001	0.763***	0.935***	0.000	−0.157	−0.444	−0.002***	−0.005***	−0.011**
$adj.R^2$	0.51%	22.53%	29.05%	2.10%	35.06%	37.01%	72.90%	88.98%	85.81%	86.54%	94.75%	89.36%	88.88%	90.44%	91.32%	69.48%	74.58%	74.59%
τ = 90th	−0.299***	3.326***	3.925***	−0.304***	3.337***	4.797***	−0.049***	1.405***	2.288***	0.118***	0.750***	1.571***	−0.013**	−0.149	−0.717	−0.002*	0.069***	0.052***
$adj.R^2$	11.02%	59.19%	60.81%	16.28%	60.23%	61.15%	82.55%	92.03%	92.87%	92.76%	98.13%	96.35%	93.40%	95.54%	96.94%	82.23%	83.92%	83.61%
τ = 95th	−0.498***	3.661***	4.003***	−0.477***	3.516***	5.123***	−0.087***	1.410***	2.331***	0.126***	0.740***	1.589***	−0.012***	−0.124	−0.727	−0.006***	0.046***	0.051***
$adj.R^2$	20.36%	57.91%	61.18%	25.17%	59.39%	64.18%	85.98%	93.12%	94.15%	93.88%	98.39%	96.95%	94.80%	96.42%	97.47%	85.58%	87.08%	86.88%

Panel B: EU diversified financials

	S&P 500 Technology Index			STOXX Europe 600 Technology Index			Global FinTech Index			US FinTech Index			Bloomberg Galaxy Crypto Index			Currency XBT Bitcoin		
	Index	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*
OLS	−0.051***	1.115***	1.683***	−0.101***	1.473***	2.095***	−0.126***	0.799***	1.820***	−0.033***	0.803***	1.191***	0.026***	0.459***	0.792***	0.001	0.033***	0.029***
$adj.R^2$	2.55%	56.99%	65.56%	10.60%	72.81%	73.56%	1.65%	55.70%	57.77%	5.48%	65.64%	35.97%	2.81%	17.35%	56.26%	2.03%	1.68%	0.44%
Quantile																		
τ = 5th	0.001	0.405***	0.477***	−0.029***	0.622***	0.848***	−0.407***	0.486***	0.570***	−0.056***	0.537***	0.460***	−0.005**	−0.164	−0.174	−0.006***	0.048***	−0.173***
$adj.R^2$	0.02%	8.28%	9.31%	1.46%	21.05%	21.29%	51.12%	62.88%	59.95%	71.26%	81.02%	78.12%	81.43%	86.24%	85.79%	42.39%	49.16%	49.82%
τ = 10th	−0.004	0.339***	0.685***	−0.054***	0.922***	1.068***	−0.358***	0.533***	0.652***	−0.056***	0.417***	0.456***	0.012	−0.162	−0.178	−0.003***	0.038***	−0.162***
$adj.R^2$	0.03%	8.86%	11.10%	2.73%	22.93%	24.53%	51.02%	62.88%	60.06%	71.03%	80.77%	78.23%	81.22%	85.92%	85.60%	42.19%	49.27%	49.97%
τ = 50th	−0.013***	1.021***	1.462***	−0.109***	1.218***	1.884***	−0.049	0.760***	1.887***	0.001	0.913***	0.924***	0.038***	−0.423	−0.800	0.001***	−0.039***	−0.011***
$adj.R^2$	0.25%	31.80%	35.84%	3.53%	42.12%	44.03%	49.22%	71.18%	71.00%	71.32%	84.89%	77.42%	82.31%	84.62%	88.77%	46.22%	51.99%	52.74%
τ = 90th	−0.0452***	1.644***	1.973***	−0.115***	1.816***	2.521***	−0.071***	1.301***	2.135***	−0.068***	0.583***	1.212***	0.012***	−0.178	−0.993	0.001	0.079***	0.071***
$adj.R^2$	2.66%	56.79%	57.02%	5.75%	68.46%	65.57%	61.55%	77.09%	79.81%	83.04%	90.34%	88.25%	83.65%	89.44%	93.53%	60.55%	65.46%	64.77%
τ = 95th	−0.196***	1.565***	1.889***	−0.235***	1.833***	2.556***	−0.077***	1.059***	2.057***	−0.065***	0.513***	1.056***	0.007***	−0.200	−1.000	0.001***	0.041***	0.058***
$adj.R^2$	13.25%	64.89%	66.24%	19.35%	74.23%	70.23%	70.96%	81.35%	84.22%	87.25%	92.20%	90.83%	87.87%	92.05%	94.92%	69.64%	73.71%	73.36%

Notes: The coefficients from the time series regression analysis with the $\Delta CoVaR$ as the dependent variable for the US and EU diversified financial sector. The independent variables are listed in the header of each column. Intercept results are not reported for the sake of space.

* Indicate significance at 10% level.

** Indicate significance at 5% level.

*** Indicate significance at 1% level.

impact of the performance of the crypto-assets indexes. From a policy perspective, we argue that while adequate measures to prevent that losses spillover from BigTech and FinTech exist in equity markets – e.g., bans on short selling and/or suspended trading; this is not the case for crypto-assets, for which a call for regulation and monitoring is required.

4.2. Systemic risk and technology revolution

The tech revolution is expected to cause tremendous changes in the asset portfolios of financial intermediaries, presumably with an increase of their exposure towards BigTechs, FinTechs and crypto-assets. From a financial stability perspective, this calls for a more in-depth analysis of the relationship between technology-driven assets' performance and financial companies' systemic risk. We indirectly tackle this issue by investigating whether and how BigTech, FinTech and crypto-assets indexes affect the $\Delta CoVaR$ of the sector of US and EU diversified financial companies (see Table 4). Moreover, we compare these estimates with those obtained when risk measures — i.e., VaR and ES; are regressed against the same SRM. Studying the impact of the performance, in terms of level and risk, of technology-driven firms and assets on the diversified financials' systemic risk allows us to draw policy implications related to the risks that the tech-revolution poses on the overall stability of the financial system. To perform this analysis, we implement a classical linear regression model, together with quantile regressions providing detailed and specific information about the tails of the distribution.

Table 4 shows the estimates of the regressions with $\Delta CoVaR$ as dependent variable and BigTech, FinTech or crypto-assets indexes as explanatory ones, with Panels A and B respectively referring to the US and EU diversified financial companies. In the column labeled "Index", we study the relationship between the level of the specific BigTech (headers 1 and 2), FinTech (headers 3 and 4) and crypto-assets (headers 5 and 6) index and $\Delta CoVaR$; in the columns labeled "VaR" and "ES", we investigate the impact on $\Delta CoVaR$ of an increase in the riskiness of tech-driven assets measured by VaR and ES of our BigTech, FinTech and crypto-assets indexes. Overall, under extreme market conditions – i.e., 90th and 95th quantiles; we find higher values of the adjusted-R^2 when FinTech and crypto-assets indexes are regressed against $\Delta CoVaR$, which suggests that both the US and EU diversified financials' systemic risk is more sensitive to tail movements in the level and risk of these types of firms/assets.

The BigTech sector seems to be the major source of systemic risk mitigation. The relationship between the level of BigTech indexes and $\Delta CoVaR$ is overall negative for diversified financials, with a magnitude that increases in tail market conditions. This indicates that when BigTech companies experience a positive performance – i.e., the BigTech indexes raise; systemic risk decreases, and suggests that the better their performance, the stronger is this mitigation effect. This effect is more pronounced in the United States, where the coefficients double, or more, those observed for EU diversified financials. In contrast, financial systemic risk is positively related to the VaR and ES of BigTech companies' indexes, with generally much higher regression coefficients in tail conditions. This entails that when these companies experience extremely negative results, and the risk stemming from being exposed towards them rises to very high levels, their contribution to systemic risk becomes more sizeable than when their riskiness is at an ordinary level. Again, we observe a greater effect for the US financial companies we are interested in.

The relationship between the level of FinTech indexes and $\Delta CoVaR$ is dependent on the location of the companies included into the indexes. When considering the US FinTech Index, we observe that a raise in its level determines an increase in the systemic risk of the diversified financials in the United States. Consistently with Li and Huang (2020), this entails a risk spillover from FinTech to financial institutions not only under a bearish situation, but also under bullish conditions, proving a high interrelationship between US FinTechs and the US financial systemic risk, with a magnitude that increases in tail conditions. We argue that positive tail conditions for the level of this index may be seen related to subsequent and sudden drop of the index itself caused by investors fear, thus entailing an increase in systemic risk. Surprisingly, a better performance of US FinTechs seems to mitigate systemic risk of the EU sector of diversified financial companies. This might be due to a lower penetration of this market by EU financial intermediaries.

In analyzing the Global FinTech Index we observe that a raise in its level reduces systemic risk of diversified financials in both US and EU, thus confirming that the risk mitigation effect prevails when there is not a perfect correspondence between the geographical area of origin of the companies included into the index and that of the diversified financials whose systemic risk we are interested in. In contrast, for both US and EU, systemic risk of diversified financials is positively related to the VaR and ES of FinTech companies' indexes, with regression coefficients that even double in tail conditions, even if they are lower than those observed for BigTechs. Based on these results, the market perceives a drop in the value of BigTech companies as more relevant, in terms of financial systemic risk, compared to that in the value of FinTechs. This might first be explained with FinTechs' lower size and younger age, compared with the BigTechs. Carstens (2019) highlights that the market capitalization of large tech companies is in some cases larger than the world's largest financial institutions and, we add, systematically larger than FinTech firms. Following Restoy (2022), we also believe that the larger impact of BigTech on diversified financials' systemic risk can be explained by a sort of "confidence (or knowledge) effect": many of the risks that BigTechs generate in the perspective of the adequate functioning of traditional financial markets stem from the mix of financial and non-financial activities that they perform. Mainstream financial intermediaries, among which the diversified financials we analyze, as well as the financial system as a whole, know much less about BigTech sector than the FinTech one, just because of BigTech companies' peculiar business model, with the combined provision of different types of financial and non-financial services. This lower proximity leads to a much lower confidence from the financial system towards BigTechs than FinTechs.

In the same vein, Crisanto et al. (2022) argue that the increasingly stronger interconnection between BigTechs and financial institutions is based on the offer of financial products and services through a variety of partnerships, whose opaqueness makes it complex to assess the type and level of risks to which financial institutions are exposed. A huge number of financial institutions use some form of public cloud and the services of data analytics, that are provided by relatively few big tech companies. Since this dependence is expected to increase in the next future, financial institutions' operational and concentration risks, and the fragility of the entire financial system, will be exacerbated in the case of disruptions in the bigtech sector. Furthermore, following Bodi et al. (2023), if compared with BigTechs, the impact of FinTechs on financial systemic risk might be mitigated by the smaller size of FinTechs' customer base, by the presence of some form of regulation, at least in the EU, disciplining Fintech companies' financial activities with retail customers, and by the few cases in which FinTechs provide services to financial institutions related to some major technology infrastructure.

When crypto-assets indexes are regressed against the $\Delta CoVaR$, we observe a quasi-null effect of a raise in the level of both the Bloomberg Galaxy Crypto Index and the Bitcoin on the $\Delta CoVaR$ of diversified financial companies, regardless of the geographical area they are from. The regression coefficients for the VaR and ES of the ordinary OLS model are positive for both crypto-assets indexes, meaning that a raise in their riskiness, irrespective of how it is measured, produces, on average, a higher systemic risk for both US and EU diversified financials. Looking at the different quantiles we account for, regression coefficients are never statistically significant for the Bloomberg Galaxy Crypto Index, for both EU and US, when both VaR and ES are used as risk measure. As far as the Bitcoin is concerned, a positive relationship between its risk measures and systemic risk of diversified financials seems to prevail over the negative one for both US and EU financial companies. However, the magnitude of the coefficients is still contained when compared to those observed for both BigTech and FinTech equity indexes.

4.3. Systemic risk interactions with technology-driven downturns

The mitigation and/or amplification effects on financial systemic risk that arise from tech-driven firms and assets might depend on the magnitude of the downturn affecting them. Thus, in this subsection, we investigate the impact of BigTech, FinTech and crypto-assets downturns by performing a sort of sensitivity analysis where we use different thresholds of downturns ranging from −2.5% to −20%. In particular, as in the test presented in Section 4.1, for each index we create a dummy that equals 1 if the index experiences a drop of −2.5%, −5%, −7.5%, −10%, −15% or −20%, respectively, and 0 otherwise. Since no significant results are found when using $D^{-7.5\%}$ and $D^{-10\%}$ for equity indexes — this being due to the low frequency of those events (see Table 2); we present the case of $D^{-2.5\%}$ (Table 5) and $D^{-5\%}$ (Table 6) for BigTech, FinTech and crypto-assets indexes and conclude our analysis by investigating the remaining thresholds when the Bitcoin is regressed against $\Delta CoVaR$ (Table 7), because of the higher frequency of downturn events meeting those thresholds for this variable.

Panel A of both Tables 5 and 6 refers to the US diversified financials and Panel B to the EU ones. Findings are relatively similar to those described in Section 4.2, with relationships that hold also when the interaction factor is used. Interestingly, the relationship

Table 5
$\Delta CoVaR$ of US and EU diversified financial companies and BigTech, FinTech and crypto-assets indexes – $D^{-2.5\%}$ as interaction factor.

Panel A: US diversified financials

	S&P 500 Technology Index			STOXX Europe 600 Technology Index			Global FinTech Index			US FinTech Index			Bloomberg Galaxy Crypto Index			Currency XBT Bitcoin		
	Index	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*
OLS	0.013	0.694***	1.061***	0.031	0.638***	0.905***	0.106*	0.225***	0.345***	0.019***	0.191***	0.235***	−0.009	0.015*	0.032***	−0.001	−0.002	−0.001
$adj.R^2$	2.00%	2.78%	3.24%	0.04%	2.80%	2.81%	0.09%	0.68%	0.46%	0.88%	2.22%	1.24%	1.12%	0.32%	0.83%	2.06%	2.22%	1.24%
Quantile																		
τ = 5th	0.023***	0.219***	0.332***	0.011	0.164***	0.226***	0.006	0.126**	0.186***	0.008	0.122***	0.112	−0.003	−0.010	−0.014	0.001*	0.000	−0.004
$adj.R^2$	0.20%	0.85%	0.99%	0.03%	0.39%	0.41%	68.97%	73.75%	73.73%	82.97%	84.69%	84.66%	86.82%	89.91%	89.92%	65.87%	71.08%	71.09%
τ = 10th	0.016***	0.198***	0.278***	0.011***	0.153***	0.222***	0.052	0.208**	0.246**	0.009***	0.115***	0.139***	0.003	−0.001	−0.001	0.001	−0.001	−0.002
$adj.R^2$	0.10%	0.67%	0.74%	0.05%	0.46%	0.45%	69.85%	74.61%	74.58%	83.72%	85.31%	85.26%	87.36%	90.47%	90.47%	66.67%	71.89%	71.90%
τ = 50th	0.060**	0.723***	1.231***	0.070**	0.582***	0.825***	0.113	0.358***	0.403*	0.013***	0.321***	0.224	−0.001	0.000	−0.002	0.001**	0.003**	0.006***
$adj.R^2$	0.06%	1.67%	2.13%	0.21%	2.32%	2.37%	72.78%	77.33%	77.25%	86.59%	87.77%	87.64%	88.88%	90.20%	90.20%	69.48%	74.57%	74.57%
τ = 90th	0.111*	1.424***	1.887***	0.164	1.286***	1.807***	0.005	0.005	0.011	0.003	0.012	0.016	−0.004	−0.001	−0.004	−0.001	0.001	0.001
$adj.R^2$	0.02%	3.53%	3.75%	0.12%	3.09%	3.11%	82.48%	83.42%	83.42%	89.93%	91.61%	91.61%	93.39%	95.43%	95.44%	82.21%	83.03%	83.03%
τ = 95th	0.425***	0.279	0.392	−0.099	0.299***	0.429***	−0.038	−0.005	−0.011	0.001	0.004	0.007	0.003***	−0.004	−0.008	0.001***	−0.001	−0.001
$adj.R^2$	0.45%	0.19%	0.22%	0.07%	0.37%	0.37%	85.61%	86.36%	86.36%	92.00%	93.33%	93.33%	94.74%	96.37%	96.37%	85.45%	86.09%	86.09%

Panel B: EU diversified financials

	S&P 500 Technology Index			STOXX Europe 600 Technology Index			Global FinTech Index			US FinTech Index			Bloomberg Galaxy Crypto Index			Currency XBT Bitcoin		
	Index	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*
OLS	0.000	0.337***	0.514***	0.010	0.319***	0.449***	−0.027	0.091	0.121	0.012*	0.119***	0.125*	0.007	0.022**	0.046***	0.001	0.011***	0.019***
$adj.R^2$	2.34%	2.05%	2.40%	1.78%	2.21%	2.17%	1.03%	1.05%	1.03%	0.17%	0.52%	0.17%	1.02%	0.61%	1.31%	1.02%	0.23%	0.24%
Quantile																		
τ = 5th	−0.004	0.049	0.071	0.001	0.045	0.061	−0.012	0.087***	0.119***	0.003**	0.039***	0.044***	−0.004	−0.005	−0.008	−0.001**	0.006**	0.0125***
$adj.R^2$	0.03%	0.04%	0.08%	0.00%	0.16%	0.17%	43.92%	50.81%	50.81%	69.58%	74.35%	74.33%	81.42%	83.59%	83.59%	40.37%	47.02%	47.13%
τ = 10th	−0.003	0.097***	0.152***	−0.004	0.110***	0.161***	−0.022	0.031	0.039	0.001	0.023	0.036	0.009***	−0.018	−0.028	0.002***	−0.007	0.023***
$adj.R^2$	0.10%	0.19%	0.24%	0.01%	0.34%	0.36%	44.94%	51.38%	51.38%	69.46%	74.08%	74.07%	81.21%	83.67%	83.68%	41.68%	47.73%	47.92%
τ = 50th	0.003	0.383***	0.578***	0.004	0.347***	0.464***	0.030***	0.079**	0.159***	0.005	0.171***	0.226***	0.031***	−0.014	−0.059	0.000	0.018***	0.033***
$adj.R^2$	0.11%	1.10%	1.29%	0.01%	0.96%	0.92%	49.14%	54.22%	54.21%	71.34%	73.33%	73.27%	80.43%	82.67%	82.78%	46.20%	51.21%	51.22%
τ = 90th	0.018**	0.538***	0.755***	0.007	0.539***	0.744***	−0.047***	0.026	0.052**	0.005***	0.021	0.039*	0.000	−0.008	−0.018	−0.001	0.001	0.002
$adj.R^2$	0.03%	2.16%	2.32%	0.02%	2.21%	2.20%	61.29%	63.79%	63.79%	77.95%	81.02%	81.01%	83.62%	88.81%	88.82%	60.50%	62.71%	62.71%
τ = 95th	0.112***	0.417***	0.549***	0.071	0.433***	0.622***	−0.105*	0.057***	0.118***	0.002	0.007*	0.013	0.002	0.000	0.000	0.001***	−0.001	−0.002
$adj.R^2$	0.11%	1.28%	1.38%	0.03%	1.48%	1.47%	70.05%	71.94%	71.94%	83.26%	85.69%	85.69%	87.80%	91.70%	91.70%	69.39%	71.20%	71.20%

Notes: The coefficients from the time series regression analysis with the $\Delta CoVaR$ as the dependent variable for the US and EU diversified financial sector. The independent variables, listed in the header of each column, interacts with the dummy $D^{-2.5\%}$ by using Eq. (11). Intercept results are not reported for the sake of space.

* Indicate significance at 10% level.

** Indicate significance at 5% level.

*** Indicate significance at 1% level.

regression coefficient observed for BigTech companies reverse its sign when interacted with $D^{-2.5\%}$ or $D^{-5\%}$ in both the United States and the European Union.

Table 7 presents the estimates of the regressions with $\Delta CoVaR$ as dependent variables, the Bitcoin interacted with the dummies from $D^{-7.5\%}$ to $D^{-20\%}$ as explanatory variables. Again, Panel A of both tables reports results referred to the US diversified financial companies and Panel B to the EU ones, respectively. While only few coefficients are found statistically significant under extreme market conditions – i.e., 90th and 95th quantiles; we find higher coefficients than those observed when: (i) $D^{-2.5\%}$ or $D^{-5\%}$ are used as interaction factor; and, (ii) no interaction factor is used (see Table 4). This implies that crypto-assets function as a separate risk source from traditional assets: crypto-assets seem not strongly impact financial systemic risk when they record low to moderate losses, whereas they can significantly contribute to an increase in financial systemic risk only in case of huge drops in their values, which happens with a relatively high frequency for a number of reasons. Overall, a large decrease in the value of such type of assets may cause fire-selling in an illiquid market with high information asymmetry (Chokor and Alfieri, 2021). The price of crypto-assets and their volatility heavily depend on many factors, including supply and demand, investor sentiment and the media hype cycle. Prior literature has acknowledged the importance of the small size of their markets, the absence, due to their digital nature, of any type of asset to back their worth and of any system of rules to discipline their use as a currency, thus their value being determined only by investors' confidence, the effect of media's coverage and their high susceptibility to speculation (see, e.g., Khan and Hakami, 2022).

Even the most-prominent and better-capitalized crypto-assets experience fluctuations, resulting in positive returns and, at times, losses (see, e.g., Kim et al., 2021). One important factor helping to interpret the differences in the impact on financial systemic risk between tech-driven companies and crypto-assets refers to the way these latter are traded. Most exchanges have limits on the amount that can be liquidated in one day, usually USD 50,000.00.[8] Investors, including diversified financials, holding significant amounts of crypto-assets might not be able to liquidate their assets fast enough to prevent enormous losses. For example, when the price of a specific crypto-assets continues to hover around USD 50,000.00, a large investor – say holding a significant amount of Bitcoins – could only liquidate one coin per day. Thus, in case other investors begin to sell, prices would plummet before anyone with more than USD 50,000.00 in coins could sell them all off, leading to large and rapid losses. We also believe our evidence to be consistent with the idea that financial markets and investors are to some extent used to the relatively higher volatility of crypto-assets. Consequently, these latter must experience larger downturns, if compared with those of FinTechs and BigTechs indexes, to have a significant impact on financial systemic risk.

[8] For further details on Bitcoin, please consult: https://www.coinbase.com/price/bitcoin.

Table 6
$\Delta CoVaR$ of US and EU diversified financial companies and BigTech, FinTech and crypto-assets indexes – $D^{-5\%}$ as interaction factor.

Panel A: US diversified financials

	S&P 500 Technology Index			STOXX Europe 600 Technology Index			Global FinTech Index			US FinTech Index			Bloomberg Galaxy Crypto Index			Currency XBT Bitcoin		
	Index	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*
OLS	0.035	0.745*	1.129***	0.041*	0.665*	0.941*	0.191	0.313	0.491	0.027	0.250	0.323	0.001	0.017*	0.036***	0.013*	−0.006	−0.007
$adj.R^2$	2.01%	2.99%	3.44%	0.08%	2.85%	2.83%	0.32%	1.10%	0.79%	1.13%	2.55%	1.56%	0.35%	0.32%	0.78%	0.18%	0.05%	0.01%
Quantile																		
τ = 5th	0.041*	0.389	0.601*	0.021	0.309	0.411	0.097	0.181***	0.257	0.019	0.219	0.261	−0.002***	−0.007	−0.009	0.002	0.005	−0.016
$adj.R^2$	0.36%	1.57%	1.77%	0.02%	0.67%	0.69%	8.18%	7.93%	7.89%	8.04%	8.10%	8.03%	65.81%	89.32%	89.32%	83.62%	69.68%	69.69%
τ = 10th	0.039*	0.362*	0.560*	0.027*	0.328*	0.433**	0.073	0.133	0.185	0.013	0.189	0.228	0.001***	−0.003	−0.005	0.017***	0.000	−0.004
$adj.R^2$	0.26%	1.41%	1.57%	0.21%	1.07%	1.06%	7.12%	7.61%	7.59%	8.60%	8.29%	8.22%	67.74%	89.65%	89.65%	83.97%	71.47%	71.48%
τ = 50th	0.032	0.599***	0.942***	0.059*	0.596	0.860**	0.154	0.451	0.452	0.018	0.369*	0.232	0.000	0.000	−0.004	0.006***	0.011***	−0.004
$adj.R^2$	0.11%	1.74%	2.09%	0.17%	2.09%	2.08%	7.16%	7.26%	7.17%	8.69%	8.01%	8.88%	68.71%	88.70%	88.70%	86.49%	72.10%	72.04%
τ = 90th	0.199**	1.608***	2.122***	0.187***	1.474***	2.099***	0.126	0.084	0.164	0.003	0.014	0.019	0.001***	−0.002	−0.006	−0.004	0.017***	0.028***
$adj.R^2$	0.03%	4.11%	4.35%	0.16%	3.60%	3.62%	8.59%	8.79%	8.79%	8.96%	9.04%	9.03%	80.30%	94.88%	94.88%	92.46%	81.38%	81.40%
τ = 95th	0.394***	0.441**	0.585*	0.0192	0.438***	0.629***	0.024	0.011	0.022	0.002	0.007	0.013	0.001	−0.005	−0.011	0.004***	0.020***	0.040***
$adj.R^2$	0.26%	0.41%	0.44%	0.20%	0.66%	0.66%	8.45%	8.57%	8.57%	9.72%	9.33%	9.32%	84.09%	96.05%	96.05%	84.19%	85.20%	85.23%

Panel B: EU diversified financials

	S&P 500 Technology Index			STOXX Europe 600 Technology Index			Global FinTech Index			US FinTech Index			Bloomberg Galaxy Crypto Index			Currency XBT Bitcoin		
	Index	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*	*Index*	*VaR*	*ES*
OLS	−0.022	0.276*	0.428**	0.001	0.278**	0.393*	−0.108	0.018	0.003	−0.006	0.028	−0.026	−0.001	0.020**	0.041***	0.002***	0.017***	0.032***
$adj.R^2$	1.03%	1.51%	1.82%	0.02%	1.83%	1.83%	0.25%	0.24%	0.24%	0.22%	0.27%	0.27%	0.35%	0.65%	1.37%	1.21%	0.51%	0.64%
Quantile																		
τ = 5th	0.002*	0.011	0.031**	0.001	0.057	0.081	0.009*	0.022	0.029	0.001	0.009	0.011	0.000	−0.002	−0.003	0.001**	0.000	−0.001
$adj.R^2$	0.01%	0.02%	0.02%	0.10%	0.16%	0.15%	4.3%	4.06%	4.05%	6.68%	7.41%	7.41%	85.71%	87.46%	87.46%	37.28%	44.5%	44.5%
τ = 10th	0.021*	0.035	0.054	0.007	0.139**	0.197*	−0.063	−0.021	−0.028	0.000	0.009	−0.004	0.000	−0.009	−0.013	0.001	−0.004	0.014**
$adj.R^2$	0.15%	0.02%	0.04%	0.02%	0.2%	0.21%	4.51%	4.87%	4.87%	6.19%	7.01%	7.01%	85.58%	87.31%	87.32%	37.62%	44.47%	44.55%
τ = 50th	0.017	0.345*	0.553***	0.008	0.332**	0.478**	−0.036	0.078	0.169	0.002	0.139	0.144	0.008***	−0.008	−0.019	0.002***	0.013***	0.026***
$adj.R^2$	0.02%	1.02%	1.23%	0.01%	1.29%	1.27%	4.73%	4.71%	4.71%	6.26%	7.83%	7.75%	84.14%	86.01%	86.05%	41.77%	46.98%	47.04%
τ = 90th	0.055	0.443***	0.613***	0.001	0.446*	0.610**	−0.205	−0.134	−0.279	−0.002	−0.105	−0.204	0.002	−0.001	−0.003	0.002***	−0.007	−0.009
$adj.R^2$	0.11%	1.88%	2.03%	0.5%	1.93%	1.92%	5.10%	6.6%	6.59%	7.83%	7.91%	7.94%	84.52%	89.18%	89.18%	57.8%	59.49%	59.49%
τ = 95th	0.131	0.355***	0.468***	0.061	0.369***	0.531***	−0.270	−0.191	−0.315	−0.022	−0.143	−0.268	0.000	0.000	0.000	0.003***	−0.006	−0.001
$adj.R^2$	0.14%	1.32%	1.41%	0.04%	1.52%	1.51%	6.67%	6.79%	6.79%	8.65%	8.55%	8.57%	88.34%	91.86%	91.86%	66.34%	67.89%	67.89%

Notes: The coefficients from the time series regression analysis with the $\Delta CoVaR$ as the dependent variable for the US and EU diversified financial sector. The independent variables, listed in the header of each column, interacts with the dummy $D^{-5\%}$ by using Eq. (11). Intercept results are not reported for the sake of space.

* Indicate significance at 10% level.

** Indicate significance at 5% level.

*** Indicate significance at 1% level.

Our findings call for the introduction of a regulatory framework for crypto-assets, which may not affect systemic risk strongly during normal market conditions, but may increase it during extreme tail events, which cannot be prevented or avoided due to the impossibility of intervention by market authorities on this type of assets.

5. Concluding remarks

The tech revolution that financial services went through over the last decades raises concerns about the intrinsic riskiness of BigTechs, FinTechs and crypto-assets, and the implications that it may have on financial system stability. Despite the substantial growth experienced by tech-driven firms and assets and the concerns raised by the Financial Stability Board (2019), no research has been done to measure how financial systemic risk is impacted by the application of new technologies to finance.

In this paper, we study the reaction of financial systemic risk to BigTech, FinTech and crypto-assets related market downturns by focusing on a specific category of financial intermediaries, namely diversified financials. Second, we investigate whether the performance and risks of these tech firms and assets affect systemic risk and whether this relationship is strengthened when interacted with several thresholds to measure the magnitude of these tech-driven market downturns. For the purpose of comparison, two geographical areas, namely the United States and the European Union, are considered, where diversified financials account for 55% and 25% of the total market capitalization, respectively. Overall, results show a stronger connection between tech-equities and systemic risk measures, with BigTechs resulting riskier than FinTechs during tail market conditions in terms of their VaR and ES. Moreover, crypto-assets seem to affect systemic risk mainly when huge drops in their value are recorded.

Our findings also highlight some differences in the impact of technology driven companies and assets in the two geographical areas we consider. From this perspective, we believe some additional comments can also be useful to pave the way for future research. As far as the reaction of diversified financials' systemic risk to downturns in the indexes referred to the BigTech sector, EU intermediaries react to downturns of US BigTechs more than US financial institutions to downturns of EU BigTechs. Our view is that the different extent of this spillover from tech-driven companies to financial intermediaries belonging to the two distinct areas depends, on the one hand, on the relatively larger size of US BigTechs and, on the other, on a reasonably broader and older familiarity of US financial system with the BigTech sector, which probably makes EU diversified financials more sensitive to a risk contagion from a bad performance of non-EU BigTechs. The same reasoning might be applied to the evidence of the stronger reaction of EU diversified financials' systemic risk to the risks stemming from US FinTech companies. Furthermore, a rise in the BigTech indexes has a much larger mitigation effect on US diversified financials' systemic risk, relative to EU ones, which also appear to record a much lower increase in their systemic risk when BigTechs experience extremely negative results. Overall, this might support the presence of a much stronger interconnection between BigTech sector and US financial system.

Table 7
$\Delta CoVaR$ of US and EU diversified financial companies and Currency XBT Bitcoin – $D^{-7.5\%}$, $D^{-10\%}$, $D^{-15\%}$ and $D^{-20\%}$ as interaction factors.

	$D^{-7.5\%}$			$D^{-10\%}$			$D^{-15\%}$			$D^{-20\%}$		
	$Index$	VaR	ES	$Index$	VaR	ES	$Index$	VaR	ES	$Index$	VaR	ES
Panel A: US diversified financials												
OLS	0.104	−0.002	0.011	0.138*	0.049*	0.056**	0.167	0.053	0.071	0.242	0.120	0.088
$adj.R^2$	0.18%	0.04%	0.06%	0.18%	0.04%	0.04%	0.18%	0.03%	0.03%	0.18%	0.03%	0.03%
Quantile												
τ = 5th	0.016	0.011	−0.002	0.114	0.107	0.062	0.166	0.178	0.093	0.172	0.251	0.111
$adj.R^2$	83.62%	66.68%	61.69%	53.62%	29.68%	26.69%	24.62%	6.32%	6.32%	14.62%	1.32%	2.68%
τ = 10th	0.073***	0.042*	0.095	0.139*	0.067	0.137	0.227	0.166	0.206	0.322	0.263	0.306
$adj.R^2$	82.97%	66.47%	64.48%	51.97%	31.47%	29.48%	19.97%	7.47%	3.48%	12.97%	1.47%	2.52%
τ = 50th	0.006***	0.102*	0.075**	0.011*	0.195	0.090*	0.046	0.218	0.134	0.0482	0.300	0.171
$adj.R^2$	79.49%	67.1%	69.04%	41.49%	37.10%	36.04%	19.49%	13.10%	2.04%	12.49%	8.11%	5.96%
τ = 90th	0.016***	0.081**	0.038**	0.011**	0.107***	0.063***	0.144*	0.206*	0.159***	0.223	0.224	0.185
$adj.R^2$	83.46%	73.38%	74.40%	45.46%	39.38%	34.40%	15.46%	15.38%	5.40%	0.46%	9.38%	7.60%
τ = 95th	0.015***	0.085*	0.116	0.071**	0.159***	0.155***	0.123**	0.227**	0.244***	0.174	0.267*	0.251*
$adj.R^2$	84.19%	82.20%	80.23%	45.19%	43.20%	50.23%	23.19%	16.20%	9.23%	12.19%	10.80%	8.23%
Panel B: EU diversified financials												
	$D^{-7.5\%}$			$D^{-10\%}$			$D^{-15\%}$			$D^{-20\%}$		
	$Index$	VaR	ES	$Index$	VaR	ES	$Index$	VaR	ES	$Index$	VaR	ES
OLS	0.040***	0.086***	0.067***	0.106*	0.167	0.165*	0.120	0.171	0.231	0.135	0.185	0.314
$adj.R^2$	1.21%	0.51%	0.64%	1.20%	0.51%	0.64%	1.19%	0.5%	0.63%	1.18%	0.50%	0.63%
Quantile												
τ = 5th	0.050***	0.066	0.068	0.112*	0.121	0.107	0.149	0.218	0.178	0.215	0.219	0.265
$adj.R^2$	34.28%	40.50%	38.50%	7.28%	15.51%	10.50%	5.28%	15.50%	9.50%	3.72%	8.52%	2.51%
τ = 10th	0.064	0.028	0.049*	0.155	0.126*	0.082	0.217	0.208	0.094	0.283	0.222	0.123
$adj.R^2$	30.62%	43.47%	44.55%	6.62%	20.47%	15.55%	6.62%	18.47%	15.55%	5.38%	9.47%	5.55%
τ = 50th	0.054***	0.101***	0.046***	0.073**	0.181	0.137	0.128	0.214	0.167	0.164	0.217	0.267
$adj.R^2$	37.77%	45.98%	41.04%	15.77%	19.98%	16.04%	15.77%	17.98%	16.04%	10.77%	9.98%	8.04%
τ = 90th	0.086***	0.015	0.002	0.143**	0.077*	0.097*	0.181*	0.176**	0.116**	0.231	0.235*	0.129
$adj.R^2$	56.80%	58.49%	51.49%	26.80%	36.49%	24.49%	26.80%	36.49%	24.49%	16.80%	12.49%	15.49%
τ = 95th	0.084***	0.067*	0.074*	0.136***	0.133***	0.173***	0.183***	0.227**	0.235***	0.203*	0.318*	0.255*
$adj.R^2$	63.34%	61.89%	65.89%	41.34%	31.89%	39.89%	37.34%	28.89%	36.89%	17.34%	12.89%	18.89%

Notes: The coefficients from the time series regression analysis with the $\Delta CoVaR$ as the dependent variable for the US and EU diversified financial sector. The independent variables is the Currency XBT Bitcoin, which interacts with the dummies $D^{-7.5\%}$, $D^{-10\%}$, $D^{-15\%}$ and $D^{-20\%}$, listed in the header of each column, by using Eq. (11). Intercept results are not reported for the sake of space.

* Indicate significance at 10% level.

** Indicate significance at 5% level.

*** Indicate significance at 1% level.

Future research might explore how country-specific characteristics, in terms of both institutional, economic, and financial factors, affect the relationship of the financial system with the FinTech and BigTech sectors. On this regard, prior studies have shown that differences in the development of the markets of tech-driven financial services can be explained by differences in countries' economic growth and financial systems' strength of regulation and intensity of competition, investor protection disclosure and efficiency of the judicial system (Claessens et al., 2018; Cornelli et al., 2020). Detecting whether and how these factors play a role in the link between the tech revolution and financial system stability can provide useful insights even for financial supervisors.

From a supervisory perspective, it becomes crucial to study the potential systemic relevance of BigTechs and FinTechs and to introduce specific mechanisms to guarantee adequate operational resilience to the financial system. For example, following what done in some jurisdictions, it would be useful to start processes to designate financial institutions and financial market utilities as being systemically important (Carstens, 2019), thus not limiting the use of the designation of "systemically important financial institution" to traditional financial intermediaries. The current supervisory framework does not address the potentially global systemic impact of BigTechs' and FinTechs' activity and of possible spillover effects to the financial sector and across all tech-driven companies' activities. Close coordination among different financial and non-financial regulators and supervisors, at both the national and global level, is therefore needed. Supervisory authorities should work also to encourage the creation of wide and reliable official data sources, a base of timely and accurate information about FinTechs' and BigTechs' activities, and financial intermediaries' exposure towards crypto-assets, that can be used to effectively pursue their mandate to guarantee global financial stability. Finally, the prospective increasing interactions between financial institutions and tech-driven companies and assets might also require to adjust current supervisory architecture and practices to adequately supervise them, which leads to the necessity to change authorities' organizational structure and acquire new and specific competencies.

We believe that our findings offer insights for national and global policymakers as well as for investors. First, policymakers should be conscious of tech related bubbles development and come up with appropriate regulations to mitigate the chances of any crash for firms involved in such business. This is particularly important because the tech industry is likely to become even more relevant in terms of market presence after the COVID-19 pandemic, which might entail sudden spill-over effects without a persistent decline in their performance (Goodell and Huynh, 2020). Our findings emphasize the pivotal role of supervisory and market authorities to continuously follow market signals, allowing for a timely intervention before any potential crash.

Another fundamental issue for policymakers is that multidisciplinary dialogue and global collaboration on a basic regulatory framework and a set of policies regarding crypto-assets are required. Crypto-assets are gaining pace globally, with their level of market penetration that differs across regions and jurisdictions, depending principally on consumer needs, financial and technological infrastructure and available capital for the required investment. There is urgent need for discussion among policymakers to define a global regulatory framework for crypto-assets, with the use of RegTech and SupTech that may facilitate the efficient and timely implementation of such approaches. From this perspective, through a joint effort, the International Monetary Fund and the Financial Stability Board have advanced policy and regulatory recommendations to identify and respond to macroeconomic and financial stability risks associated with crypto-assets (Financial Stability Board, 2023). Enhancing regulation and supervision of licensed or registered crypto-asset issuers and service providers is crucial and, in this sense, appropriate reporting requirements can effectively contribute to reduce current and no more negligible data gaps.

CRediT authorship contribution statement

Domenico Curcio: Conceptualization, Investigation, Writing – review & editing. **Simona D'Amico:** Conceptualization, Investigation, Writing – review & editing. **Igor Gianfrancesco:** Conceptualization, Investigation, Writing – review & editing. **Davide Vioto:** Conceptualization, Data curation, Investigation, Methodology, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Appendix A. Additional robustness checks

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