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Banking FinTech and stock market volatility? The BIZUM case

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This paper investigates whether and how the adoption of FinTech by incumbent banks affects their stock price volatility. BIZUM, a Spanish FinTech real-time digital payment solution was adopted by incumbent banks in 2016 and therefore provides new evidence of real-world *ex-post* implementation. The results indicate that the adoption of BIZUM by incumbent banks had a significant effect, reducing their stock price volatility after it was launched. This finding suggests that investors were informed of and acknowledged the advantages of BIZUM, thus, use their adoption of FinTech Start-up strategy to offset adverse market circumstances. This paper provides insights for investors and international institutions regarding the role of the pricing of banking related assets, implications for incumbent banks whose portfolios are exposed to investments in disruptive technology and for banking regulators and authorities vis-à-vis risk related considerations of the adoption by banks of FinTech strategies.

1 Introduction

No sector is driven by the use of smart technology as much as financial organizations, such as banks. From chatbots to Artificial Intelligence (AI), Blockchain to digital payment solutions, among many others, financial organizations try to keep up with the latest tech trends (Staykova and Damsgaard, 2016).

Incumbents are shocked by new digital players like FinTech, which introduce disruption and value. These new actors orchestrate in the Ecosystem Economy by deploying new strategies (Jacobides, 2019) and challenging established banking business models, promoting the democratization of finance in a more efficient and transparent financial ecosystem (Visconti-Caparrós and Campos-Blazquez 2022).

The Spanish banking system has experienced dramatic changes in line with the rest of the industry. FinTech companies can trigger a disruptive evolution due to the new alternatives they offer for improving service efficiency and quality (Ferrari, 2016).

In banking, three possible theoretical scenarios can be retrieved, as suggested by Li et al. (2017). The first is that FinTech will undermine or even replace retail banks. The second, put forward by Jun and Yeo (2016), is that FinTech will complement incumbent banks and lead to positive impact, since banks are incorporating disruptive technologies in their business models. The third is that incumbent banks are too big and too robust to be influenced by FinTech and no impact of FinTech is channelled to them. The future

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suggests a scenario of collaboration between these new players and traditional companies, with a consequently difficult challenge for regulators to guarantee the same conditions of competition for new entrants and incumbents (Agarwal and Zhang, 2020; Lee and Shin, 2018; Moro-Visconti et al., 2020).

In particular, the payment business is an increasingly profitable, high-growth activity. In fact, many payment companies are already worth more in the stock market than banks themselves (Lander, 2019) Previous research has also shown that technology shocks have a significant impact on stock behaviours. The current price of a stock equals the optimal expected forecast based on the information available (Mishkin, 2016) so expectations about future profits from disruptive technology will also be reflected as having an impact on stock return volatility.

BIZUM is the brand name of the Sociedad de Procedimientos de Pago, S.L. company and was created in 2015 in response by the Spanish banking industry to the announcement by the European Central Bank (ECB) to all European countries of its intention to shift towards immediate transfers, with the aim of creating a simple, immediate, and secure online payment method.

Among the reasons for BIZUM's success and rapid growth, we can highlight that it is a pioneering application at the European level whose main competitive advantage is the almost instantaneous availability of the funds sent to the user's bank account, all without the need to change banks, since it works for any of them that support it. It was also hoped that BIZUM would meet the demand for novel payment solutions (Elconfidencial.com, 2022). Following its joint launch in 2016 by 27 Spanish banks, BIZUM provided the infrastructure to enable a real-time payment system in Spain. However, the most outstanding solution that BIZUM provided was to serve as a first defence mechanism for Spanish banks against the new FinTech entering the payment industry. BIZUM has been adopted quickly and massively by more than 70 % of the Spanish banking population in the first five years (Visconti-Caparrós and Campos-Blázquez, 2022). As of January 2022, the participating banks already hold a market share of almost 99 % and had over 19 million users in 202 (Blaze Trends, 2022) In this context, BIZUM provides us with an ideal scenario in which to research the relationship between the adoption of a FinTech strategy and stock market behaviour.

This paper reviews whether and how the adoption of FinTech by incumbent banks affects their stock price volatility. BIZUM provides new evidence of real-world *ex-post* implementation.

To this end, the daily stock returns of the six largest traditional Spanish banks (Bankia, Bankinter, BBVA, CaixaBank, Sabadell and Santander) are selected for the period from 01/07/2013–30/01/2020 and a GARCH-M GED approach with an event-related dummy variable was used to capture the predictable components of the changes in volatility when the incumbent banks started to operate with BIZUM. Risk and return fundamentals are used to explain the results. The underlying rationale proposed by this research is that investors build expectations with regard to the performance of incumbent banks that adopt a FinTech strategy, which will impact price movements and volatility (Johnstone, 2021).

The motivation for this paper is to provide insights for investors and international institutions regarding the role of the pricing of banking related assets and implications for disruptive technology for banks whose portfolios are exposed to investments in disruptive technology. It also gives banking regulators and authorities a better understanding of the challenging task of ensuring financial stability and prudential soundness while allowing for the development of technological innovation.

We found that that the adoption of BIZUM led to a significant reduction in the stock price volatility of incumbent banks. The results may suggest that investors have anchored the benefits and competitive advantages of disruptive technologies such as BIZUM, thus welcoming the potential of incumbent banks adopting a FinTech startup strategy.

In our literature review no previous research has been found to confirm this proposition from the perspective of the impact of an *ex-post* implementation on stock return volatility in banking. This research gap is partly bridged by this paper.

The remainder of this paper is organized as follows. The second section presents the background literature on related financial and theoretical considerations and provides a brief overview of Spanish banking and digital payment. The third section is concerned with the methodology used for this research. The fourth section describes and discusses the data. The fifth section presents the results, and the sixth section offers a discussion and certain directions for future research.

2 Literature review

2.1 Stock volatility

From a financial theory perspective, we would expect stock markets to react promptly to the rapid adoption by financial organizations of disruptive solutions, since stock prices reflect expectations regarding new information arriving in the market. Since the current price of a stock equals the optimal expected forecast based on the information available (Mishkin, 2016) expectations about future profits from disruptive technology will also be reflected.

It is very difficult to estimate the fundamental value of novel technologies and most empirical studies have found that radical or breakthrough inventions are identified only by their major *ex post* impact on future technological development (Ahuja and Morris, 2001; Schoenmakers and Duysters, 2010), product performance (Leifer et al., 2001) or market structure (Mascitelli, 2000).

To better understand how technology-related shocks might be channelled into stock market dynamics, it is worth recalling some basic financial concepts. Stock valuation is, *per se*, forward-looking since the value of an asset is mainly defined as the present value of the actual future payoffs (dividend) that the investor will receive. The common component and forward-looking features of asset valuation are the interest rates or growth rates that are used to discount the future payoffs. However, when analysing the fluctuation of those rates, stock valuation models are expected to imply significant volatility driven by those economic components. Hence, the perception of an economic slowdown is enough to generate large changes in stock market prices (Peralta-Alva, 2007)

Studies such as Shiller (1981) and Schwert (1989) suggest that volatility cannot only be explained by changes in fundamentals.

Significant amounts of volatility in asset prices may be driven by different factors that impact an investor's decision, such as the presence of investor underreaction and overreaction (Bathia and Bredin, 2018) as stated by behavioural finance theory. For example, volatility may be defined as the sum of transitory volatility caused by noise trading and unobserved fundamental volatility caused by the arrival of stochastic information (Hwang and Satchell, 2000). Investors induce the variability of prices in the stock market by interpreting the flows of information.

2.2 Disruptive technology, stock behaviour and banking

The study of disruptive technologies and FinTech is relatively new to the literature, but it has developed considerably in the last decade. FinTech may help incumbents to adapt to a new game (Navaretti et al., 2018). On productivity, the results are mixed. For example, Brynjolfsson et al. (2018) and Wu et al. (2019) found that it is promoted by digital technology adoption, but Babina et al. (2020) found that AI adoption has no impact on productivity. On the other hand, evidence suggests that digital transformation promotes firms' innovation abilities (Trocin et al., 2021; Usai et al., 2021). Existing literature has found that the adoption of disruptive technology improves performance (Chen and Srinivasan, 2022; Ferreira et al., 2019; Mikalef et al., 2020; Rialti et al., 2019; Babina et al., 2020). Meanwhile, Chen and Srinivasan (2022) studied the implication on firm value and performance of non-technology companies engaging in activities related to digital technologies, and Rock (2019) found that market valuation increases the number of AI adopters.

On the specific relationship between stock prices, stock price returns and technological disruption, the literature is still limited. However, below we cite some articles that shed some light on different nuances related to the constellation of FinTech developments and stock market behaviour. Lin et al. (2017) found that firms operating with old capital are riskier and hence offer higher expected returns, given that old capital firms are more likely to upgrade earlier and are therefore more exposed to shocks driven by the technology frontier.

Majid et al. (2021) studied the impact of overall innovation over a period from 2013 to 2018 on S&P100 firms and found that innovation acts as a resource to enable a firm to obtain positive abnormal returns, remaining consistent in the presence of noise trading and investor biasedness. Draven et al. (2019) showed that there are positive abnormal stock returns for firms that acquire FinTech in the short-term but in the long-run, FinTech M&A does not create any additional value for these acquirer firms.

Andersson and Styf (2020) identified a slight increase in systematic risk regarding stock return and a slight reduction in terms of total risk of the stock return of the Swedish OMX PI Index due to the introduction of Blockchain technology. Sahi (2017) studied market reactions to FinTech companies in their analysis of acquisitions and initial public offerings in OECD Countries. The results indicate that FinTech acquisition announcements create a positive abnormal return of 1.08 % one day after the announcement and that FinTech IPO companies' stocks experience an average increase of a 22.64 % market-adjusted return on the first day of trading.

An empirical angle on FinTech in Banking is mostly available in the literature for Asian countries, while for Europe it is limited. Fung et al. (2020) reported that FinTech enhances stability in emerging (developed) financial markets and impacts it through profitability. Daud et al. (2022) found that FinTech promotes financial stability via artificial intelligence, cloud technology, and data technology and that bank concentration complements the effect of financial stability. Wang et al. (2021a) Wang et al. (2021b) testify the relationship between FinTech and different types of commercial banks and find that FinTech can boost the latter's productivity in China. Le et al. (2021) found that the relationship between FinTech credit development and efficiency in banking is two-way, highlighting how a negative relationship implies that FinTech credit is more developed in countries with less efficient banking systems and a positive impact suggests that FinTech credit may serve as a wake-up call to the banking system.

On the relationship between FinTech and stock price behaviour in banking, Low and Wong (2021) studied the varying effects of disruptive FinTech growth across six members of the Association of Southeast Asian Nations (ASEAN) on incumbent banks' stock returns, using the funding for FinTech digital banking start-ups to measure this growth, and found that the results vary across respective geographical areas. For example, a significant positive effect was found for Singapore and the Philippines, but an insignificant negative impact was observed for Indonesia and an insignificant positive impact in Vietnam. For Malaysia and Thailand, no effect was found of FinTech growth on incumbent stock returns. Phan et al. (2020) studied the Indonesian market using a sample of 41 banks and data on FinTech firms, and found that FinTech negatively predicts bank performance. Asmarani and Wijaya (2020) analysed the impact of FinTech on the stock returns of retail banks listed in the Indonesian Stock Exchange for the 2016–2018 period and found no significant effect. Li et al. (2017) conducted research using panel data regression to evaluate whether FinTech impacts retail banks' stock returns using a sample period from 2010 to 2016. They use volume of funding (in dollars) and number of deals to capture the importance of FinTech start-ups. The results suggest complementarity between FinTech and traditional banking, but the results on the banking industry level are not statistically significant, and the coefficient signs for about one-third of the banks are negative.

Wang et al. (2021a) found that the development of FinTech exacerbates banks' risk-taking and that the relationship between these two factors follows a U-shaped trend. Arenas and Gil-Lafuente (2021) found that emerging new technology is relevant for capturing the volatility of Spanish banking. Jiang et al. (2022) found that digital transformation, proxied by textual analysis, significantly reduces the risk of stock price crash, being impact-dependent on firm size, analyst attention, industry, and regional trust. Cheng and Qu (2020) construct a bank FinTech index using web crawler technology and word frequency analysis and found that FinTech significantly reduces credit risk in Chinese commercial banks, the effects being weak among large, state-owned, and listed banks.

2.3 Spanish banking in the digital payment landscape

Spanish banking is a key economic driver and is as relevant as it is in any economic system. The banking industry provides liquidity to invest in the future, matching up creditors and borrowers, but banks are also essential for the domestic and international payment system.

To provide some context on the Spanish banking industry, the financial crisis began in 2007 with the bursting of the property market bubble and a number of consequences for the global economy. The Spanish banking industry was especially impacted, since a sovereign debt crisis was triggered (Arghyrou and Kontonikas, 2012), whereby sovereign risk premia and credit default swap rates reached record levels (Lane, 2012). Additionally, the domestic real estate bubble burst, leading Spanish saving banks to suffer critically serious management problems (Ruiz et al., 2016). As a result, a banking reform was implemented by the Spanish Central bank and supported by the European Commission, the main objective of which was to safeguard the sustainability of the Spanish financial system by encouraging concentration and recapitalization (Blanco-Oliver, 2021).

Most Spanish banks today are the outcome of various mergers and acquisitions, such as the recent acquisition of the British TSB Bank by Banco Sabadell in 2015, of the domestic Banco Popular Español by Banco Santander in 2017, of the Portuguese BPI in 2018, as well as the domestic Bankia by CaixaBank in 2021, to mention just a few. This means they can draw on other investments when integrating their own legacy systems into the digital framework.

Wherever technology arrives, severe changes occur, and the financial sector has been one of the fastest growing in recent years for this reason. We can define FinTech ('Financial Technology') as the sector where companies use technology and its different applications to improve financial services and processes. It has been used to improve everything from electronic banking to savings and investment applications through a spectacular increase in user experience.

The banking industry has had to face a very important transformation process due to the changes to its customers' habits in recent years. The appearance of new 100 % online competitors that have grown rapidly thanks to their simplicity and user-friendliness has caused the more traditional financial institutions to evolve in a very dynamic way so as not to end up disappearing in the medium and long term.

With the onset of the financial crisis in late 2007, the Spanish financial system was seriously weakened, producing a process of reduction and concentration of banks that has lasted to this day. The incorporation of technological innovations by many of the resulting financial entities has endowed them with credibility and confidence in the face of increasingly demanding customers in terms of quality of service.

Indeed, if FinTech is applied in the correct way, it could be used to overcome the social and economic gaps that exist worldwide (Schmidt and González, 2020). More than 40 % of FinTech companies operating globally do so in the payment industry (Lander, 2019). Statista (2021) estimates for Spain that the expected annual growth rate of total transactions in the digital payment segment will reach 13.45 % between 2022 and 2026 and that its total value of transactions is expected to reach 73,817.37 million euros in 2022.

The existing relationship between the companies in the sector and the more traditional financial entities has been the object of study on several occasions since it can be considered difficult at first, because the latter may be threatened by the former (Navaretti et al., 2018). Over time, it has been observed that the financial industry is increasingly interested in forming partnerships with the most disruptive companies in the sector, or investing in them to advance faster in the process of digitizing the financial system.

FinTech provides many digital solutions driven by the information provided by the user and that allow adaptation to changing consumer preferences (Badi et al., 2018). New companies have emerged that have used technology to innovate and digitize the financial sector; and concepts such as online loans and credits, mobile payments, mobile banking and blockchain are now familiar to us.

At a global level, mobile payments are considered one of the sectors with the greatest potential within the financial services sector and offer a wide range of possibilities for financial institutions. In addition, favourable regulatory changes are taking place with the aim of increasing transparency and competition in the banking industry. For example, the European Commission brought forward a proposal to reduce the price of cross-border payments in euros in non-euro member states of the European Union (EU) (Spinaci, 2019) and the European Central Bank (ECB) created the Target Instant Payment Settlement Service (TIPS) in 2018, with an eye to creating a pan-European solution for instant payments (Badi et al., 2018).

In other words, the payment business has growing income potential and the collaborative action between the different Spanish banks to create BIZUM is a clear example of the strategic mentality of incorporating the shift towards a FinTech-driven business model.

The different mobile payment applications developed by financial institutions face competitive pressure from established companies, such as banks or credit card issuers and, secondly, they compete with other innovative FinTech and non-bank applications.

The payment system, in this context, is a function performed by FinTech but that is still supported by banks, who lose a proportion of their margin but maintain the final interface with their clients (Navaretti et al., 2018). FinTech Start-ups complement incumbent banks in their activities, but they are unable to expand their activity.

2022 has brought the development of the European Payments Initiative (EPI), a model that has the support of the main European banks but has received little enthusiasm since only six European countries have joined, and the only Spanish bank is Banco Santander. The others have abandoned the program due to the damage they feel it will cause to BIZUM and the resources that they have invested in its development.

3 Methodology

Given the increasing complexity of banking's business model and operations, it is difficult to measure and observe true risk (Begley et al., 2017; Ho et al., 2020). A variety of approaches have been proposed for the quantification of bank risk (Baele et al., 2007; Sawada, 2013; Anginer et al., 2014; Bennett et al., 2015; Laeven et al., 2016; Demirer et al., 2018; Ho et al., 2020). However, one of the most commonly adopted measures is the return volatility of bank stocks, since these provide a reasonable and readily available alternative

(Neuberger, 1991).

Empirical evidence suggests that bank stock returns are time dependent (Tai, 2000; Ryan and Worthington, 2004; Joseph, 2006; Khan and Zia, 2019; Hu et al., 2020). To adequately model the parameters, these should be allowed to be reflective of the observed time variations in bank stock volatility. Additionally, since investors are not indifferent to the volatility of the stock they hold, this feature should also be considered intuitively. GARCH-M modeling satisfies this requirement (Sreenu and Naik, 2022).

Incorporation of volatility in the mean equation is especially important in banking because in this industry the high leverage ratio and the prevalence of the contagion effect makes investors more sensitive to changes in volatility than in the case of non-financial firms (Elyasiana and Mansur, 1998). The numerical specifications are detailed below.

3.1 GARCH fundamentals

GARCH is a predominant approach in the literature to the modeling and forecasting of volatility (Kalev et al., 2004, 2020). It was developed by Bollerslev (1986) to generalize the ARCH model proposed by Engle (1982). Bollerslev (1987) also shows that GARCH (1, 1) does adequately complement most economic time series data.

Consider the following autoregressive moving average, ARMA (p, q), model,

$$y_t = \delta + \sum\nolimits_{i=0}^{p} \varnothing_i y_{t-i} + \sum\nolimits_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t, \tag{1}$$

where δ is a constant term, $\varnothing_i$ the i_{th} autoregressive coefficient, $\theta_j$the j_{th} moving average coefficient, and $\varepsilon_t$the error term at time t. p and q are the orders of autoregressive and moving average terms, respectively. Suppose that ε_t has a changing variance over time and can be modelled as,

$$\varepsilon_t = \sqrt{v_t} z_t, \tag{2}$$

where z_t is a white noise sequence with mean 0 and variance 1. Assume that v_t is conditional on the l previous errors and can be estimated by the following equation,

$$v_t = \vartheta_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots + \alpha_l \varepsilon_{t-l}^2, \tag{3}$$

where ϑ_0 and α_i are constant coefficients. In this case, ε_t is said to follow an autoregressive conditional heteroskedastic process of order l, expressed as ARCH(l)(Engle, 1982) If the current conditional variance depends on the previous conditional variance, Eq. (3) can be generalized to the following form,

$$v_t = \vartheta_0 + \sum\nolimits_{i=1}^{l} \alpha_i \varepsilon_{t-i}^2 + \sum\nolimits_{i=1}^{k} \beta_i v_{t-i}, \tag{4}$$

In this notation, the error term ε_t is said to follow a GARCH process of orders l and k, denoted by GARCH (k, l) (Bollerslev, 1986)

The tendency for shock persistence is given as the sum of the coefficients $\alpha_i + \beta_i$ which must be less than or equal to unity for stability to hold in the GARCH process. If the magnitude of this sum is close to unity, the process is said to be integrated-in-variance, which means that the current information remains relevant to forecasts of the conditional variance for all horizons (Engle and Bollerslev, 1986).

3.2 GARCH in mean

The GARCH-in-mean (GARCH-M) model, which was developed by Engle et al., (1987), adds a heteroscedasticity term to the mean equation to show the influence of volatility on the mean prediction. More recently different authors have made contributions with this model as Lee et al, (2002), Lovreta and Pascual, (2020), and Sreenu and Naik, (2022).

Here, the GARCH model could take any form, such as NGARCH or EGARCH. For instance, for an ARMA-GARCH-M model with ARMA (p, q) and GARCH (k, l), the specified mathematical form is,

$$y_t = \delta + \sum\nolimits_{i=0}^{p} \varnothing_i y_{t-i} + \sum\nolimits_{j=1}^{q} \theta_j \varepsilon_{t-j} + \gamma_0 v_t + \varepsilon_t, \tag{5}$$

$$v_t = \vartheta_0 + \sum\nolimits_{i=1}^{l} \alpha_i \varepsilon_{t-i}^2 + \sum\nolimits_{i=1}^{k} \beta_i v_{t-i}, \tag{6}$$

where the residual process $\varepsilon_t = z_t v_t$ and z_t is independently and identically distributed.GARCH – M has the advantage that the specification is a generalization of GARCH, ARCH, and the most commonly used traditional constant variance models.

3.3 GARCH in mean for variance dummy variable

To determine whether the introduction of BIZUM had effects on the returns of Spanish bank stocks, a qualitative variable was included to identify variations after the moment when it was launched as a payment method, as shown in the following variance equation:

$$v_t = \vartheta_0 + \sum_{i=1}^{l} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{k} \beta_i v_{t-i} + \xi d_t, \tag{7}$$

where ξd_t is defined as the dummy variable for a particular event window $\{s_1, s_2\}$ $d_t = 1$ if $s_1 \leq \text{t} \leq s_2$; 0 otherwise.

The Likelihood function can be expressed as follows,

$$l(\varphi) = \frac{-1}{2} \sum_{t=1}^{\tau} \tag{8}$$

The coefficient on the qualitative explanatory variable ξ represents the volatility variation in absolute terms. To evaluate the impact of the adoption of BIZUM on the volatility of returns of Spanish banks, the following set of hypotheses will be tested:

$$H_0 : \xi \geq 0$$

$$H_1 : \xi < 0$$

3.4 Distributional assumptions and estimation

In GARCH models, unconditional distributions are non-normal, leading to fatter tails than the normal distribution. In practice, $e_t$is assumed to be normally distributed or in non-normal distributions. These non-normal distributions have been proved to perform well for modeling the fatter tails (leptokurticity) observed in GARCH residuals. The non-normal distributions are the Student t distribution proposed in Bollerslev (1987) and Generalized Error Distribution (GED) proposed by Nelson (1991). For references regarding comparison of GARCH with different distributions, see Vee et al. (2011), Gao et al. (2012), Wiśniewska and Wyłomańska (2017). The standardized GED proposed by Nelson can be simplified as follows:

$$f(z_t, v) = 2^{-1} v \Gamma \left(\frac{3}{v}\right)^{1/2} \left[\Gamma \left(\frac{1}{v}\right)^{3/2}\right]^{-1} \exp \tag{9}$$

where, z_t is the non-normally distributed residual as in Student t and GED, $-\infty < z_t < \infty$and $v > 0$. The GED reduces the normal distribution at $v = 4$. At $0 < v < 2$, the distribution has thicker tails than the normal distribution. Tables 1 and 2

4 Data description

The 27 incumbent Spanish banks that jointly launched BIZUM in 2016, are:

The main promoter of the project was CaixaBank, which is why it has held the greatest weight in the shareholding of the new company from the beginning. It is followed by BBVA and BSCH.

The incumbent banks were selected based on data availability (Bloomberg, 2021) and are CaixaBank, BBVA, Banco Santander, Banco Sabadell, Bankia and Bankinter.

1. CaixaBank was founded in 2014 when La Caixa, which was founded in 1904, was transformed under the guidelines set out in Act 26/2013 of December 27. It has its registered office in Valencia and at the end of the first quarter of 2022 had a volume of assets of 680,036 million EUR and more than 4800 branches. It has also a relevant presence in Portugal, with 2 million customers from the acquired BPI in 2018. Following the recent integration of Bankia in 2021, CaixaBank, is now the largest financial institution in Spain based on domestic assets alone (Caixabank.com, 2022)
2. BBVA is domiciled in the Basque Country and was created in 1857 as Banco Bilbao. It is a global reference with a presence in various Latin American countries and Turkey. BBVA operates through Retail Banking, Corporate and Business Banking (CBB), Corporate

Table 1
Founding partners of BIZUM.

CaixaBank	Liberbank
BBVA	Caja Laboral
BSCH	Evo Banco
Banco Sabadell	Banca March
Bankia	Cecabank
Banco Popular	Caja Rural CM
Kutxabank	Caja de Crédito Ingenieros
Banco Cooperativo	BNP Paribas
Unicaja	Banca Pueyo
IberCaja	Banco Caixa Geral
Cajamar	Banco Mediolanum
Abanca	Caja Rural de Almendralejo
Bankinter	Self Trade Bank
Banco Mare Nostrum	

Source: elconfidencial.com

Table 2
Shareholding composition.

Bank	Percentage
CaixaBank	22.92 %
BBVA	15.90 %
Banco Santander	13.60 %
Banco Sabadell	10.30 %
Bankia	8.90 %
Banco Popular	4.66 %
Kutxabank	3.10 %
Banco Cooperativo	3.10 %
Unicaja	2.70 %
Rest	22.90 %

Source: sabi-bvdinfo.com 2022

and Investment Banking (CIB), BBVA Seguros and Asset Management. It is listed on the New York Stock Exchange, the Euro Stoxx 50 and the IBEX-35, among other markets. In the third trimester of 2022, it has a volume of assets of more than 738,680 million EUR (BBVA.com, 2022).

3. Banco Santander has its headquarters in Madrid and is the leading international bank with around 10,000 branches worldwide including Spain, Brazil, UK, Mexico, USA, Portugal, Chile, Argentina, Poland, and Germany. In the third trimester of 2022 it has a volume of assets of more than 1815,000 million EUR and more than 154 million customers. It is listed on different stock indexes, particularly including the IBEX-35 and the Euro Stoxx 50 (Santander.com, 2022).
4. Banco Sabadell is a bank founded in 1881 that was initially rooted in Sabadell, a small town near Barcelona and has subsequently expanded nationally and internationally, being present in the United Kingdom and Mexico. It is listed on the IBEX-35 and has a volume of assets in the third trimester of 2022 of more than 260,000 million EUR (BancSabadell.com, 2022).
5. Bankia was created in 2011 out of the rescue by the Spanish Government of seven savings banks due to the collapse of the real estate sector (Caja Madrid, Bancaja, Caja Canarias, Caja de Ávila, Caixa Laietana, Caja Segovia and Caja Rioja). For 10 years it has been active in the market with the aim of recovering as many of the invested funds as possible and became the fifth largest bank in Spain with a volume of assets exceeding 209,000 million EUR when it was absorbed by CaixaBank in late 2021 (Cincodias.elpais.com, 2022).
6. Bankinter was founded in 1965 as a subsidiary of Banco Santander and Bank of America. It is currently listed independently on the Spanish Stock Market and in the third trimester of 2022 it exceeded 110,000 million EUR in assets. It has been able to diversify its business thanks to some extremely shrewd management, such as the creation of Línea Directa Aseguradora, a leading insurer with a very aggressive pricing policy (Bankinter.com, 2022).

The selected sample period is from 01/07/2013–30/01/2020, thus covering the three-year period before the incumbent banks started to operate with BIZUM on 03/10/2016, and also the four years afterwards. As stated by Miller and Liu (2014) and Sood and Tellis (2009), the possibility of future disruptive pressures can suppress incumbents' stock prices, so in this study stock returns were selected to retrieve stock price movements. Stock returns on the adjusted closing prices of the incumbent banks' stocks in EUR are calculated by the following formula:

$$r_i = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

Table 3 presents the summarized statistics for the sample of daily returns for the incumbent banks' stocks. The data was plotted to check for outliers and the date stamp of each observation was examined for any repetition within the set. A cubic spline framework was used to limit the impact of outliers.[5]

The data are available to the public at www.finance.yahoo.com (Yahoo.com, 2022).

Fig. 1 plots the daily returns of the six Spanish banks' stocks, which are shown to be around zero. Bankia and BBVA have slightly negative mean returns, whereas Bankinter has the highest mean return. Sabadell has the highest standard deviation of 0.0215, followed by Bankia with 0.0206. The kurtosis values of all return time series are higher than three, so the returns distribution could be fat-tailed. As the skewness values are negative, they are the asymmetric tail, except for Bankia.

The Jacque-Bera results are statistically significant and reject the null hypothesis of a normal distribution (Brooks et al., 2000). However, our analysis is robust. Indeed, the GARCH-M GED specification is robust in non-normal cases.

First, we determine whether the analysed series are stationary, employing the augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1981), and the Phillips-Perron (PP) test developed by Phillips (1988). A stationary time series is mean-reverting and

[5] The following events led to large spikes in the return series: Brexit referendum on 23 June 2016 during the third quarter of 2016 for all six Spanish banks. Sabadell acquired the British TSB bank in the first quarter of 2015. Santander in the first quarter of 2015 after fundraising was announced. Bankia in second quarter 2014 following reverse split in first quarter of 2013 and in the second quarter when the Fund for Orderly Bank Restructuring (FROB) sale was announced.

Table 3
Summary statistics for daily returns from 01/07/2013–30/01/2020.

	Bankia	Bankinter	BBVA	CaixaBank	Sabadell	Santander
Mean	-0.00007	0.00052	-0.00007	0.00020	0.00003	0.00007
Median	0.00000	0.00050	-0.00010	0.00000	0.00000	0.00025
Maximum	0.10788	0.08162	0.07060	0.07021	0.12998	0.07309
Minimum	-0.07951	-0.06473	-0.07408	-0.10492	-0.09525	-0.07223
Std. Dev.	0.02065	0.01619	0.01671	0.01921	0.02152	0.01718
Skewness	0.29805	-0.02029	-0.10497	-0.10687	0.26298	-0.02041
Kurtosis	4.58337	4.20908	4.38866	4.44738	5.70686	4.45970
Jarque-Bera	200.9655	102.7521	138.4828	150.2863	533.8468	149.7115
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	-0.122029	0.882789	-0.118414	0.335008	0.050115	0.112337
Sum Sq. Dev.	0.718172	0.441606	0.470125	0.621511	0.7801	0.496801
Observations	1685	1685	1685	1685	1685	1685

Source: Eviews 10 University Version.

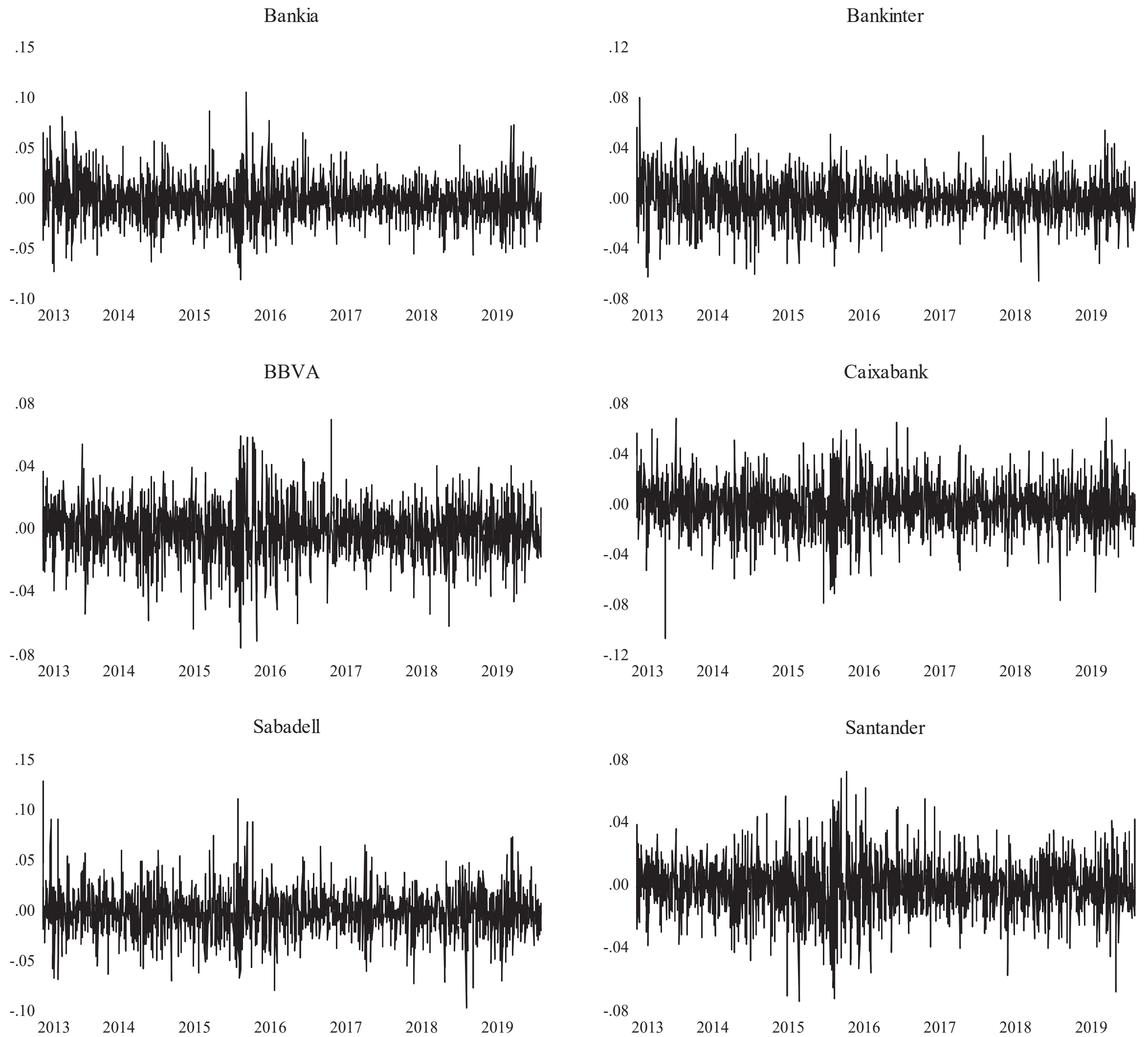

Fig. 1. Daily returns of Spanish bank stocks from 01/07/2013–30/01/2020.

has a finite variance that guarantees that the process will never drift too far away from the mean. Table 4 shows the results of the ADF test and PP test for the weekly logarithmic returns. The hypothesis of a unit root is rejected for all the Spanish banks' daily returns at 90 %, 95 % and 99 % of confidence, which implies that the logarithmic returns of prices are stationary.

Table 4
ADF Test, daily returns of Spanish bank stocks from 01/07/2013–30/01/2020.

Variable	Augmented Dickey-Fuller test statistics	Phillips-Perron test statistics
Bankia	-39.31017***	-39.30022***
Bankinter	-41.07401***	-41.07395***
BBVA	-39.81536***	-39.80249***
CaixaBank	-39.94841***	-39.94310***
Sabadell	-38.66418***	-38.66230***
Santander	-39.89692***	-39.88994***

Notes:
*significant at level of 10 %,
**significant at level of 5 %,
*** significant at level of 1 %.
Source: Eviews 10 University Version.

The BDS test by Brock, Dechert and Scheinkman was run to confirm the nonlinearity of the series as described in Brock et al. (1986). The results (see Table 5) reveal the presence of a nonlinear structure in the daily returns of incumbent banks' stock. For most of the return series, the nonlinearities can be modelled by a GARCH process. Hence the nonlinear structure in the incumbent banks' stock returns can be viewed as being caused by the conditional heteroscedasticity. The GARCH effect sheds light on the amount of information reaching the market cluster(Engle, 1982)or alternatively reflects the time needed by the market participant to process the new information.

Having determined that the variables are stationary and nonlinear, we need to model their stochastic dynamic structures. The results of modeling the stochastic dynamics of the incumbent banks' daily returns are unique and are presented in the following section.

5 Empirical results

In this section, we estimate the GARCH-M generalized error distribution (GED) for the returns of incumbent banks' stocks and volatility using data for the period from 01/07/2013–30/01/2020 and an augmented expression of the model, where the qualitative variable is added to the variance equation (see Eq. 7) as a proxy to retrieve the impact of Spanish incumbent banks when they started to operate with BIZUM on 03/10/2016.

The Akaike Information criterion (AIC) proposed by Akaike (1973) suggests the random walk as the optimal specification for Bankia, Bankinter, BBVA, CaixaBank, Sabadell and Santander. Therefore, the first mean equation only contains an intercept. The results are shown below:

To evaluate the model, the test in the residual is a Lagrange multiplier (LM) test for autoregressive conditional heteroscedasticity (ARCH) (Engle, 1982) This test (see Table 6) indicated the absence of ARCH in the residuals, since the null hypothesis of non-heteroscedasticity is not rejected, even for Bankinter, whose test coefficient is greater at first glance than that of the other banks. The insignificant Ljung-Box (Q) statistic for the standardized residuals indicates that there is no serial correlation in the disturbances (see Table 6). Based on these statistics, the GARCH-M model appears to perform reasonably well.

The coefficients estimated in the mean equation are all statistically significant at 99 % confidence. The mean equation indicates that the intercepts for all Spanish incumbent banks are close to zero and the coefficient associated to the GARCH-M (γ_i) is positive except for CaixaBank. The statistical significance of the GARCH-M coefficients indicates that investors are not indifferent to the volatility of the stocks they hold; as uncertainty in stock returns varies, the risk premia required by investors will also change.

The positive signs related to the GARCH-M coefficient makes sense with the fundamental assumption that investors need to compensate additional risk with higher expected return, since traditional asset pricing theory (e.g., Sharpe 1964 and Lintner 1965)

Table 5
BDS Test, daily returns of Spanish incumbent bank stocks from 01/07/2013–30/01/2020.

BDS Statistic					
Dimension	***2***	***3***	***4***	***5***	***6***
Bankia	0.007274***	0.016569***	0.024003***	0.027611***	0.028250***
Bankinter	0.010640***	0.021523***	0.028935***	0.032431***	0.032898***
BBVA	0.007033***	0.015756***	0.020845***	0.022657***	0.022989***
CaixaBank	0.006644***	0.017467***	0.025136***	0.027747***	0.026762***
Sabadell	0.006893***	0.017201***	0.023028***	0.025250***	0.025026***
Santander	0.011682***	0.023897***	0.033812***	0.037830***	0.038126***

Notes:
*significant at level of 10 %,
**significant at level of 5 %,
*** significant at level of 1 %.
Source: Eviews 10 University Version.

Table 6
GARCH-M GED for Spanish bank stocks from 01/07/2013–30/01/2020.

	Bankia	Bankinter	BBVA	CaixaBank	Sabadell	Santander
	Coefficient	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*	*Coefficient*
Conditional Mean Equation						
δ	-0.00202***	-0.000647***	-0.002305***	0.000499***	-0.002544***	-0.00196***
γ	3.582713***	2.348935***	7.754087***	-1.676242***	5.674869***	7.900342***
Conditional Variance Equation						
ϑ	0.0000133***	0.0000183***	0.00000831***	0.0000973***	0.0000194***	0.00000581***
α_1	0.053134***	0.077388***	0.036107***	0.102074***	0.043339***	0.049467***
β_1	0.936178***	0.915224***	0.947138***	0.721759***	0.925068***	0.946813***
ξ	***-0.000004****	***-0.000011****	***-0.000002****	***-0.000029****	***-0.000005****	***-0.000001****
Log Likelihood	4192.701	5415.455	4554.879	5225.645	4186.939	4516.183
Akaike	-4.96938	-5.23918	-5.39926	-5.05290	-4.96254	-5.35333
Scharwa	-4.95005	-5.22282	-5.37993	-5.03654	-4.94321	-5.33400
HQ	-4.96222	-5.23318	-5.39210	-5.04690	-4.95538	-5.34617
ARCH LM	0.03333	1.17468	0.03840	0.23548	0.22431	0.12771
LJUNG-BOX(Q)	0.03340	1.17670	0.03850	0.23590	0.22410	0.12780
Variance	***- 31.13 %***	***- 60.11 %***	***- 35.14 %***	***- 30.73 %***	***- 27.63 %***	***- 25.30 %***

Notes:
*significant at level of 10 %,
**significant at level of 5 %,
*** significant at level of 1 %.
Source: Eviews 10 University Version.

implies that investors are risk averse. CaixaBank has a negative sign, and it can be argued that investors are better equipped to bear risk in riskier periods and look to save more during uncertain times. CaixaBank has a negative sign, so it can be argued that if it is less affected by random shocks that the other banks, investors will switch to it in response, and will avoid the other banks.

The variance equation sheds light on the volatility dynamic of the returns of Spanish incumbent banks' stocks. The presence of ARCH and GARCH effects are identified for the six incumbent banks' returns, in accordance with the literature (Comin, 2009; Campbell et al., 2001; Pástor and Veronesi, 2005). The large sum of these coefficients (α_i and β_1) implies that a large return will lead future forecasts of the variance to be high for a protracted period.

Own conditional ARCH effects (α_1), which measure short-term persistence, are important for explaining the conditional volatility (Table 6). The estimated coefficients on the own conditional volatility effects, the α_i terms, are statistically significant at 99 % confidence in each of the GARCH-M models. For each *i*, the estimated α_1 values are smaller than their respective estimated $\beta_i$values, indicating that own volatility long-run (GARCH) persistence is greater than short-run (ARCH) persistence. The variance intercept is close to zero and statistically significant at 99 % confidence in each of the GARCH-M models.

Own conditional GARCH effects (β_i), which measure long-term persistence, are clearly important for explaining conditional volatility (Table 6). The large values of the GARCH effect mean that large changes in volatility will affect future volatility, which will volatilize for a long period of time since the decay is slower. For a particular *i*, the estimated coefficients for β_i are unique across the models. BBVA shows the greatest long-term volatility persistence of 94.71 %, followed by Santander with 94.68 % and Bankia with 93.61 %. CaixaBank has the lowest long-term volatility persistence with an β coefficient of 72.17 % and the highest short-term volatility persistence with 10.20 %, indicating that overall, its volatility persistence decays less slowly than that of the other banks.

Nevertheless, and coming back to the main purpose of this paper, it is the associated coefficient of the qualitative variable in the variance equation ξ that will provide insights into how the volatility structure of Spanish banks was modified by the implementation of BIZUM as a disruptive payment solution for the traditional banking industry.

At first glance, the signs of the ξ coefficient are statistically significant at 99 % confidence and with negatives signs for all banks. We initially interpret those results as showing how investors are not indifferent to the adoption of the disruptive technology in the context of underlying stock return volatility. Secondly, the negative sign highlights that an impact of the adoption of a disruptive technology by the incumbent banks led to a reduction in their stock return volatility.

The results of the magnitude of the ξ coefficient indicate that in terms of variance, Bankia, Bankinter, BBVA, CaixaBank, Sabadell and Santander's volatility decreased by 31.13 %, 60.11 %, 35.14 %, 30.73 %, 27.63 % and 25.30 %, respectively.

Bankia's level of volatility before BIZUM was launched was 0.0000133, which implies a decrement of 31.13 % (-0.00000414/ 0.0000133) in terms of variance. Bankinter's level of volatility before BIZUM was 0.0000183, which implies a decrement of 60.11 % (-0.000011/ 0.0000183) in terms of variance. Bankinter turned out to be the bank that was most impacted by the implementation of BIZUM. BBVA's volatility was on a very similar level to Bankinter at 0.00000831, but the impact on its return volatility was not as much at 35.14 % (-0.000002/0.00000831) in term of variance. CaixaBank and Sabadell's volatility decreased by 30.73 % and 27.63 % in terms of variance, calculated as −0.000029/ 0.0000973 and −0.000005/0.0000194 respectively. Santander is the Spanish bank that was impacted the least with a reduction in its return volatility of 25.30 % (-0.000001/0.00000581).

The results provide evidence that as a FinTech Start-up strategy used by incumbent banks in Spain, BIZUM is a proven success, and this is also reflected by the stock market, as the volatility of the six incumbent banks that started to operate with BIZUM significantly decreased.

6 Discussion

This paper reviews the effect of BIZUM, a real-time digital payment solution, on the volatility of the stock returns of Spanish incumbent banks. It was introduced in 2016 as a joint venture of the Spanish banking system to remain competitive in an increasingly disruptive FinTech Start-up environment. For this purpose, a GARCH-M GED approach was used to model the returns and volatility of those Spanish banks in the period from 01/07/2013–30/01/2020, using a qualitative variable in the variance equation as a proxy for the launch of BIZUM in 2016 and to discriminate the impact on volatility.

The findings show that the control variable reflects the effect of significant change in the stock price volatility of the six studied incumbent banks after BIZUM was launched in 2016. The statistical significance and negative signs for the ξ coefficient associated to the control variable of BIZUM adoption of all banks indicates that investors are not indifferent to the adoption of a disruptive technology in the context of the underlying stock price volatility, and that an impact of FinTech adoption by the incumbent banks led to a reduction in the volatility of their stock prices.

The decrease in stock price volatility oscillates between 25.30 % and 60.11 %. with a median of 30.96 %. Bankinter is the most impacted bank in terms of decreased volatility, while Santander is the least impacted.

Since BIZUM is a FinTech solution that was adopted by incumbent banks in Spain, one might suspect investors to have anchored the benefits and competitive advantages that FinTech might offer, and which have proven to be so successful. These results are in line with the theoretical argument proposed by Jun and Yeo (2016) that FinTech will complement incumbent banks and lead to positive impact, since banks are incorporating disruptive technologies into their business models. In other words, the market reacted positively to the risk of incumbent banks in Spain onboarding FinTech strategies.

The practical contribution is especially relevant from an investment perspective. The evidence suggests that investors were informed and acknowledged the advantages of BIZUM and expected volatility to decrease. This result supports rational investor behaviour. If investors know that a FinTech Start-up strategy will reduce risk in the incumbent banks, then a rational investor will invest in those stocks. Also, information disclosed about the usage and advantages of BIZUM could be considered positive signals to the market. As volatility decreased when the BIZUM technology was introduced, this generates incentives for risk adverse profiles to invest. The paper also gives banking regulators and authorities a better understanding of the challenging task of ensuring financial stability and prudential soundness while allowing for the development of technological innovation, providing insight on bank stress test scenarios and other risk related considerations, such as the adoption of FinTech strategy. Banking regulators and authorities can play a role by mitigating related risks, particularly bearing in mind this paper's findings regarding forward planning for policy design and implementation. A further reflection on how Fintech relates with banking is the increased dependence on and exposure to IT service availability and exposure to cyber risk, which may be tackled by banking authorities and regulators in the form of a collateral scenario.

To summarize, this paper provides insights into the role of the pricing of FinTech and banking-related assets and has other important implications for investors and international institutions that include FinTech or banking-exposed investments in their portfolios.

To the authors' best knowledge, no previous study has researched the relationship between FinTech and stock price behaviour on the basis of a real-world *ex-post* implementation, and neither have any studied the relationship between FinTech and incumbents in Spain.

This research shows how stock volatility was impacted by the introduction by incumbent banks of a disruptive FinTech Start-up strategy, namely BIZUM, a digital real time payment solution. It contributes to the FinTech literature and to the academic field regarding risk and innovation.

However, it must be emphasized that more empirical research is needed to draw statistically significant conclusions, for this paper is not without its shortcomings, while future research directions can also be drawn. First, there is a need for a more fundamentally defined econometrical model to represent the returns of Spanish bank stock behaviour. Second, the sample might be too small to draw conclusions for a longer period. A more prolonged sample over time would provide greater insights and additional nuances on the events. Third, different market conditions may shed further light on the relationship between FinTech and incumbents, and thus help to generalize the results. Fourth, the paper focused on a case study in the Spanish banking industry. Future research could extend the analysis by studying different countries, which may have differently structured retail banking industries and impacts to that of Spain. Moreover, examination of the effect of different investment stages on the incumbents' stock prices and stock price volatility might provide further insight into the fast-growing FinTech industry.

Finally, we emphasise that this article is part of a line of research and is only a preliminary attempt to shed some light on the context and present the opportunity for future lines of research.

CRediT authorship contribution statement

Laura Arenas: Conceptualization, Methodology, Writing – original draft, Software, Data curation. **Emili Vizuete-Luciano**: Methodology, Resources, Writing – review & editing, Visualization, Validation, Supervision. **Anna Maria Gil-Lafuente**: Conceptualization, Writing – review & editing, Visualization, Supervision.

Data availability

Data will be made available on request.

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