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THE IMPACT OF DISRUPTIVE TECHNOLOGY ON BANKING UNDER SWITCHING VOLATILITY REGIMES

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Abstract. This paper uses the case of Spain to investigate whether and how disruptive technology impacts banking stock returns under a high volatility regime and a low volatility regime. For this purpose, a two-factor model with heteroscedastic Markov switching regimes has been applied. The results indicate that disruptive technologies have an impact on Spanish banking stock returns and that the effects are volatility regime dependent, having a relevant positive impact in high volatility regimes and a less relevant negative impact in low volatility regimes. These findings suggest that investors are informed about and acknowledge the advantages of disruptive technologies and will use their adoption as a business strategy to offset adverse market circumstances. During stable market conditions, on the other hand, Spanish banking seems to have less expectations about disruptive technology as a business strategy. To summarise, this paper provides insights into the role of the pricing of banking-related assets and has other relevant implications for investors that include disruptive technology or banking exposed investments in their portfolios.

Keywords: banking, disruptive technology, volatility, factor model, Markov heteroscedastic regime switching, volatility clustering, asset pricing.

JEL Classification: C58, G12, G21, O33.

Introduction

This paper studies the implications of disruptive technological change on asset pricing in Spanish banking under different market circumstances. If a certain technology plays a critical role in a disruptive innovation, it can be defined as a "disruptive technology (DT)" (Bower & Christensen, 1995). Schumpeter was among the first authors to highlight the important role of innovation in his Theory of Economic Development (1912), where he described economic development as the disruption of the regular circular flow caused by the introduction of novelties.

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The financial technology revolution is thriving globally the industry. From chatbots, to Artificial Intelligence (AI) and Blockchain, among many others, financial organizations seek to keep up with the latest tech trends. In this context, the current market and non-market circumstances surrounding the tech trend are particularly challenging, from demanding customers looking beyond traditional services, new competition such as Fintechs, technology giants and neobanks, and the increasing level of regulation, while geopolitical tensions are arousing awareness and uncertainty. Disruptive technology and its impact on the financial industry in general is leading to structural transformation, which is emphasized by digitalization and disintermediation. On the other hand, the incentives to provide a more open and inclusive financial system are also targeted as major socio-economic benefits of technological disruption in banking, in line with a general shift towards responsible investment and financial wellbeing. Banks are relevant for financial stability and thus, understanding the challenges and opportunities of the disruptive technology trend, particular critical.

Stock markets react promptly to the increasing presence of disruptive technologies and the rapid adoption by financial organizations of Fintech solutions. Some literature claims that the New Economy impacts the market valuation process (Campbell et al., 2001; Kearney & Potì, 2008), leading to an association between novel technologies and stock volatility. Since stock prices are assumed to reflect expectations of future profits (Pástor & Veronesi, 2009), (Mazzucato, 2006), it makes sense for expectations about the outcome of a disruptive technology to also be reflected by stock prices and volatility. Uncertainty about new technologies may affect stock price levels and volatility, and since volatility is commonly used as a proxy for uncertainty, and disruptive technology highlights the uncertainty relating to new technology, we consider disruptive technology to be an example of true uncertainty (Knight, 1921) and interpret its context through the lens of stock price volatility.

Despite the recognized importance of how disruptive technologies impact market volatilities in the descriptive literature, there have been surprisingly few empirical studies on the matter (Ying et al., 2018). Also, the root causes of the uncertainty that might drive risk premia in asset pricing are still highly debated (Laitner & Stolyarov, 2019).

On the other hand, an understanding of the relationships between banking and the performance of disruptive technology under different market circumstances is especially interesting due to the increasing importance of technologies as drivers of financial market volatility (Campbell et al., 2001; Mazzucato, 2002; Mazzucato & Tancioni, 2008) and market spillover effects.

Spanish banking is making a major effort to keep up with new technologies, and this is also channelled to the stock market, resulting in specific exposure of the sector to such technologies (Arenas & Gil Lafuente, 2021).

The objective of this research is to investigate whether disruptive technology impacts the performance of Spanish banks and also how the impact of disruptive technology evolves under different market conditions and volatility regimes. For this purpose, a two-factor model with heteroscedastic Markov switching regimes has been applied. Daily log returns were used covering a period from November 26th, 2015 to January 30th, 2020, where the IBEX35 BANCA index was selected as a proxy for the Spanish banking sector, the MSCI ACWI IMI Disruptive Technology ESG Filtered Index as a proxy for disruptive technology and the MSCI WORLD as a proxy for the global market portfolio.

We found that disruptive technology increases daily log returns in Spanish banking in high volatility regimes and slightly decreases the same returns in low volatility regimes. These findings suggest that investors are informed about and acknowledge the advantages of disruptive technologies and will use their adoption as a Fintech business strategy to offset adverse market circumstances.

This article contributes to the innovation and finance literature in a variety of ways. First, it presents a significant relationship between disruptive technology and Spanish banking. Second, it provides evidence that disruptive technology positively impacts Spanish banking returns under unfavourable market conditions and does so negatively under stable market conditions. Third, it shows that intensity also depends on the market circumstances reflected through volatility regimes, having a more significant influence under unfavourable market conditions and less influence under stable market conditions. From another perspective, the results highlight how banks may use disruptive technology to tackle increased volatility among markets.

This article provides insights for investors and international institutions regarding the role of the pricing of banking related assets. It also has important implications for disruptive technology and/or for banks whose portfolios are exposed to investments in disruptive technology. The article may also provide insight for banking regulators and authorities in terms of providing insight for bank stress test scenarios and other risk related considerations.

The conclusions open many avenues for future research, such as comparing the impacts of disruptive technology on returns in different sectors, a cross-country approach, considerations of long and short timeframes, and potentially viable novel approaches to financial regulation.

The remainder of the article is structured as follows. Section 1 provides a brief overview of the current state of the Spanish banking sector. Section 2 reviews the literature to provide relevant background for our research design. Section 3 describes the methodology. Section 4 details the data. Section 5 presents the empirical results, and the last Section outlines the conclusions and provides certain directions for future research.

1. The Spanish banking sector

Banking is a key driver of economic growth in Spain and is important for the whole economic system. Spanish banking has a turbulent recent history, having been significantly impacted by the financial crisis in 2007, the bursting of the property market bubble and a variety of repercussions for the global economy. A crisis was triggered in the country (Arghyrou & Kontonikas, 2012) when sovereign risk premia and credit default swap rates reached record levels (Lane, 2012) and when the domestic real estate bubble burst, this led Spanish saving banks to suffer serious management problems (Rodríguez-Ruiz et al., 2016).

The Spanish Central Bank, supported by the European Commission, implemented a drastic banking reform, the objective of which was to safeguard the sustainability of the Spanish financial system by encouraging concentration and recapitalization (Blanco-Oliver, 2021).

Today the landscape of the Spanish banking sector has been affected by various mergers and acquisitions. For example, the recent purchases 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. This latter case suggests that banks can draw on other investments when integrating their own legacy systems into the digital business model.

The banking sector has had to undergo major transformation due to the changes to its customers' habits, and especially the rapid emergence and rise of new purely online competitors. This has caused traditional banks to evolve dynamically as they strive to stay competitive in the medium and long term. Fintech, the sector where companies use technology and its different applications to improve financial services and processes, has been used to upgrade everything from electronic banking to savings and investment applications through spectacular improvements to the user experience.

Spanish banking is seeking new business models to absorb and gain competitive advantages from digitalization, such as gaining access to potential new customers through the internet and mobile devices, increasing computing power, achieving more sustainable storage, creating new collaborative working environments, and shifting from a "product" centric to a "user" centric model.

As a knock-on effect, the number of domestic branches in Spain fell by 48.12% from 43,164 at the end of 2010 to 22,392 at the end of 2020 (Bloomberg, 2021) (see Figure 1) and the number of employees in the banking sector fell to 181,000 in 2019, which is a 31% decrease on the 2010 figure of 263,715 (Statista, 2021).

In 2020, 50% of financial products were being sold online, and 6 out of 10 Spaniards had replaced physical banking with digital banking (KPMG, 2020), while the use of electronic money reached 196 million EUR in 2020 compared to 69 million EUR in 2010 (European Central Bank [ECB], 2021) (see Figure 2).

Even though cash is still widely used in Spain, the trend is towards increased reliance on PoS card payments. The number of PoS terminals increased by 24% in only 4 years from 2016 to 2020.

Spanish banking is an economic driver. Despite the overall downward trend in the economy, in 2019 the banking sector's total assets as a percentage of GDP was still 217%.

Negative-rate scenarios since 2015 (see Figure 3) and the COVID-19 crisis have driven banks to accelerate their digitalization prospectuses.

In contrast, the non-performing loan ratio has been recovering since 2013 (see Figure 4) and the overall risk of the sector has been decreasing, as the BIS Ultimate Risk Total from Spain Banks shows (see Figure 5), which highlights the fact that there are potential drivers, such as improved efficiency and asset quality, behind the evolution of the structural profitability of the banking system.

If disruptive technologies or indeed Fintech are applied in the correct way, they could be used to overcome the social and economic gaps that exist worldwide (Schmidt & González, 2020).

Digital payment, followed by Neobanking and digital investments, are the main trends in Spanish Fintech, with the total transaction value of the digital payments segment rising from 25.93 billion EUR in 2017 to 43.56 billion EUR in 2020, that of the neobanking segment from 2.56 billion EUR in 2017 to 18.23 billion EUR in 2020 and that of digital investment from a total transaction value of 0.21 billion EUR in 2017 to 0.23 billion EUR in 2020, based on data provided by Statista (2022).

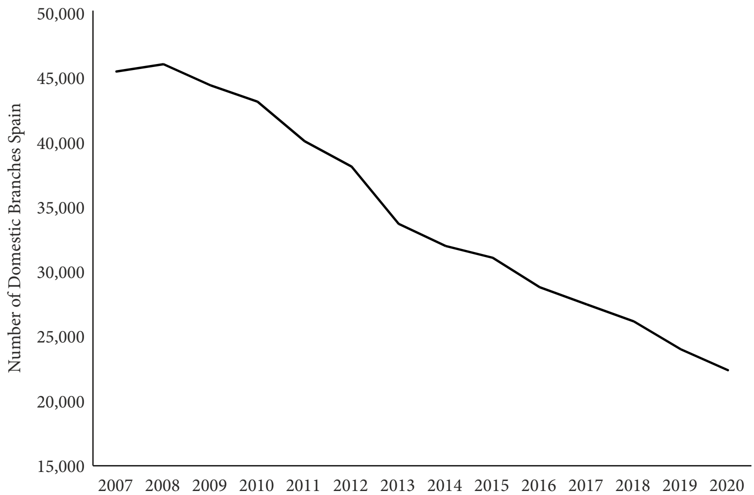

Figure 1. ECB MFIs structural indicators of domestic branches in Spain (2007 to 2020). Data from Bloomberg

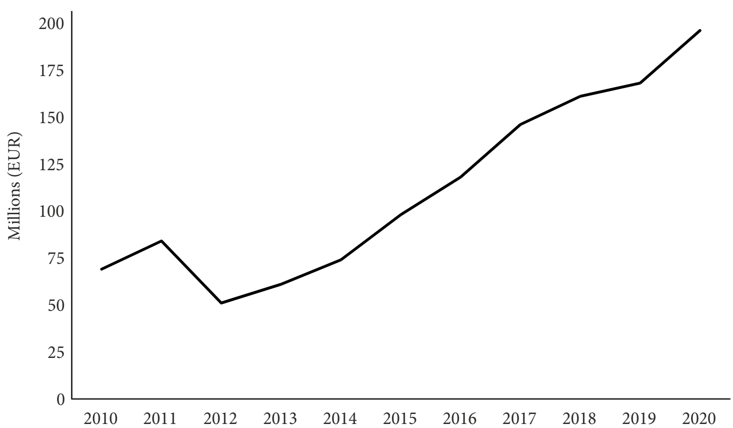

Figure 2. Electronic money – Total reported by electronic money institutions in Spain (stock) (2014 to 2020). Data from ECB Statistic Datawarehouse

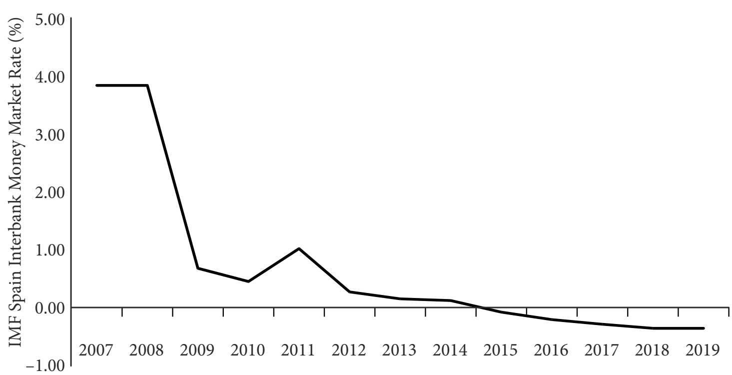

Figure 3. IMF Spain interbank money market rate (2007 to 2019). Data from Bloomberg

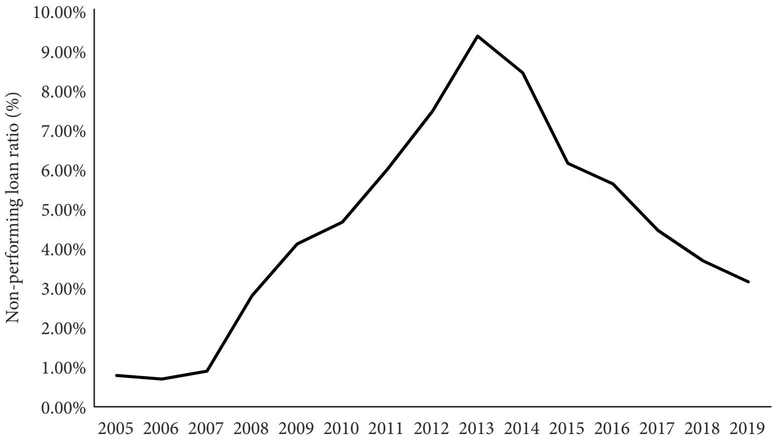

Figure 4. Non-performing loan ratio (2005 to 2019). Data from Statista

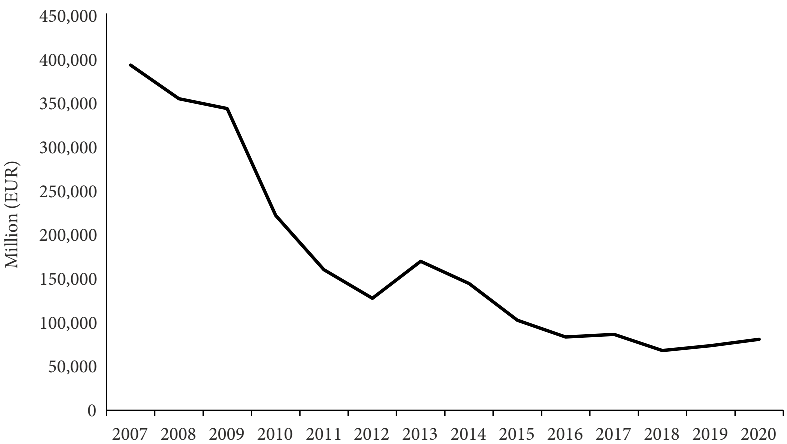

Figure 5. BIS ultimate risk total from Spain banks (2007 to 2019). Data from Bloomberg

2. Literature

2.1. Technology and stock behaviour, some context

The stock market plays a significant role in facilitating technological novelties, since funds flow into them as investors seek to make extraordinary gains from disruptive technologies. Brown et al. (2017) agree that a developed stock market is especially relevant for making innovation-intensive, high-tech industries uniquely suited for financing technology-led growth.

Questions persist about how new disruptive technology could be a macroeconomic factor and a source of uncertainty, and how technological change might explain phenomena of the asset market, such as driving risk premia in stock markets. In a similar context, it seems difficult to link short-term stock market fluctuations with economic theory. Very small fluctuations in economic fundamentals such as profit, dividends and output growth should explain the market value of a stock (Peralta-Alva, 2007). In this vein, some literature, for example

Kydland and Prescott (1982), proposes that technology shocks that impact the macroeconomy, channelled by the stock market, might explain short-term fluctuations. Jovanovic and Rosseau (2001) document long lags in the operation and diffusion of new technologies, and associate fluctuations in the stock market with three technological revolutions: Electricity, World War II, and IT.

During such radical technological changes, excess volatility peaks precisely because of the associated uncertainty (Shiller, 2000), and therefore fundamental information is less useful for making predictions about future values (Tushman & O'Reilly III, 1996). Technological innovations play a major role in explaining the long-term volatility observed in stock markets (Iraola & Santos, 2007). However, to better understand how technological 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). Basically, forecasters of future profits, also called technology optimists, and historical economic performance measures such as economic statistics, tend to be in the greatest disagreement during times of technological change (Brynjolfsson et al., 2019).

Stock prices may also reflect expectations regarding disruptive technology. 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.

Pérez (2012) states that it is when old technology is replaced by a new technology that excess funds flood the market, driven by over-excitement and decoupling the temporary price from its fundamental valuation. In the context of disruptive technology, it makes sense for enthusiastic investors to bid up to twice the stock price, since the future course of a disruptive technology will be especially influenced by investors' beliefs.

Pástor and Veronesi (2006), Gharbi et al. (2014) and Schwert (2002) take their evidence from the levels of disruptive or frontier technology firms, which exhibit unjustifiably high stock returns and volatility.

Some authors associate stock price behaviour during times of technological revolution with bubble-like patterns. Shiller (2000) and Pérez (2003) attribute this pattern to market irrationally and Pástor and Veronesi (2009) relate it to uncertainty about future productivity and the time-varying nature of this uncertainty.

The literature that studies the link between technological innovation and stock prices from a more theoretical and cyclical perspective seems to generally agree that new technologies cause the stock market to drop (Greenwood & Jovanovic, 1999; Hobjin & Jovanovic, 2001; Laitner & Stolyarov, 2003; Manuelli, 2000). The expectation of lower future profits among firms that purchase a technology that is soon to become obsolete drives their market value down (Manuelli, 2000) and raises future returns on new investments (Laitner & Stolyarov, 2019). When the new technology becomes available, it is gradually adopted by new firms, leading to a period of high investment.

Pástor and Veronesi (2009) state that it is the time-varying nature of initially idiosyncratic risk, with adoption of the new technology evolving systematically, that leads new economy stocks to initially command a high market value. As the probability of adoption increases, systematic risk pushes discount rates up and thus lowers stock prices in both the new and old economies.

Greenwood and Jovanovic (1999) and Manuelli (2000) study the behaviour of macroeconomic variables and the stock market in times of major technological change. Pástor and Veronesi (2009) present a macroeconomic model where if the productivity of a new technology is uncertain, its learning process drives a boom-bust pattern in the stock market. Laitner and Stolyarov (2019) develop a model suitable for studying risk premia and asset-pricing phenomena related to technology diffusion and demonstrate that large-scale, disruptive shocks increase economic mechanisms, producing a sizeable equity premium, a low risk-free rate, and stock returns that are both volatile and predictable. Iraola and Santos (2007) provide a model of technology adoption to explore the possible channels of influence that technological innovations have on stock prices, where the value of the stock market incorporates the option value of the arrival and adoption of future technologies.

Recent papers have targeted this issue from an empirical perspective, but there has been surprisingly little study of this specific constellation of disruptive technology and stock market returns, or of its effect on banking.

However, Fintech developments, for example, can be viewed as disruptive innovations, and particularly automated financial services that transform market liquidity and private markets that create alternatives to traditional financing and trading.

2.2. Empirical evidence: disruptive technology and stock behaviour

In the context of disruptive technologies and stock market returns, recent studies have attempted to provide evidence on the value creation side of Fintech. Navaretti et al. (2018) found that Fintech increases the uncertainty of liquidity demand in the financial market, which may augment market volatility and *per se*, additional return. Majid et al. (2021) studied the impact of innovation on S&P100 firms over a period from 2013 to 2018 and found that it acts as a resource to enable a firm to obtain positive abnormal returns, which remain consistent in the presence of noise trading and investor bias. The study by Agrawal et al. (2004) shows a significant increase in idiosyncratic and total stock return volatility when a firm initiates e-commerce, accompanied by positive abnormal returns of stock prices. Ba et al. (2013) found that the stock market reacted positively to announcements of global green vehicle innovation over a 14-year time span and that overall green product development decisions, such as innovation type and market segment choices, have a direct influence on a firm's market value.

Regarding Blockchain technology, Hassani et al. (2018) argue that a "stable coin" such as a digital token will have low price volatility due to being pegged to some underlying fiat currency. On the other hand, Andersson and Styf (2020) identify a slight increase in the systematic risk and a slight reduction in the total risk of the stock returns of the Swedish OMX PI Index due to the introduction of Blockchain technology. Akyildirim et al. (2020)

document that companies that partake in "crypto-exuberant" naming practices become more volatile and offer substantial and persistent stock market premiums. Based on 175 corporate announcements between 2015 and 2019, Klöckner et al. (2022) conducted a study of international events to estimate the impact of blockchain initiatives on the market value of firms. The results suggest that involvement in a blockchain project attenuates the positive stock market reaction and that more innovative firms do not experience a stronger stock market reaction to blockchain announcements.

In relation to AI technology, Lui et al. (2021) study the impact of 119 AI-related announcements by 62 listed firms that have invested in AI and found a reduction of 1.77% in firm stock price. Firms with weak information technology capabilities or low credit ratings were more negatively impacted.

2.3. Empirical evidence: disruptive technology, stock behaviour and banking

After the financial crisis, Fintech firms were allowed to extend their services at a much cheaper price with greater convenience – affecting the earning and market share of traditional banks (Buchak et al., 2018; Vives, 2019).

Recent evidence for the relationship between stock processes, stock price returns, disruptive technologies and banking is still limited. However, below we cite some articles that shed light on different nuances in this regard.

Low and Wong (2020) study the effects on incumbent banks' stock returns of the disruptive growth in Fintech across six ASEAN countries and found that these, as well as the incumbents' stock returns, vary across different geographical areas and could be considered when studying the impact of innovation on stock market performance. Likewise, Li et al. (2017) claim that there is a positive relationship between growth in Fintech funding or deals and the contemporaneous stock returns of incumbent retail banks. They conducted research using panel data regression to evaluate whether Fintech would impact retail banks' stock returns using a sample period from 2010 to 2016. The results suggest complementarity between Fintech and traditional banking, but those on the banking industry level are not statistically significant, and the coefficient signs for about one-third of the banks are negative. Asmarani and Wijaya (2020) analysed the impact of Fintech on the stock returns of retail banks listed in the Indonesia Stock Exchange for the 2016–2018 period and found no significant effect. Phan et al. (2020) show that Fintech negatively influences bank performance in Indonesia.

Setiawan et al. (2021) find that artificial intelligence programs in banks lead to greater financial performance.

Arenas and Gil-Lafuente (2021) investigate emerging technology as a factor that captures the volatility of the Spanish banking sector using the GARCH and diagonal BEKK approach, and found evidence of significant stock return volatility clustering, spillover, and persistence.

A case study by Visconti-Caparrós and Campos-Blázquez (2021) of the Bizum instant payment system, which has been incorporated by traditional banks in Spain, revealed that the creation of digital value is a winning strategy to ensure the incumbents' survival, which may be viewed as positive factors in the overall market perception of banking.

Chen et al. (2022) studied the potential risk of Fintech to the achievement of sustainable development by commercial banks in China, and found that the financial risk first increases and then decreases along with Fintech development.

3. Methodology

Given the increasing complexity of the business models and operations of the banking system, it is difficult to measure and observe the true risk (Begley et al., 2017; Ho et al., 2020). A variety of methods to quantify bank risk have been proposed (e.g. Stiroh, 2006; Sawada, 2013; Anginer et al., 2014; Bennett et al., 2015; Demirer et al., 2018; Ho et al., 2020). However, one of the most commonly adopted measures is the return volatility of bank stocks, whose behaviour provides a reasonable, and readily available option (Neuberger, 1991).

The CAPM model developed by Sharpe (1964) and Lintner (1965) is still one the most common asset pricing models used by academia and practitioners to model the relationship between expected return and risk of an investment security. According to the CAPM, the risk of an asset is explained by its beta, which is the covariance between the asset returns and the market portfolio returns. However, studies such as Fama and French (1992, 1993, 1996) have reviewed and tested the CAPM with constant beta and found that the model is unable to make exceptions of asset pricing anomalies.

The development of multiple factor models assimilated the theoretical advances of the Arbitrage Pricing Theory developed by Ross (1976), splitting residual risk into specific and common factor risks. The premise on which the multifactor framework is based is that similar stocks present similar returns that are driven by market information.

In turn, Fama and French (1993) expanded the original CAPM by adding size risk and value risk to the market risk factors, which eventually led to the Fama and French three-factor model. Carhart (1997) added a momentum factor to produce what is known as the four-factor Carhart model. In 2015, Fama and French used the dividend discount model to obtain additional factors, namely investment and profitability, resulting in the five-factor model. Following this trend, several multifactor models have emerged in the literature in order to explain a variety of market anomalies, commonly including additional factors to the baseline of the market return.

Certain properties of financial time series are known as stylized factors. These are volatility clustering, heteroscedastic variance, non-normal leptokurtic distribution, and leverage effect, which can all lead to unexpected changes in financial time series behaviour. The underlying rationale is related to the rate of information arriving in the market (Lamoureux & Lastrapes, 1990), errors in the learning processes of economic agents (Mizrach, 1996), and the artificial calendar timescale in lieu of an operational one (Stock, 1988).

Regime switching models are capable of capturing those unexpected changes in behaviour (Ang & Timmermann, 2012). Particularly, Markov regime-switching (MRS) models, which are widely applied in finance and macroeconomics, suppose that an observed process is triggered by an unobserved state process. Evidence supports the statement that MRS modelling outperforms static mean-variance strategies (e.g., Ang & Bekaert, 2004; Kritzman et al., 2012; Dou et al., 2014). Quandt (1960) introduced the methodology to estimate a single switching point position for a linear regression system and the MRS model was presented by Goldfeld and Quandt (1973). A multivariate generalization of the univariate MRS process to model the U.S. business cycle was proposed by Hamilton (1989).

Based on the previous context, in this paper we propose a heteroscedastic regime switching two factor model for Spanish banking stock returns, which are explained by a CAPM structure that has been extended into a two-factor model and is allowed to switch between heteroscedastic regimes. Such a regime switching CAPM or multifactor application is common in the financial literature (Huang, 2000; Abdymomunov & Morley, 2011; Chen & Kawaguchi, 2018; Vendrame et al., 2018).

The CAPM expresses expected returns as a function of systematic risk. For any asset the expected return in excess of the risk-free rate is proportional to beta,

$$E\left(R_i\right)=R_f+\beta_i\left(E\left(Rm\right)-R_f\right), \tag{1}$$

where $(E(Rm) - R_f)$ is the risk premium, $E(R_i)$ is the expected excess return on stock i, $E(R_m)$ is the expected return to the market portfolio, R_f is the risk-free rate, and β_i is the standardized covariance between asset i and the market portfolio. The standard CAPM test typically that $R_f = 0$ and $(E(Rm) - R_f) > 0$.

For this study, the standard CAPM model was extended by including an additional factor in the specification, thus producing a two-factor model, where the stock's return is explained as a linear combination of exposures to the market and the disruptive technology plus an unexplained alpha. In this context, the model can be represented as below:

$$R_{it}=\alpha_i+\beta_i\left(Rm_t\right)+\gamma_i(DT_t)+e_{it}, \tag{2}$$

where α_i is the intercept, $(R_{it} - R_{ft})$ is R_{it}, $(Rm_t - R_{ft})$ is Rm_t, γ_i is the sensitivity of the stock i to the DT disruptive technology factor in time t. Lastly e_{it} is the is the random disturbance for stock i in time t.

To model properly the volatility regimes that the Spanish banking stock return presents, we allow the two-factor model to switch among heteroscedastic regimes. However, the statistical test resulted that the α_i and the β_i are invariant across the volatility regimes, thus only γ_i and the volatility where switching among the regimes. This Two-factor MRS structure can be represented as:

$$R_{it}=\alpha_i+\beta_i\left(Rm_t\right)+\gamma_{i,v}(DT_t)\left(s_t\right)+\sigma_v\left(s_t\right)+e_{i,t}, \tag{3}$$

where $e_t \overset{iid}{\sim} N\left(0,1\right)$, and v = 1, 2 represent high and low market volatility; α_i comprises a common intercept to both regimes[1] as the unknown stock return of stock i; Rm_t is the non-switching independent variable and whose effect β_i is non *regime-varying*[2]; DT_t is the disruptive technology factor return whose effects $\gamma_{i,v}$ are *regime-varying*; note that the variance σ_v^2 is also allowed to change between regimes.

The *unobserved* state variable s_t describes the two regimes in which process R_{it} may occur. Regime probabilities *given past information* ζ_{t-1} are specified via a first-order Markov process in which

$$P\left(\zeta_{t-1}\right)=P\left(s_{t-1}=j\right)=p_{jk}\left(t\right), \tag{4}$$

where j, k = 1, 2 and for all t (time invariant). We further require the transition matrix of the Markov process to be

[1] A non-significant *Wald test* for the difference between regimes' intercept was obtained, supporting a constant intercept model.

[2] A non-significant *Wald test* for the difference between regimes' β was obtained, supporting a non-switching independent variable.

$$\begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \tag{5}$$

where each p_{jk} represents the probability of transiting from regime j to k. The process described through (3–5) corresponds to the MRS model. The resulting probability function yields the log-likelihood function

$$\sum_{t=1}^{n} \ln \sum_{v=1}^{2} \frac{1}{\sigma_v} \varphi\left(\frac{y_t - x_t \beta_v}{\sigma_v} \right) P\left(s_t = v \mid \zeta_{t-1}\right), \tag{6}$$

where $\varphi(\cdot)$ is the standard normal density function, which is maximized to estimate the parameters (see Kim and Nelson (2017) Chap. 4 for more on model formulation and computational details).

4. Data

For our analysis, the IBEX35 BANCA index provided by BME Market Data (2021) is used as a proxy for Spanish banking. This index is composed of the IBEX35 BANCA constituents that represent the banking subsector, namely Santander, BBVA, CaixaBank, Banco de Sabadell, Bankia, and Bankinter as of December 2020. Banco Popular Español was dismissed from the index in 2016.

The calculation methodology is the same as for the IBEX35 index, market capitalization weighted, and is based on capitalization, liquidity, and traded volume. In Figure 6, the weight of the composites of the IBEX35 BANCA are represented from 2015 until 2020.

The MSCI ACWI IMI Disruptive Technology ESG Filtered index (MSCI, n.d.-a) is used as a proxy for disruptive technology, based on the index design appropriate for the purpose

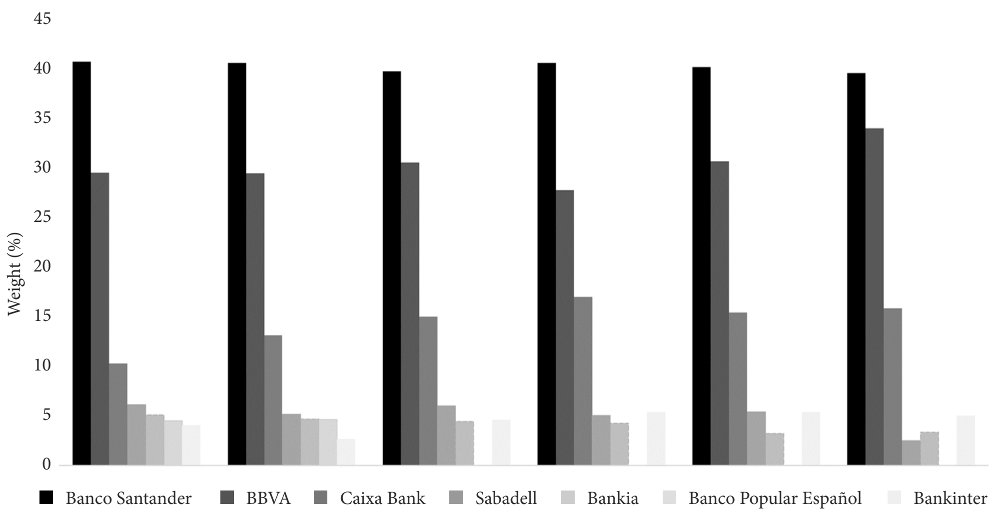

Figure 6. Percentage weight composites of the IBEX35 BANCA End of Year Index (December 31st, 2015, to December 31st, 2020). Data from Bloomberg

of this paper. This index is designed to represent the performance of companies aligned to fields that are commonly associated with or described as “disruptive technology”.

The widely tracked MSCI WORLD index (MSCI, n.d.-b) was retrieved from Investing (n.d.) to construct the market portfolio, and since its values were expressed in USD, we converted them using the USDEUR exchange rate published by OFX (n.d.), while the TBILL 3-month rate retrieved from the Federal Reserve Bank of St. Louis (n.d.) was used to calculate excess return. It is common practice to model Spanish banking stock returns against the global market portfolio since the exposure of Spanish banks to the global market portfolio and the significant contagion that may be driven among global capital markets are highly interconnected.

The sample period is from 25/11/2015 to 1/30/2020 in term of price level, delimited by data availability and with the objective to cover the pre-COVID period, eliminating any noise caused by the pandemic’s. To formalize, the following expression was used to obtain the form of log returns for the used times series:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right), \tag{7}$$

where r_t is the log return, P_t the closing price and P_{t-1} the previous day closing price, calculating the first data point as the log return obtained from the previous closing price on 25/11/2015 to the closing price on 26/11/2015. The data was plotted to check for outliers. To limit the impact of outliers (Brexit in June 2016) on our data, we examined the daily log returns of the sample within a cubic spline framework.

In Table 1, the series for the Spanish banking daily log returns and the disruptive technology daily log returns report means close to zero and kurtosis values greater than three, implying a fat-tailed distribution. As they are generally negative, the asymmetric tail is defined by the skewness value since the Jacque–Bera results are statistically significant and the null hypothesis of a normal distribution for the Spanish banking and disruptive technology daily log returns is rejected. The pronounced peak and heavy tails in the distribution of the index returns are typical for unconditional densities of normal observations subject to heteroscedasticity, as mentioned by Turner et al. (1989). However, our analysis is robust, as are models applying Huber-White robust standard errors in non-normal cases.

Figures 7 to 12 illustrate the daily closing prices and daily log returns for the time series of Spanish banking. The Market portfolio is proxied by the MSCI World and Disruptive technologies are proxied by the MSCI ACWI IMI Disruptive Technology ESG Filtered index.

MRS models, as used in this paper, represent in themselves a well-known illustration of non-linear time series models. In this context, the BDS test proposed by Broock et al. (1996) was run to confirm the nonlinearity of the series. The results for the BDS test, as shown in Table 2, suggest that we can reject the hypothesis of linearity in this sense, while nonlinearity is confirmed for the Spanish banking index and the disruptive technology index log returns. We also confirmed that the analysed series are stationary using the Augmented Dickey–Fuller (ADF) test proposed by Dickey and Fuller (1981), and the Phillips–Perron (PP) test proposed by Phillips and Perron (1988), see Table 3.

Table 1. Summary statistics for Spanish banking, market portfolio and disruptive technology daily log returns

	Spanish banking	Market portfolio	Disruptive technology
Mean	−0.01264	−0.01204	0.00049
Median	−0.01316	−0.01095	0.00137
Maximum	0.06680	0.02355	0.03956
Minimum	−0.07220	−0.04740	−0.04765
Std. Dev.	0.01853	0.01046	0.01187
Skewness	0.45074	−0.23927	−0.54594
Kurtosis	4.06778	3.32765	4.34960
Jarque-Bera	86.90061	14.96779	134.10670
Probability	0.00000	0.00056	0.00000
Sum	−13.49622	−12.85794	0.52435
Sum Sq. Dev.	0.36635	0.11672	0.15044
Observations	1068	1068	1068
VAR 1%	−0.05574	−0.03637	−0.02713
VAR 5%	−0.04312	−0.02924	−0.01904

Figure 7. Daily closing price, Spanish banking (November 25th, 2015 to January 30th, 2020)

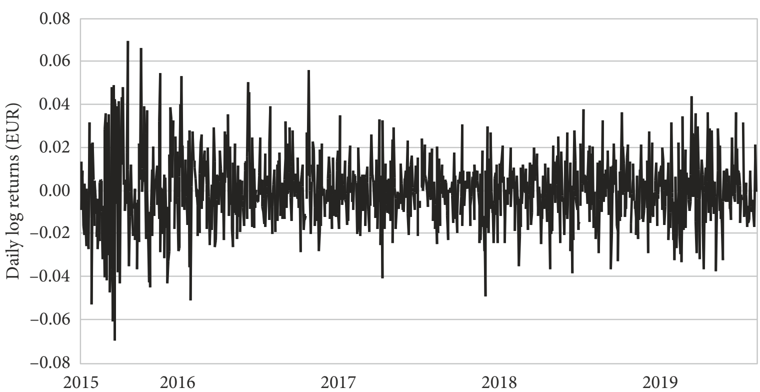

Figure 8. Daily log returns, Spanish banking (November 26th, 2015 to January 30th, 2020)

Figure 9. Daily closing price, Market portfolio (November 25th, 2015 to January 30th, 2020)

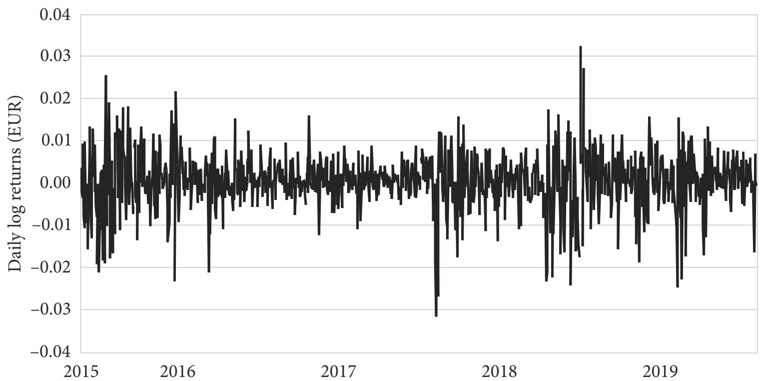

Figure 10. Daily log returns, Market portfolio (November 26th, 2015 to January 30th, 2020)

Figure 11. Daily closing price, Disruptive technology (November 25th, 2015 to January 30th, 2020)

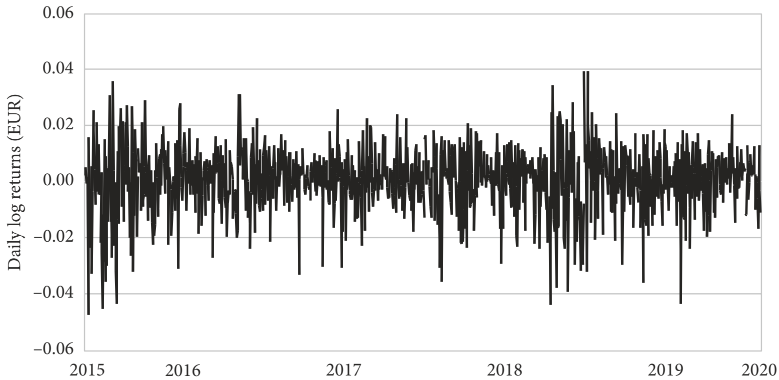

Figure 12. Daily log returns, Disruptive technology (November 26th, 2015 to January 30th, 2020)

Table 2. BDS Test for Spanish banking daily log returns

BDS statistic					
Dimension	2	3	4	5	6
Spain banking sector	0.018204***	0.040554***	0.055004***	0.061279***	0.061839***

Note: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table 3. ADF Test for Spanish banking daily log returns

ADF Test Statistic		
Dimension	Augmented Dickey-Fuller	Phillips-Perron
Spain banking sector	−3.031180***	−30.53979***

Note: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

The two structural break tests are the CUSUM of squares test and Bai Perron test. The CUSUM of squares test was developed by Brown et al. (1975) based on a plot of the cumulative sum of the squared one-step-ahead forecast error resulting from iterative estimation between two critical lines (see Figure 13 below). The movement outside the critical line indicates parameter or variance instability.

The Multiple breakpoint Bai–Perron test determined the existence of one break for the Spanish banking index log returns (see Table 4 below).

Table 4. Multiple breakpoint Bai–Perron test for Spanish banking daily stock returns

Dimension	Breaks	F-statistic	Scaled F-statistic	Critical Value
Spain	0 vs. 1 *	242.7435	242.7435	8.58

Note: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

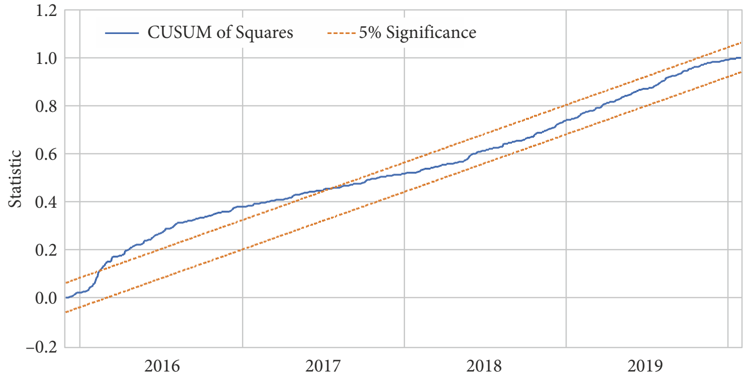

Figure 13. CUSUM of Square Test for Spanish banking

5. Results

A two-factor model with heteroscedastic Markov switching regimes was estimated for Spanish banking to analyse the impact of disruptive technology and thereby cover the following research objectives: first, to investigate whether disruptive technology impacts the performance of Spanish banks; and second, how the impact of disruptive technology evolves under different market conditions or volatility regimes.

The two-factor model is composed of market returns and disruptive technology returns to identify the specific sensitivity of the Spanish banking returns exposed to these factors. The Spanish banking returns were not observed to be constant in time, so the MRS methodology is deemed suitable for this purpose. In this context, the intercept and the market portfolio factors are constant in time as confirmed by the Wald test, and are hence modelled as non-switching regressors. However, the Wald test confirmed that the variance as Log(Sigma) and the coefficient of the disruptive technology factor are switching between two volatility regimes and are thus modelled in function of both regimes.

The results are shown in Table 5. For the fitted model, the Akaike information criterion (AIC) (Akaike, 1973), Schwarz Bayesian criterion (SBC) by Schwarz (1978) and Hannan-Quinn criterion by Hannan and Quinn (1979) and Hannan (1980) were calculated. The Ljung–Box Q test indicates absence of autocorrelation on the residuals, as shown in Table 6.

The Log(sigma) that corresponds to the logarithms of standard deviation of each heteroscedastic regime is statistically significant for the fitted model with a 99% confidence level, indicating that the identified high and low volatility regimes are relevant for our model and that the two-factor model with heteroscedastic Markov switching regimes is appropriate. The common intercept tends to zero, but the coefficient is not statistically significant, which is aligned with traditional CAPM theory and the circumstances of a market of zero interest rates during the studied period. The coefficient associated to the market portfolio equals 1.12 and is statistically significant with a 99% confidence level, which theoretically indicates that Spanish banking is more volatile than the market portfolio.

The coefficient associates to the disruptive technology factor, which explains why the impact of disruptive technology on Spanish banking led to a score of 0.71091 under the high volatility regime and –0.12680 under the low volatility regime, both coefficients being statistically significant with a 99% confidence level. The results are threefold. First, the disruptive technology factor impacts Spanish banking significantly. Second, the impact of disruptive technology varies across volatility regimes, being positive in the high volatility regime and negative in the low volatility one. Third, it is shown that intensity also depends on the market circumstances reflected through volatility regimes, having a more significant influence under unfavourable market conditions and less influence under stable ones.

Table 5. Two-factor heteroscedastic MRS for Spanish banking and disruptive technology in two regimes

		Spanish banking	
		High vol.	Low vol.
Disruptive Technology (γ)		0.710909***	−0.126800***
Log(sigma) (Log σ)		−3.910062***	−4.476969***
Sigma (σ)		0.020039***	0.011367***
Intercept (α)		0.000933	
Market portfolio (β)		1.12902***	
Mean dependent var.		−0.012637	
Constant Transition Prob.	(h, h) (l, l)	0.929055	0.983774
	(h, l) (l, h)	0.070945	0.016226
Constant expected duration (days)		14	61
AIC		−5.804815	
SCH		−5.767560	
HQ		−5.790701	
Wald Test		78.58493***	

Note: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.
Wald Test for null hypothesis: Log $(\text{sigma})_h$ = Log $(\text{sigma})_l$.

Table 6. Ljung–Box Q test of Spanish banking daily log returns

Spanish banking		
Lag	Q-Stat	Prob
1	0.1353	0.713
2	0.3243	0.85
3	0.6378	0.888
4	1.3486	0.853
5	1.9204	0.86
6	2.0419	0.916
7	2.1338	0.952
8	2.2346	0.973
9	3.1942	0.956
10	3.2486	0.975

Note: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

The results can be interpreted as revealing that Spanish banking increases its linkage with or adoption of disruptive technology under high volatility regimes, since investments in disruptive technology may be used as a strategy to compensate for market instability. From an investor perspective, a risk spread of 0.83771 will be gained to compensate for the additional risk taken by investing in disruptive technology in a high volatility regime compared to a low volatility one.

The Markov-chain transition probability exhibits how Spanish banking returns fluctuate across regimes. We observed that the probabilities of remaining in the same are regime greater than the probability of transiting from one to another.

The average probabilities of the Spanish banking system staying in the high and low volatility regimes are 0.92905 and 0.98377, respectively. The probabilities of transiting from the high volatility regime to the low volatility one and vice versa are 0.070945 and 0.016226, respectively.

The likelihood of each regime remaining in the same interval illustrates the presence of volatility clustering among Spanish banking returns. Strictly speaking, a high volatility observation is preceded by a low volatility observation, and vice versa; also, no re-estimation of the heteroscedastic MRS structure with restrictions on the transition matrix was required since none of the transition probabilities have values close to zero. Figure 14 illustrates the probability transitions for the high volatility and low volatility regime MRS estimation.

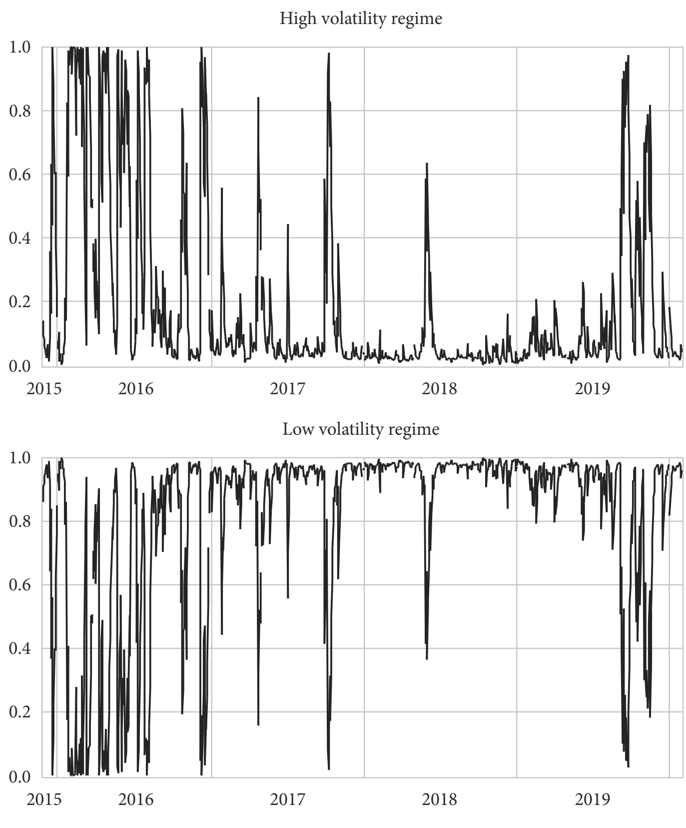

Figure 14. Markov Switching Filtered Regime Probabilities for Spanish banking

Regarding to the expected duration of regimes, for Spanish banking the average for the high volatility regime is 14 days and for the low volatility regime it is 61 days, which is aligned with the behaviour of innovative technology contingent on short-term noise across stock markets. The Spanish banking system will recover from a high volatility regime to its equilibrium level faster than it will from a low volatility regime from shocks entering in the market.

Conclusions

This article reviews whether and how disruptive technology impacts the performance of Spanish banking under a high volatility regime and a low volatility regime. For this purpose, the fundamental CAPM is evolved into a two-factor model with heteroscedastic Markov switching regimes. The IBEX35 BANCA index as a proxy for Spanish banking is used as the dependent variable, the disruptive technology factor is proxied by the MSCI ACWI IMI Disruptive Technology ESG Filtered Index and the market portfolio factor is proxied by the MSCI WORLD index as the explanatory variables in the form of daily log returns covering the period from November 26th, 2015 to January 30th, 2020. Excess returns are calculated using the T-bill rate.

The results are threefold. First, the disruptive technology factor impacts Spanish banking significantly. Second, the impact of disruptive technology varies across volatility regimes, being positive in the high volatility regime and negative in the low volatility one. Third, the intensity depends on the market circumstances reflected through volatility regimes, having a more significant influence under unfavourable market conditions and less influence under stable ones.

The positive impact of disruptive technology on the Spanish banking sector is relevant in the high volatility regime, providing a netted capital gain of 0.83771 for investors compared to a low volatility regime, which is aligned with the overall contention between risk and return. In other words, under a more adverse scenario, investors are compensated for the additional risk they incurred by investing in adverse circumstances.

Also, a presence of volatility clustering was identified in Spanish banking returns through the lens of the decision to invest in disruptive technology. Disruptive technology risk is of dynamic nature during its adoption, so the arrival of that news in the market will be highly relevant for patterns of stock return volatility.

Focusing on the objective of this study, these findings suggest that investors are informed about and acknowledge the advantages of disruptive technologies and will use their adoption as a Fintech business strategy to offset adverse market circumstances. From a competitive perspective, a collaborative constellation between traditional banking and disruptive Fintech strategist emerged.

However, the results of the relatively less relevant negative impact of disruptive technology on Spanish banking in low volatility regimes means we can assume that under more stable market conditions, Spanish banking seems to have less expectations with regard to the adoption of a Fintech business strategy at a time when the disruptive technology sector is growing. It is especially noted that under stable conditions, traditional banking tends to be positioned in a competitive constellation, as opposed to the high volatility regime where a collaborative or integrated strategy seems to be more convenient.

Other factors may be involved, such as different reactions to external news and events depending on the market conditions. However, these considerations do not fall within the scope of this paper.

In the context of portfolio diversification, during low volatility regimes disruptive technology can be used to offset potential risk in the Spanish banking sector, while this strategy is not recommended for high volatility regimes or adverse market circumstances.

Overall, and based on the foregoing argumentation, the results indicate that Spanish banking is still at an exploratory stage with regard to disruptive technology strategies.

Additional insights include the presumed role of the pricing of banking-related assets and other relevant implications for investors and international institutions that include disruptive technology and/or banking exposed to disruptive technology investments in their portfolios. The article may also provide insight for banking regulators and authorities in terms of bank stress test scenarios and other risk-related considerations.

However, it must be emphasized that more empirical research is needed to draw generalized conclusions. This article has some limitations, which may open many avenues for future research. First, it only focuses on the Spanish banking sector, which may offer a relatively good sample size, but more evidence from different countries is required before the conclusions can be generalized. A cross country approach would help to provide more valid and general conclusions. Second, the study is delimited to a timeframe of 5 years from November 26th, 2015 to January 30th, 2020, which is acceptable and is due to data availability. However, a longer timeframe would provide more details and thus produce more reliable results. Third, a more fundamentally defined econometrical model needs to be considered to represent the returns of Spanish bank stock behaviour.

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Author contributions

L.A.; devised the study and was responsible for the design and development of the data analysis, L.A.; Responsible for the formal analysis, L.A.; Investigation, L.A.; Methodology, L.A., A.M.G.-L. and J.B.R.; Validation, L.A.; Writing – original draft, L.A., A.M.G.-L. and J.B.R.; Review – editing.

All authors have read and agreed to the published version of the manuscript.

Disclosure statement

The author(s) declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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