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From Code to Capital: A Study of How Emerging Technologies Shape Stock Markets

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PhD in Business

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I dedicate this thesis to my son Leo, who have made me stronger, better, and more fulfilled than I could have ever imagined. I love you infinitely and more that every word and could express.

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1 Introduction

The digital era is taking us on a roller coaster, with Blockchain, Cloud Computing, Chat Bots, Artificial Intelligence (AI), Deep Learning (DL) and so on redefining the ways we live and interact with the world. Over the ensuing decades, cinema, for example, has persistently explored our collective imagination, portraying both utopian aspirations and dystopian fears related to the boundless capabilities of emerging technologies. Films such as *The Matrix*, *Robocop* and *Wall-E* exemplify this enduring fascination with the transformative potential of emerging technologies.

Also, recent white papers have described how emerging technologies will shape the future (World Economic Forum, 2017) and how institutions are responding to the increasingly salient trend (EU Commission, 2021)[1].

Emerging technologies have been defined as those that are just beginning to exist, grow and develop (Cambridge, 2023). By nature, these can be associated to uncertainty since the final stages of their development are, indeed, uncertain. In practice, the level of uncertainty inherent to an emerging technology is determined by the complexity of predicting its development and whether the market will accept its new features or not. Technical and market developments can accelerate, curb, or completely interrupt those dynamics and must hence be reviewed case by case. The novel characteristics of an emerging technology can also have a potentially dramatic impact on the socio-economic system. Indeed, the latest Risk Report 2024 published by the World Economic Forum (2024) lists "*misinformation and disinformation*" among the most serious adverse outcomes of AI technologies, due to the general lack of understanding of the implication of this technological developments. This argument can be associated (Boon & Moors, 2008; Martin, 1995; Porter, Roessner, Jin, & Newman, 2002; Small, Boyack, & Klavans, 2014; Rotolo, Hicks, & Martin, 2015) to the concept of the "*Techno-economic paradigm*" (Pérez, 1983; Pérez, 1985) introduced by the socio-economist and historian Carlota Pérez. This concept addresses the nature of shifts and progress in the cycle of technological revolution and its links to the economic lifecycle, and thus societal implications.

From an investment perspective, emerging technology offers major potential for growth, but also entails considerable uncertainty and risks. Radical or breakthrough innovations often generate shocks (Leydesdorff & Rafols, 2011), whose impact on future technological developments (Ahuja & Morri Lampert, 2001; Schoenmakers & Duysters, 2010) and their adoption only become apparent *ex post*, thus making them harder for investment analysts to estimate. Shock effect, costs of future ownership, the provision of complementary inputs, the establishment of dominant standards and possible related obsolescence (Hall & Rosenberg, 2010) are just some of the factors that might drive the uncertainty of an emerging technology.

Along similar lines, one general challenge faced by science is to link short-term stock market fluctuations with long-term technological innovation processes. Fluctuations in well-known classical economic fundamentals such as profit, dividends and output growth should explain the market value of a stock (Peralta-Alva, 2007). However, some literature (for example, Kydland & Prescott, 1982) proposes

[1] "*Future & Emerging Technologies*" (FET) program by the EU Commission (2021) that invest in frontier research and innovation to benefit the economy and society.

that technology shocks that impact the macroeconomy are channeled by short-term stock market fluctuations. Jovanovic and Rosseau (2002) associate fluctuations in the stock market with technological revolutions, as in historical cases such as electricity, World War II, and IT. However, to better understand how technological shocks might be channeled into stock market dynamics, it is worth recalling some basic financial concepts related to this context.

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 used to discount the future payoffs to the present. However, when analyzing how those rates fluctuate, stock valuation models are expected to imply certain volatility, driven by the perception of those economic components. Hence, the perception of an economic slowdown *via* economic components, is enough to generate large changes in stock market prices (Peralta-Alva, 2007).

Stock prices may also reflect expectations regarding emerging technology, since the current price of a stock equals the optimal expected forecast based on the information available (Mishkin, 2016). Thus, expectations about future profits from emerging technology will also be reflected.

Interestingly, it is during times of technological change that forecasters of future profits, called technology optimists, tend be in the greatest disagreement with statistical measures of historical economic performance (Brynjolfsson, Rock & Syverson, 2019). Pérez (2012) claimed that when an old technology is replaced by a new one, excess funds flood the market, driven by over-excitement and decoupling the temporary price from its fundamental value. Thus, it makes sense for enthusiastic investors, driven by the rush of optimism, to bid up to twice the stock price, since the future course of an emerging technology will be especially influenced by investors' beliefs and expectations.

Also, narratives and storytelling might be exploited to drive speculation on such uncertain ground, leading investors to use these optimistic predictions to justify their investment decisions. Pástor and Veronesi (2006), Gharbi, Sahut and Teulon (2014), and Schwert (2002) take their evidence from the unjustifiably high stock returns and volatility of disruptive or frontier technology firms. As a consequence of such radical technological changes and excess volatility peaks due to the increased uncertainty (Shiller, 2000), economic fundamentals are less useful for making predictions about future values (Tushman & O'Reilly III, 1996). Some authors associate stock price behavior during times of technological revolution with bubble-like patterns. Shiller (2000) and Pérez (2003) attribute this pattern to market irrationally.

From a more theoretical and cyclical perspective, the literature seems to generally agree that that new technologies cause the old stock price, embedding the obsolete technology, to decline (Greenwood & Jovanovic, 1999; Hobjin & Jovanovic, 2001; Laitner & Stolyarov, 2003; Manuelli, 2000). The rationale behind this argument is the expectation that profits to be gained when firms with obsolete technology have to buy the new technology will drive and raise future returns on new investments (Laitner & Stoylarov, 2019). When the new technology becomes available, it is gradually adopted by new firms, leading to a period of high investment.

The adoption process of new technology also inherently contributes to the risk structure within the stocks of the involved firms and markets, which exhibits time-varying characteristics. At the beginning of the adoption process, the risk is idiosyncratic. Nevertheless, with the adoption of the new technology, the risk evolves and becomes more systematic. The new technology stock initially has a high market value (Pástor & Veronesi, 2009) and as the probability of adoption increases, systematic risk pushes discount rates up and thus lower stock prices in both the new and old economies.

To further explore this context, Pástor and Veronesi (2009) present a macroeconomic model in which the uncertain productivity of an emerging technology drives a boom-bust pattern in the stock market through the learning process. Laitner and Stoylarov (2019) develop a suitable model 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 to be 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. Jensen (1993) finds that investments in innovations can increase the risk of the firm. However, due to the assumption that emerging technologies will make business processes more efficient and boost investor trust, stock returns should decrease volatility in the long term.

Another noteworthy consideration pertains to knowledge and understanding of complex and emerging technologies, underscoring the relevance of trust as a key factor to be considered in the context of emerging technology (Ying, Jia, & Du, 2018) and market volatility (Bitterly, 2023). Trust plays a pivotal role in human interaction with emerging technologies, particularly with AI.

To summarize, recent papers have targeted this issue, but there has been surprisingly little study of the specific constellation of emerging technologies and stock market behaviors, or of their effect on the financial industry, which is a major gap in the research in the financial literature. Hence, the main objective of this thesis is to investigate whether emerging technologies impact asset return volatility. The previous statement can be conceptualized in the following sub-objectives:

- Establish the state of the art of the interplay between emerging technologies, disruptive technologies, and volatility, an understanding of which is especially interesting due to the increasing relevance of technologies, and particularly emerging and disruptive technologies and general changes in volatility behavior.
- Help scholars, practitioners, and policymakers to understand the phenomenon of emerging technologies, disruptive technologies, and volatility by building a framework and contributing empirical evidence.
- Provide relevant insight on the scope of the implications of emerging and disruptive technologies for banking and finance and thus for the economy.
- Foster understanding and awareness of the new opportunities arising from emerging and disruptive technologies from the perspectives of the economy, social implications, and environmental stability.
- Guide policymakers and provide some suggestions for the future by exploring different hypothetical scenarios.
- Publish the outcomes in a variety of formats, such as quantitative and qualitative research papers and theoretical research papers for financial, economic, and international peer-reviewed journals, business practitioner reviewed journals and book chapters.

The longitudinal research methodology used in this thesis is designed to accomplish deductive, quantitative research. Rooted in objectivist ontological assumptions and an epistemologically positivist approach, the aim is to yield axiological, value-free results.

1.1 Theoretical Framework and Key Concepts

1.1.1 What is technology and its evolution

The Greek root of the concept of technology is *techné*, which means "pertaining to the arts, crafts, or skills" and is related to tactics, which in turn is defined as "a specific action intended to get a particular result" (Cambridge, 2023). Hickman (2001) understands technology as "the intelligent production of new tools, including conceptual and ideational ones, for dealing with problematic situations". Rooney (1997) interprets it as an indissoluble partner to aesthetics, politics, institutions, and economics by defining four types of technology – (1) technologies of production, (2) technologies of sign systems, (3) technologies of power and (4) technologies of the self.

A common trait of the ancient *techné*, and which is used by Ellul (1964), Schmookler (2013) and Weber (2015), is the idea that the technical or technological elements of the production process are a diverse set of variables that can include cultural and intellectual elements, but which are separate from society and thus, societal implications. Volti (2009), in contrast, interprets technology by means of the schematic definition presented in the text titled "*Society and Technological Change*", where it is defined as "a system created by humans that uses knowledge and organization to produce objects and techniques for the attainment of specific goals." In his book titled *"Elements of Technology*" published in 1829, Bigelow provided what is still one of the most widely used definitions today (Li-Hua, 2009), whereby technology (at that point in time) was "*understood to consist of principles, processes, and nomenclature of the more conspicuous arts, particularly those which involve applications of science, and which may be considered useful, by promoting the benefit of society, together with the emolument of those who pursue them*" (Bigelow, 1829). This links to the positive societal effects of technology. Thus, the definition *per se* of technology involves an action with a desired output, which can also be perceived as a result-driven process. However, the role of the human being is central for technology.

Indeed, Hickman (2001) asserts that technology constitutes a central aspect of human existence, influencing both our interactions with the natural world and our interactions with fellow humans. Hickman (2001) further posits that technology encompasses a collection of techniques. These techniques serve as inquiries into tools and artifacts, with habitual and traditional methods of addressing various challenges. Additionally, Hickman (2001, p. 183) defines technology as the intelligent creation of novel tools, including conceptual and ideational ones, specifically designed to tackle complex or problematic situations. Nowadays, technology is defined by the Cambridge Dictionary (2023) as the study and knowledge of the practical, especially industrial, use of scientific discoveries, with a particular focus on this latter aspect. Brey (2009) states that the public knows what technology is and how it can support human activity, but the concept remains ambiguous and ill-defined. A holistic definition that can inform all theories, whatever the phenomenon in question or its field of application, is still vague (Arthur, 2010).

Coccia (2019) categorized the definition of technologies into three groups; first the economic conception of the production function, the second as the *Pythagorean concept* based on patent statistics and chronologies of innovations, and third the systems concept of technology conceived in terms of technical performance of its characteristics. However, this author also highlights the limitations of these three groups of definitions and proposes a new definition of technology in a theoretical framework of systems and purposive behavior.

Turning to the understanding of the development of technology, the latter can be interpreted in the context of the evolution of the biological system across generations and fields of studies (see Basalla, 1988; Arthur, 2010; Wagner & Rosen, 2014). From an evolutionary perspective, organisms grow, change, or mature over time and these changes are embedded into their development. All kinds of living mechanisms have an almost universal natural need to evolve, grow and survive. Technological evolution can be viewed in the same way. But let's first better understand the concept of biological evolution.

Biological evolution involves gradual changes in inherited traits over successive generations in populations of organisms. Adaptation is a key part of the evolutionary process, whereby variations in traits and species are adjusted by natural selection to make them better suited for survival in specific ecological habitats. The environment serves as a catalyst for shaping the evolutionary changes that drive development. Hickman (2001) states that: "*Progress is rather a cycle of production: this includes the production of new significances, the production of new feelings, the production of new means of enjoying, and the production of new techniques of production*."

Under the lens of biological evolution, technology can be interpreted as an organism that seeks to survive in a habitat or environment that is populated with their own species and other species and will even try to bypass and compromise other organisms or the habitat if the natural selection process so requires. However, until a certain point in time, technology as an organism is merely performing the actions that a human being is telling it to perform. It is programmed by human need and decision rather than being driven inherently by a natural need to survive. Knowledge is accumulated and this leads to technological change in a lifecycle that is not unlike that of an organism.

Each technology has its own lifecycle, which is brought to life, matures, and will reach obsolescence and eventually disappear, while preparing the ground for more complex technologies, to ultimately be replaced by them. From another angle, by accumulating knowledge while refining skills and tactics, *techné*, through experience, technology will increase in complexity while gaining terrain.

In biological evolution, survival is the outcome of natural selection. In technological evolution, however, it is not the technology that strives to survive, it is driven by humans who make the decisions based on their meeds. Nevertheless, AI is already offering clear examples where the technology itself can be a decision-maker, ultimately challenging the level of human dependency in its actions[2]. Hosler (1994) argues that technology and its development are, at least to some extent, influenced by "*technical choices*", which express social and political factors, and "*technical requirements*", imposed by material properties. Thus the "*technical choice*" is taken by the human being as the ultimate agent. In economics, patterns of

[2] AI was created by humans and is capable of performing tasks intelligently without being explicitly instructed, and of thinking and acting rationally and humanly, and is hence a potential agent. AI can be trained based on data that is generated by humans, and since humans are rational, the trained algorithm will make decisions rationally as well.

technology emerge and evolve within the technological paradigms and trajectories in specific economic, institutional, and social environments (Dosi, 1988). Nowadays, there is no question that technology plays a key role in the social and economic change of human societies (Basalla, 1988; Berg, Wustmans, & Bröring, 2019; Freeman & Soete, 1987; Hosler, 1994; Moehrle & Caferoglu, 2019), particularly when it comes to disruptive technologies.

To conclude, the concept of technology is one of the most discussed and relevant concepts in science and it is therefore essential for it to be clearly defined in the context of any scientific discussion or further development. However, a generalized concept of technology is still being revised and debated (Coccia, 2019).

1.1.2 The Concept of Emerging Technologies and Disruptive Technologies

The Cambridge Dictionary (2023) defines the concept of an emerging technology as something that is just beginning to exist, grow and develop. When it comes to business investments, this especially means a technology that is beginning to achieve economic power or success. The concept of emerging technology covers a variety of characteristics, including the potentially dramatic impact a new technology has on the socio-economic system, significant uncertainties, and novel features (Martin, 1995; Porter et al., 2002; Boon & Moors, 2008; Small, 1973; Li, Porter, & Suominen, 2018). One literature review (see Rotolo et al., 2015) combined previous work by several authors to present a conceptual framework of emerging technology consisting of the following five characteristics: radical *novelty, relatively fast growth, coherence, prominent impact, and uncertainty* and *ambiguity*. Based on the aforesaid conceptualization, emerging technology implicitly bears uncertainty. In the management literature, emergence is often observed from the perspective of technological adoption. Extensive literature has also connected emerging technologies to innovation management. Cozzens et al. (2010) place the term in the context of contemporary innovation theory.

The relevant literature on emerging technologies is much more extensive than that related to disruptive technologies. An emerging technology could fail over time, or become a generalized technology, or even a disruptive one (Li et al., 2018).

The Cambridge Dictionary (2023) defines disruption as the action of preventing something, especially a system, process, or event, from continuing as usual or as expected. In his book "*The Innovators Dilemma*", Christensen (1997) refers to disruptive technology as superior to an innovation, and one that surpasses former products, processes, or strategies, causing the latter to fall out of favor. Yu and Hang (2010) review the concept based on how it evolved from Schumpeter (1942) to Foster (1986), Bower and Christensen (1995), Christensen (1997), Henderson and Clark (1990) and Christensen and Overdorf (2000). However, the concept of disruptive technology was modified by Christensen (2003) to disruptive innovation in order for it to more holistically include phenomena other than the purely technological, for disruptive innovation can occur in any established marketplace as a result of both technological and non-technological factors (Christensen, 2003).

Since then, disruptive technologies seem to have been increasingly absorbed into the conceptualization of disruptive innovation (Christensen, 2015; Christensen & Overdorf, 2000; Christensen, Verlinden, & Westerman, 2002; Christensen, 2003; Danneels, 2004). For example, Blockchain technology has been argued to be a disruptive technology, given its potential to change the nature of organizations in a global environment (Frizzo-Barker, Chow-White, Adams, Mentanko, Ha, & Green, 2020).

From all these different perspectives, there is an indisputable common link between emerging and disruptive technologies and their societal impact. Hence, when we speak of disruptive technology, we are speaking of a technology with the potential for major impact on society, and which can eventually modify existing societal structures, organizations, markets, and governments. However, the disruption phase is finite, and will only last until societal adaption has reached its full potential.

However, scholars may continue to employ the adjective ‘disruptive’ even after a technology has completed its disruption of society, for it will continue to be known as a technology that led to some kind of disruption in societal terms.

To conclude, this thesis is grounded on the definition of emerging technology proposed by Rotolo et al. (2015), which consists of the following characteristics: *radical novelty*, *relatively fast growth*, *coherence*, prominent *impact*, and *uncertainty* and *ambiguity*. Disruptive technology is an emerging technology that, as Frizzo-Barker et al. (2020) claim, is capable of changing the nature of organizations in a global environment. The rationale behind each of these concepts with regard to the perspective of risk and uncertainty is discussed in depth in chapter 2 entitled “*The Rubik’s cube of emerging technologies and stock volatility”*.

1.1.3 The Concepts of Uncertainty, Risk and Volatility

Uncertainty about the future is the main reason for performing a risk analysis. The idea is to identify and anticipate factors and events that will reduce investment losses and thus predict the performance of an investment in consideration of certain states. It was Knight who initially identified the significance of risk and uncertainty in economic analysis (Knight, 1921) due to the need to properly evaluate all the potential costs and benefits. However, Knight also emphasized the distinction between the two concepts, which are often still used today to express the same notion. Uncertainty refers to events that cannot be expressed mathematically in probabilistic terms, while risk can be quantified by assigning subjective probabilities to a state of risk.

Uncertainty and risk are not mutually exclusive. The key element when making the distinction between risk and uncertainty is probability, which refers to the likelihood of a particular phenomenon or event occurring under well-defined conditions. Observing the distinction from a pure probability perspective, we can distinguish between absolute certainty, uncertainty, and risk. Risk is a feature of all probability distributions, and probability and risk can be interpreted objectively and subjectively (Isaic-Maniu, 2006). Objective probability is based on historical records of statistical data, answering questions such as "how often event A occurs in a dataset", taking the number of occurrences as a percentage of the total and using this premise to calculate the probability of occurrence. Subjective probability encompasses the inherent personality, behavioral and experiential aspects of each person, including attitudes, habits, and a certain degree of intuition. Risk management may reduce uncertainty, but uncertainty will never be completely managed away. An overview of the definition of Risk versus Uncertainty is shown in Table 1.1.

Attitudes to risk and uncertainty are important in economic activity. The advantage of knowing about risks is that we can change our behavior to avoid them (Engle, 2004). However, evidence shows that people are less sensitive to uncertainty than they are to risk (Toma, Chiriţă, & Şarpe, 2012).

Volatility is another well-known concept in this lexical field and measures the dispersion of short-term shocks around a long-term mean. Uncertainty in this context may represent the difficulty to forecast the distribution of returns, including the long-term mean.

Table 1.1.: Definitions of Risk and Uncertainty by different authors.

Authors	Uncertainty	Risk
The entrepreneur	Objective attitude	Subjective attitude
Dual trend	Ignorance of the future	Consequence of decision-makers' actions
Hey J.	Lack of certainty	Uncontrolled certainty
Keynes J.M.	Unquantifiable	Quantifiable
Knight F.H.	Non-probabilistic determination	Certainty, a probability
Neo-classical	Vague non-compensatory risk	Certain equivalent uncertainty
Neo-Keynesians	Unpredictable damage	Predictable loss
The skeptics	Indifference	Reticence
Subjectivists	Independence from the decision maker	Mainly belonging to decision-makers
Roumasset	State of mind	Customize a given situation

Source: (Toma et al., 2012).

Several methodologies have been developed to track risk and volatility. Volatility is a way of describing the degree to which share price values fluctuate and is used as *proxy* to quantify risk since risk is also known in practice to refer to the probability of investments declining in value. For example, we could cite the well-known CBOE Volatility Index (also known by its ticker symbol, VIX), as well as the Average True Range (ATR), and Bollinger Bands, which are tools used to gauge relative levels of volatility across stock markets. The CBOE Volatility Index is updated throughout the trading day and is computed using an option-pricing model that reflects the current implied or expected volatility that is priced into a strip of short-term S&P 500 Index options (CBOE, 2023).

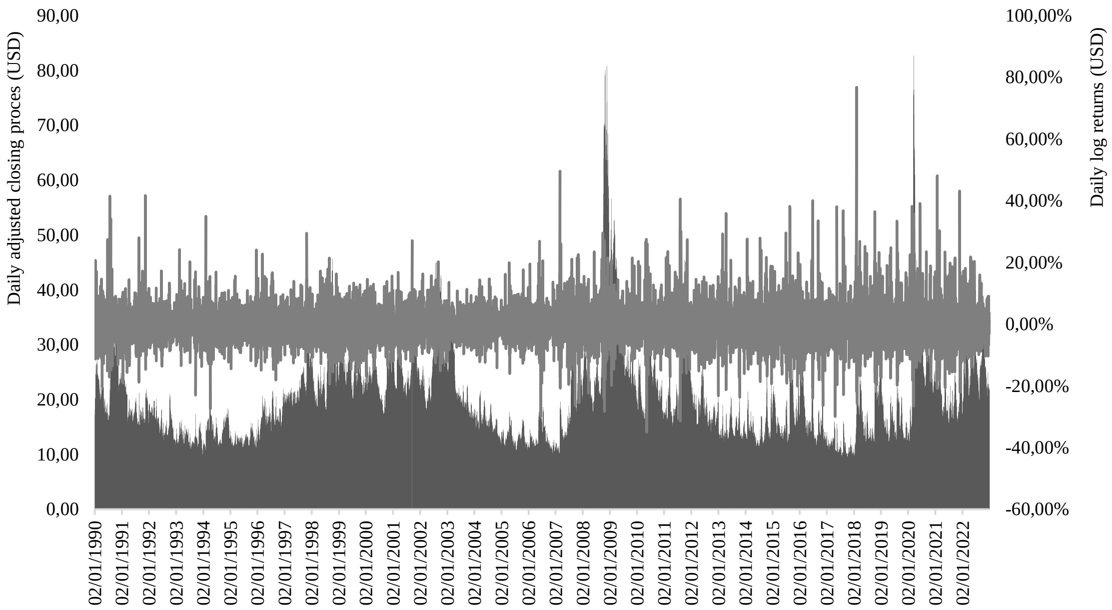

Figure 1.1.: CBOE Volatility Index (January 2, 1990 – January 2, 2023).

When it comes to application of the concepts, Harry Markowitz (1952) and James Tobin (1958) linked the concept of risk to the variance in the value of a portfolio, deriving risk avoidance to portfolio optimization. William Sharpe (1964) later developed the still widely applied Capital Asset Pricing Model (CAPM), which reflects the natural implications of investors with the same information following the same objective. In 2004, Robert Engle created a revised version. Fisher Black and Myron Scholes (1972) and Robert Merton (1973) developed a model to evaluate the pricing of options, which was consistent with the CAPM and for which the authors were recognized with the 1997 Nobel Prize in Economic Sciences.

The rationale behind this model is to recognize that a Put Option can be viewed as a kind of insurance. If it is purchased, the risk can be eliminated from the portfolio. A put option provides the option buyer with the right (but not the obligation) to sell a specific quantity of an underlying security at a predetermined price for a specified time period. The autoregressive conditional heteroskedastic (ARCH) introduced by Engle (1982) has become a useful model to explain the behavior of asset return volatility over time. Bollerslev (1986) introduced the generalized ARCH (GARCH) model, an extension of the ARCH model. Conditional variance, as a function of its own lags, is the predominant approach in the literature and is used to model and forecast volatility (Kalev, Liu, Pham & Jarnecic, 2004; Ho, Shi, & Zhang, 2013; Ho, Shi, & Zhang, 2020). It was developed by Bollerslev (1986) to generalize the ARCH model proposed by Engle

(1982).

Further models have been developed as part of the ARCH family, including nonlinear generalizations such as Glosten, Jagannathan and Runkle's (1993) threshold GARCH (TGARCH) model, Higgins and Bera's (1992) and Nelson's (1991) EGARCH model, Sentana's (1995) quadratic GARCH model, and Zakoian's (1994) threshold ARCH model.

1.2 Research Philosophy

Research philosophy as a concept covers the source, nature, and development of knowledge (Bajpai, 2011), which means that its ultimate meaning is a certain belief in the way that input data should be collected, reviewed, analyzed, and utilized for a particular phenomenon.

The pursuit of knowledge is a key element of the research philosophy of this thesis. By collecting and analyzing secondary data, the aim is to answer the research questions and ultimately create new knowledge. Swartz, Money, Williams, and Remenyi (1998) suggested several questions that a researcher needs to consider when performing research, such as "How to research?", "What to research?" and the more philosophical matter of "Why research?", the latter being a reflection on knowledge development within a particular field. Research philosophy also refers to the assumptions and beliefs that are present throughout the process (Saunders, Lewis & Thornhill, 2016), which can be views within human knowledge and different perspectives regarding reality. Personal values and experiences tend to influence the research process. It is essential to conduct coherent research and make credible research choices (Saunders et al., 2016).

By becoming familiar with the philosophies inherent to business research, authors have reflected on their own beliefs and assumptions. Saunders et al. (2016) argue that active choices regarding the research method should be informed and justified. The research process is reflexive and operates on both theoretical and empirical levels.

1.1.4 Epistemology

Epistemology is the theory of knowledge, encompassing its methods, validity, and scope, as well as distinguishing between justified belief and opinion. It explores the nature of knowledge, addressing what true and trustworthy knowledge might be, the judgment of what is objective or subjective being one of the core premises of epistemology. The objective considers whether certain facts, numbers, events or phenomena can be identified using generalized laws. The subjective approach concerns narratives and opinions with specific contexts and motives (Saunders et al., 2016). From a positivist approach, true and valid knowledge arises from observable observations, and researchers should have an objective stance on and distance from the researched phenomenon (Collis & Hussey, 2014). As stated by Tuli (2010), the nature of social reality for positivists is that empirical facts exist, apart from personal ideas or thoughts; they are governed by laws of cause and effect; patterns of social reality are stable and knowledge of them is additive (Crotty, 1998; Neuman, 2003; Marczyk, DeMatteo & Festinger, 2010).

The goal of science is to develop the most objective methods possible to obtain the closest approximation to reality, as a basic assumption of the paradigm (Tolley, Ulin, Mack, Robinson, & Succop, 2016). This thesis only pursues valid knowledge obtained through objectively analyzed data results. Hence it is positivist, its ultimate objective being to expand the generalizability, validity, and reliability of the results. The epistemological assumption refers to the positivist paradigm, true knowledge, and the belief that social observations should be treated as entities in much the same way that physical scientists treat physical phenomena.

1.1.5 Axiology

The term Axiology originated from the Greek word *axios*, meaning value. In research, Axiology, refers to the values and ethics that researchers defend, and which influence their decision-making processes (Killam, 2013). According to the positivist approach, researchers should be independent from the studied phenomenon and hence their results should also be value-free. The opposite applies to interpretivism, where the results are value-laden because of the influences and involvement of the researchers in the study (Collis & Hussey, 2014). The study of emerging technologies in the context of Business Administration Management and Finance, strictly speaking, is still in its infancy, so a neutral stance was taken. Also, as the authors have no previous experience of this field, no personal views will influence this thesis.

1.3 Problem Statement and questions

Before defining the problem and developing the questions, we shall first recall the main considerations. Markets react promptly to unexpected shocks such as technological change and in particular emerging technologies. The finance industry is particularly integrating into the New Economy by introducing emerging and disruptive technologies to their business models. Examples include cryptocurrencies, the rapid rise of decentralized finance (DeFi), biometric data used for digital ID systems, the use of Big Data by Big Techs and the rising threats derived from such developments, such as hackers accessing sensitive information.

Moreover, emerging technologies in finance are providing new market opportunities, which entail novel volatility patterns. An understanding of the impact of these events on financial stability is of utmost importance to businesses and regulators.

The links between emerging technologies, stock market returns and return volatility also need to be explored by contrasting long-term economic structures against short-term financial market behaviors to uncover the hidden connections.

Which brings us to the problem statements and questions of this thesis. A variety of potential root causes are debated.

- The main research question of this thesis is: Do emerging and disruptive technologies impact asset return volatility, in which direction and to what extent?
- A secondary research question: How does the impact of disruptive technology evolve under different market conditions?
- A tertiary research question: How does the intensity of the impact of disruptive technology evolve under different market conditions?

- And a quaternary research question: How are traditional financial institutions benefiting from the integration of emerging and disruptive technologies via FinTech strategies?

To address these research questions and outline the main features of this thesis' narrative, we shall begin with the research dimension and then move on to the sub research questions and the discourse used to analyze the different chapters.

The thesis begins with an overview of the existing literature in terms of the theory and empirical evidence, in order to present the knowledge base that already exists. What does economic and financial theory have to say on this matter? What is the empirical evidence telling us? What knowledge or statistical features can be identified across the literature, and which can be further examined from quantitative approaches?

Second, the relationship between risk and return within the context of emerging technologies needs to be analyzed, thus paving the way for further exploration of emerging technologies as proxies. What, in the context of emerging technologies, are risk and return being associated with? Can we observe any casualty?

Third, once the construct of the relationship between risk and return in the context of emerging technologies has been made clear, we can start looking in depth at the research objective, which is to analyze whether the evolution of emerging technologies is impacting the finance industry and its asset return volatility, in which direction and to what extent?

Fourth, having identified that the evolution of emerging technologies does indeed have an impact on asset return volatility in the finance industry, we assess whether the identified impact varies across market circumstances. The results of this investigation shed light on the potential risk strategies used by financial institutions. Is the identified impact of emerging technologies on the finance industry's asset returns different in high volatility and low volatility market episodes and to what extent? How can these results be used by financial institutions to gain strategic advantages when participating in the market?

Fifth, we examine the behavior of incumbent financial institutions when they are faced by an increasingly more competitive environment in terms of digitalization in the New Economy. Has the integration of FinTech strategies into the business models of incumbents' financial institutions had a positive or negative impact in relation to market volatility? How can these results be used by financial institutions to gain strategic advantages when participating in the market?
Five specific views are considered in detail in this thesis:

1. The view of the existence of a common understanding of the relationship between emerging technologies and asset returns volatility across the literature (Chapter 2).
2. The view that there is a relationship in a certain direction between the idiosyncratic risk and existing asset returns using the case of the High-Tech industry (Chapter 3).
3. The view that the development of emerging technologies impacts the asset returns of the finance industry across different scales (Chapter 4).
4. The view that the impact and its intensity of disruptive technologies (in the framework of emerging technology) on asset returns volatility in the finance industry is regime dependent (Chapter 5).
5. The view that incumbent financial institutions might adopt a FinTech approach to define business strategies based on stock market behavior (Chapter 6).

1.4 Research approach and methodology

All research is individual and requires its own methodology, with its associated strengths and weaknesses, and any choice inevitably involves loss as well as gain (Schulze, 2003). The research approach and methodology depend on the paradigm and premises of the activities, the researcher's beliefs about the nature of reality and humanity (ontology), the theory of knowledge that informs the research (epistemology), and how that knowledge might be gained (methodology) (Tuli, 2010).

In social science, the most common approaches to research are deductive and inductive. The goal of deductive research is to test already existing models or theories by means of empirical observation (Collis & Hussey, 2014) and generally implies advancing from the general to the particular.

Quantitative research methods focus on executing empirical investigation of observable and measurable variables for the purposes of theory testing, prediction, and determining relationships between and among variables using statistical analysis. There are two data sources for quantitative research, called Primary data and Secondary data. Primary data collection involves directly gathering fresh and firsthand information from the specific source or intended population. This method focuses on collecting data that has not been previously documented, recorded, or made public. Secondary data collection implies statistical analysis of data collected by other researchers or organizations. The qualitative research method focuses on examining the topic via cultural phenomena, human behavior, or belief systems, for which purposes several sub-approaches have been identified. The Case Study involves describing learning from a given experience and a generic qualitative inquiry is conducted when the researcher encounters a qualitative research question, but the research requires a different method than the two aforementioned ones. The choice of whether to use a qualitative or quantitative methodology is determined by the nature of the questions being asked, the state of the field, and the feasibility of any given approach depending on the population of interest.

This thesis is composed of five chapters, and each one entails certain particularities regarding the research approach and methodology, which are detailed in each individual chapter. However, a common onboarding approach used to answer the research question is the one depicted in Fig. 1.2.

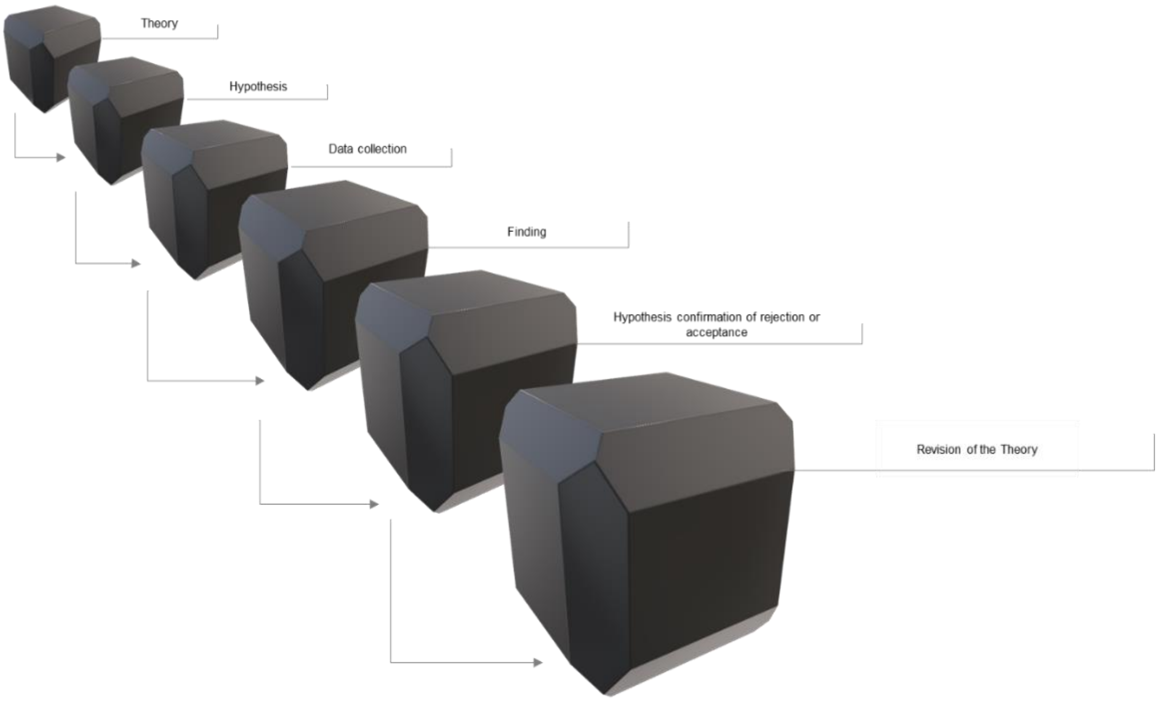

Figure 1.2.: Approach used to answer the research question. Chart self-made bases on (Bryman, 2016).

1.5 Limitations of the research

The main limitation of the chapters of this thesis is the availability of data on the variables used to pursue the quantitative approaches in Chapter 3, Chapter 4, Chapter 5, and Chapter 6. First, the availability and accessibility of times series such as asset risk and returns for use as proxies for emerging and disruptive technologies is limited, since time series reflecting this content is relatively new, meaning that the assets traded are reported for a relatively short time history. Second, the information on key asset prices and indices is not public and is hence relatively costly, which restricted the quantitative approach in terms of functional scope and time.

Opportunities to work on richer data inputs would shed greater light on the unknown relationship and impact of emerging technologies with regard to asset returns in the finance industry. Another limitation is the need for more empirical research to draw generalized conclusions, and to broaden the scope of observation across a greater range of individual research events, which might include cross-country or cross-industry analysis. However, the thesis generally concentrates on studying the impact of emerging technologies on the finance industry and its asset risks and returns using the statistical time series approach. Hence one area for future research would be to analyze the matter using fundamental financial variables as proxies for the specific performance of the finance industry.

1.6 Context and introduction to the chapters

The main implications derived from the work presented in this thesis are the following. To estimate asset risk and return movements in the finance industry, it is important to take into account the impact of emerging technologies from the risk management perspective. Investors, international institutions, and regulators, should acknowledge previous statements and, thus, integrate additional factors of emerging technologies that are considered in the pricing of asset risk and return trade off in the finance industry, and the resulting implications for decision-making concerning the adoption of FinTech strategies.

The thesis contributes to the financial economics and finance literature in a variety of ways. First, it investigates and presents a significant relationship between emerging technologies and stock market dynamics. Second, it provides evidence that the impact of emerging technologies on the stock market varies depending on the stock market conditions. Third, it shows that the intensity of the impact also depends on the market circumstances reflected through volatility regimes. From an investor perspective, and as the general objective, the thesis showcases and encourage investors and risk analysts to use emerging technologies tactically but also underscore the strategically importance to engage with market return and volatility.

This thesis is a comprehensive and self-contained scientific document. Each chapter broadly follows the original contribution developed during the author's time as a PhD candidate at the University of Barcelona. The second chapter provides the *state of art* on the central theme of the thesis, namely emerging technologies, and financial market dynamics. This objective is onboarded by performing a systematic literature review of the constellation of emerging technologies and asset return volatility, documenting several potential explanations as to why the former drive the latter. This paper entitled "*The Rubik's Cube of Emerging Technologies and Stock Volatility"* was published as chapter 12 of the book *Innovation and Sustainability in Governments and Companies: A Perspective to the New Realities* by River Publishers in 2023 (Arenas & Gil Lafuente, 2023) and presented at the *International Congress on Innovation and Sustainability* (ICONIS) in 2021 (Arenas, 2021). The third chapter is a contribution to the field of asset pricing entitled "*Regime Switching in High-Tech ETFs: Idiosyncratic Volatility and Return*" published in *Mathematics* in 2021 (Arenas & Gil Lafuente, 2021). This paper was also presented at the AMSE International Congress in 2020 in Barcelona (Arenas, 2020). The fourth chapter entitled "*Impact of emerging technologies in banking and finance in Europe: A volatility spillover and contagion approach*" contributes to the financial contagion literature. The paper was published by *Journal of Intelligent & Fuzzy Systems* (Arenas & Gil Lafuente, 2021) and presented at the International Workshop on Innovation, Complexity and Uncertainty in Economics and Business in Barcelona (Arenas, 2019). In this context a related presentation entitled "*How the emerging technologies and stock markets came into play with the COVID-19 pandemic: A Range-Based GARCH"* was given at the Robotics and Artificial Intelligence Congress (Arenas, 2021). The fifth chapter, "*The impact of disruptive technologies on Spanish banking under different volatility regimes",* contributes to the innovation and finance literature. This paper was published as the *"Technological and Economic Development of Economy"* (Arenas, Gil Lafuente, & Reverter, 2023). A presentation of the same name was given at the 2nd International Symposium on Automation, Information and Computing at Beijing Jiaotong University (Arenas, 2021). The sixth chapter, *"Banking FinTech and stock market volatility? The BIZUM case",* contributes to the innovation and finance literature as well as investor decision-making and is currently under revision. The objective of this chapter is to review whether and how the adoption of FinTech by incumbent banks affects their stock price volatility. A related presentation was given at the *2nd Global Summit on Applied Science, Engineering and Technology* in Rome, Italy (Arenas, 2023).

I also collaborated as coauthor of a paper entitled "*Determinantes de la satisfacción con la vida en adultos mayores en México*" that was published by *Cuadernos del CIMBAGE* in 2021 (Salazar Cantú, Arenas & Gil Lafuente, 2021) and published a congress proceeding entitled *"A Multicriteria hierarchical approach to ESG Investment Location Choice: Evidence from Latin America"* (Arenas, Alvarez, Muñoz, & León-Castro, 2022). A book chapter entitled *"Tecnología disruptive y banca española: Un enfoque de conmutación de regímenes de volatilidad*" was published in 2022 by the Librería Univeristaria S.L., Barcelona (Arenas & Gil Lafuente, 2022), as well as another entitled *"Multicriteria Hierarchical Approach to Investment Location Choice"* published by Springer Nature Switzerland (Arenas, Palma, Carrillo, Castro, E & Gil Lafuente, 2023). I contributed as well as Co-Editor for the Springer book denominated *"Science and humanism: the challenges of computational intelligence"* currently in Press.

We are currently extending the research scope to analyze the insurance sector and its relationship with emerging technologies, the goal being to further understand the impact of emerging technologies on the finance industry. Second, we are examining the contagion and spillover effect of the identified relationships between emerging technology and market volatility across different markets. Third, we are onboarding the potential impact of the regulatory environment and trust, on the constellation of emerging technologies and the way they impact asset return and volatility patterns.

Table 1.2: Overview of objectives, approach, methods, and findings of the chapter.

Paper Title	Objectives	Theoretical approach	Methodology	Main findings
Chapter 2 The Rubik's cube of emerging technologies and stock volatility.	• Carry out a systematic literature review of the relationship and impacts of emerging technologies and stock volatility behavior. • Understand specific features of emerging technologies	• Positivist • Deductive • Quantitative	• Literature review to establish generalizable facts about a topic. • Collection of secondary data.	• The main finding is that emerging technologies systemically contributes to an increased stock return volatility driven by their inherent uncertain nature, the greater complexity to calculate fundamental values, over-enthusiastic and novice investors, and their idiosyncratic properties. • Properties of emerging technologies are explored and defined as diffusive, persistent, heterogeneous, and momentum oriented.
Chapter 3 Regime Switching in High-Tech ETFs: Idiosyncratic Volatility and Return.	• Identify the significance of idiosyncratic risk in explaining the return of nine high-tech ETFs.	• Positivist • Deductive • Quantitative	• Collection of secondary data. • Econometric model, Markov regime-switching (MRS) methodology for heteroscedastic regimes on secondary data.	• The main finding is that the evidence showcasing a significant relationship between idiosyncratic risk and return, and it provides evidence that idiosyncratic risk is priced negatively or positively depending on volatility regimes. • These results suggest that idiosyncratic volatility matters in high-tech ETF pricing, and that the effects are driven by volatility regimes, leading to changes across them.
Chapter 4 Impact of emerging technologies in banking and finance in Europe. A time series approach for volatility clustering and spillover effects.	• Investigates whether and how emerging technologies impact market behavior in terms of correlation dynamics and volatility transmission.	• Positivist • Deductive • Quantitative	• Collection of secondary data. • Econometric model, GARCH, BEKK.	• The main finding is that emerging technology is relevant for capturing the volatility of the Spanish banking sector, the Spanish market portfolio and the EU-wide finance industry through volatility clustering, volatility spillover and volatility persistence. • As a secondary finding, the Spanish banking sector is most exposed to volatility spillover. • The EU-wide finance industry is most affected by the volatility persistence, shedding light on increasing integration. • The findings indicate the importance of considering sector, industry, and market specific features that need to be contemplated and can result in heterogeneous insights into the relationship between emerging technology and assets risk a return.
Chapter 5 The impact of disruptive technologies on Spanish banking under different volatility regimes	• The goal of this chapter is to investigate whether and how disruptive technology impacts banking stock returns under high and low volatility regimes.	• Positivist • Deductive • Quantitative	• Collection of secondary data. • Econometric model, two-factor model, Markov regime switching on secondary data.	• The main findings show that disruptive technologies have an impact on Spanish banking stock returns. • 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.

Paper Title	Objectives	Theoretical approach	Methodology	Main findings
Chapter 6 Banking FinTech and stock market volatility? The BIZUM case	• The goal of this chapter is to investigate whether and how the adoption of FinTech by incumbent banks affects their stock price volatility. • The case of BIZUM, a Spanish FinTech real-time digital payment solution, is used as a real-world ex-post implementation.	• Positivist • Deductive • Quantitative	• Collection of secondary data • Econometric model, GARCH in Mean for Variance Dummy Variable on secondary data	• The main finding is that the adoption of BIZUM by incumbent banks had a significant effect by reducing their stock price volatility. • This finding suggests that investors were informed of and acknowledged the advantages of BIZUM and expected incumbent banks' stock price volatility to decrease after it was launched.

2 The Rubik's cube of emerging technologies and stock volatility

Abstract. It is argued that emerging technologies lead to increased stock volatility. However, the empirical results are mixed, and the causes are unclear. This paper analyses the topic by applying a systematic literature review. We find that stock volatility has increased overall because of emerging technologies and identify the main drivers as: the uncertain nature of emerging technologies, greater complexity to calculate fundamental values, over-enthusiastic and novice investors, and the idiosyncratic attribute of emerging technologies. Additionally, some properties of emerging technologies are explored.

Keywords: Emerging Technologies; Stock Markets; Stock Return; Stock Volatility.

2.1 Introduction

Understanding the behaviour of time series of stock returns is one of the key research lines in finance. Perhaps one of the most intriguing findings in this area, is that stock returns may be related to the fast-changing and growing technological environment. Since the 4th industrial revolution is leading to an overall transformation of the systema, driven by emerging technologies, stocks return, and stock return volatility react quickly.

Emerging technologies have been defined as technologies been developed and produced in a research environment, but that have necessarily been fully deployed in the market. Emerging technologies include disruptive technologies resulting from radical innovations (e.g. genetic engineering) and evolutionary technologies, the last derived from long trajectories in different research fields (e.g. wireless technologies and the Internet) (Day & Schoemaker, 2000). Emerging technologies involves significant uncertainties and novel features that can potentially have a dramatic impact on the socio-economic system (Boon & Moors, 2008; Martin, 1995; Porter et al., 2002; Small et al., 2014; Rotolo et al., 2015). The last argument can be linked to the "techno-economic paradigm" (Pérez, 1983; Pérez 1985) as introduced by the socio-economist and historian Carlota Pérez.

On the other hand, investments in emerging technologies are considered risky due to the implicitly high degree of uncertainty their surround them.

Radical or breakthrough innovation, as per the contextualization of emergence, comes as a surprise (Leydesdorff & Rafols, 2011), which is only uncovered by their relevant ex post impact on future technological development (Ahuja & Morris Lampert, 2001; Schoenmakers & Duysters, 2010) and adoption. The uncertainty, concerning the performance of emerging technologies may be associated to several aspects that are discussed in this chapter, however, the surprise effect, costs of future ownership, the provision of complementary inputs, the establishment of dominant standards and possible related obsolescence (Hall & Rosenberg, 2010) are some shades that may lead to the uncertain nature.

From a single firm perspective, adopting emerging technologies might be beneficial to stakeholders. Investing and adopting of emerging technologies is stimulating mainstream interest for investors, since it promotes process efficiency and a means to improve firm performance, thus shareholders would expect the firm to improve their economic performance in the future, being reflected in increasing return.

Regarding the market perspective in which the firms operate and adopt emerging technology, advances, and new technologies, make information available on a timelier basis, thus emerging technologies should improve the quality and flow of data used for asset valuation purposes, providing an input to strength certainty proxied by decreasing stock return volatility.

However, contradictory as it might appear at a first glance, that uncertainty about new technologies tends to increase stock market volatility. Several factors are considered as the explanation behind this phenomenon. For example, the option effect, that is when the value increases with the uncertainty proxied by the risk of the underlying asset. The last suggests, that innovation increases the complexity of transactions (Allen, 2012). West (1988), Shiller (1981a), Shiller (1981b), Leroy and Porter (1981) explain that despite improved information about future cash flows, these are more substantially discounted, since news are arriving timelier, increasing stock price and stock return volatility.

The stability of the market valuation, is also being impacted by the new economy, resulting in an overall increased stock price and stock return volatility (Campbell, Lettau, Malkiel, & Xu, 2001; Iraola & Santos, 2007; Kearney & Potì, 2008). A different matter, but relevant to consider in the discussed context, of emerging technology under financial, economic, and social considerations, is the contradiction of the exponential growth of new technologies versus the observed slowdown in productivity (Brynjolfsson et al., 2019). A variety of potential root causes are debated, nevertheless this phenomenon may shed light on the potential inability of current productivity measures to reflect the real benefits of the new technological waves, these emerging technologies.

Moreover, technologies emerging in finance are providing new market opportunities, which entail novel volatility patterns. The linkage of emerging technologies and market return volatility should be explored by connecting long-term economic structure with short term financial market behavior to uncover unrevealed intersections.

This review analyzes whether emerging technologies lead to an increase in stock return volatility and suggests what the main drivers behind this might be.

From a Knightian standpoint, the outcomes of an investment in an emerging technology can be considered uncertain, and since volatility is commonly used as a proxy for uncertainty, the notion of exploring emerging technologies in context of stock return and stock return volatility is aligned with the theoretical notion of uncertainty.

The chapter document several potential explanations as to why emerging technologies drive stock volatility. The rationales proposed are motivated principally by:

- the uncertain nature of emerging technology that shapes specific stock volatility patterns
- the greater complexity for calculating fundamental values
- over-enthusiastic and novice investors leading to noise around the markets
- emerging technologies driven by idiosyncratic attribute

Also, specific features of emerging technologies can be described as diffusive, persistent, heterogeneous, and momentum oriented.

This review takes the form of an agenda and is organized as follows: Section 2.2 discusses the concept of emerging technology. In section 2.3, the rationales for the linkage between emerging technologies and stock volatility is examined. In section 2.4, certain properties related to emerging technologies are discussed and in section 2.5, a closer look at recent empirical evidence on the link between emerging technologies and stock return volatility is provided, examining phenomena such as FinTech, AI, Blockchain, Cloud Computing, and so on. Section 2.6 ends with some concluding remarks.

We use the specification of 'emerging technology' as proposed by Rotolo et al. (2015) and which is attributed as radical novelty, relatively fast growth, coherence, prominent impact, and uncertainty and ambiguity.

2.2 The Concept of Emerging Technologies

The concept of "emerging technologies" has been the subject of much discussion in the academic and professional literature, with frequently casual and ambiguous usage of the term for a specific technology (Li et al., 2018; Fan, Lau, & Leon, 2015; Linton & Walsh, 2008), mainly due to the wide range of different views and domains the concept was adopted. (Li et al., 2018) found the existence of multiple theoretical lines of research on technological change, disruption, and emergence promote conceptual cross-fertilization and consideration of interdisciplinary approaches to technological emergence.

Reviewing the literature, from a science policy perspective (Martin, 1995) was quick to position the concept of "emerging technology" in relation to broad economic and societal impacts. Porter et al. (2002) redefined this vision by adding that "emerging technologies" improve economic leverage in the coming (roughly) 15-year horizon, and Boon and Moors (2008) highlight the role of aspects, regarding emerging technologies, that are still uncertain and non-specific. Hung and Yee-Yeen (2006) and Porter et al. (2002) start from emergence and focus on the economic influence and impact of competition driven by novel technologies, looking at the concept from the macro-level perspective.

Another view of emerging technology arises in the management literature, where emergence is often observed from the perspective of technological adoption. There is also extensive literature connecting emerging technologies to innovation management. Cozzens et al. (2010) place the term in the context of contemporary innovation theory.

A micro level view is offered by Riordan and Salant (1994), proposes a micro level angle of the concept, looking at company dynamics when introducing new technologies to their portfolios. Li (2005) stresses the impacts of network externalities on emerging technology markets. Srinivasan (2008) conceptualizes it in terms of the sources, characteristics, and effects of emergent technologies, highlighting the effect of shifting value chains, digitalization of goods and the changing locus of innovation. Halaweh (2013) defines the characteristics of emerging (IT) technologies as uncertainty, network effect, unseen social and ethical concerns, cost, limitation on countries, and a lack of investigation and research. Rotolo et al. (2015) present a conceptual framework of emerging technologies by integrating previous works. The framework consists around five characteristics of radical novelty, relatively fast growth, coherence, prominent impact, and uncertainty and ambiguity. This is the definition that is used in this article. An emerging technology could fail over time, or become a generalized technology, or even a disruptive technology (Li et al., 2018).

The concept of emerging technology targets various characteristics, including significant uncertainties, novel features (Boon & Moors, 2008; Martin, 1995; Porter, et al., 2002; Small et al., 2014) and the potentially dramatic impact on socio-economic systems (Rotolo et al., 2015), latter might be aligned within the frame of a the "techno-economic paradigm" (Pérez, 1983; Pérez, 1985) introduced by socio-economist and historian Carlota Perez.

2.3 Emerging technologies as drivers of stock return volatility

In the following section we will discuss certain drivers of stock return volatility spreading from the emerging technology phenomena.

2.3.1 Uncertain nature of emerging technology

Uncertainty about the future, is the main reason for performing a risk analysis, identify and anticipate factors or situations that will reduce or result in investment losses and thus, to anticipate how an investment will perform considering certain states. It was Knight who first determined that risk and uncertainty are relevant for economic analysis (Knight, 1921) to entail the evaluation of cost and benefits. However, Knight also highlighted the distinction between two concepts that are often used to express the same notion. Uncertainty refers to events that cannot be expressed mathematically in probabilistic terms, while risk can be quantified by assigning subjective probabilities to a state of risk. Uncertainty and risk are not mutually exclusive. Risk management may reduce uncertainty, but uncertainty never will be completely managed away.

The efficient market hypothesis state that new information randomly arriving the market drives price volatility. The weak form of efficient market hypothesis link stock price and return volatility relates stock price volatility with technical analysis and calendar effect, and the semi/strong version of the efficient market hypothesis relates stock price volatility with fundamentals and corporate announcement. Empirical studies as Shiller (1981a) and Schwert (1989) suggest that volatility is driven by more factors then solely changes in fundamentals. For example, irrational investor doing noise trading participate significantly in stock price volatility. In this context, volatility can be defined as the sum of transitory volatility caused by noise trading and unobserved fundamental volatility caused by the arrival of stochastic information (Hwang & Satchell, 2000).

Emerging technology is characterized as a radical novelty that is uncertain and ambiguous, and indeed not all novel inventions will result to be successful (Fleming, 2001) and result in profits for its investors.

Stock markets have an important role in promoting new technologies and inventions. First, the stock market channel funds from investors expecting to gain from innovation to firms involved in emerging technology and second, as a platform to monitor the progress and performance of emerging technologies by tradable financial asset behviour. Without a stock market platform, no tradable financial assets, tracks the supply, demand, progress, adoption, and performance of the emerging technology via financial behaviour, no market fluctuation, or indeed stock return volatility can be monitored as representative for investors' expectations. In this context, the stock market is especially relevant for making the innovation-intensive, high-tech industries uniquely suited for financing technology-led growth (Brown, Martinsson, & Petersen, 2017) and information source of emerging technology adoption as investments vehicle.

The implication of a high level of capital fluidity is twofold. It facilitates to attract investments; however, it makes it easier to withdrawn capital as well. With the previous notion, funding, and trading of emerging has been associated with the speculative type of funding and venture capital financing (Bartholomew, 1997; Gompers & Lerner, 2003; Ranciere, Tornell & Westermann, 2008). Traders may be drawn to speculative stocks due to their higher volatility, which creates an opportunity to generate greater returns—albeit at greater risk.

Pástor and Veronesi (2006), Gharbi et al. (2014) and Schwert (2002) provided evidence of new or frontier technology firms that exhibit unjustifiably high stock return and volatility. Some authors associate stock price behavior during technological revolution with a bubble-like pattern (Shiller, 2000; Pérez, 2003; Pástor & Veronesi, 2009). Bubbles may also be provoked by technology in presence of uncertainty, narratives related to new technologies, entrance of novice investors, and the pure play implemented by tech-firms to engage investors as argued by Goldfarb and Kirsch (2019). Shiller (2000) and Pérez (2003) attributed this behavior to market irrationality and (Pástor & Veronesi, 2009) for example, relate the uncertainty around new technologies to expectations about future productivity and the time-varying nature of this uncertainty itself.

The literature that covers the linkage between technological innovation and stock prices in levels, onboard this topic mostly from an aggregate macro perspective to the economy and the overall contention, is 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 by firms that purchase a soon-to-be obsolete technology, drives their market value down (Manuelli, 2000) and raises future returns on new investments (Laitner & Stoylarov, 2019). When the novel technology becomes available, it is gradually adopted by new firms, leading to a period of high investment that gradually adapt evolving back to an equilibrium.

Pástor and Veronesi (2009) state that it is the time-varying nature of risk, which is initially idiosyncratic and becomes systematic as the new technology is adopted, 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 hence drive stock prices down in both the new and old economies.

Greenwood and Jovanovic (1999) and Manuelli (2000) study the behavior of macroeconomic variables and the stock market, given major technological changes. Pástor and Veronesi (2009) present a macroeconomic model where the productivity of a new technology is uncertain, and its learning process drives a boom-bust pattern in the stock market.

Benner (2007) found that incumbent firms' stock prices will decline and there will be negative reactions from the stock market, the subsequent response hence being penalized due to institutional pressures from financial markets.

Laitner and Stoylarov (2019) develop a suitable model for studying risk premia and asset-pricing phenomena related to technology diffusion. When examining the diffusion of an emerging technology, most models suggest that this diffusion drives some degree of uncertainty reduction, which to a certain extent is a perpetuating feature of uncertainty reduction (Mansfield, 1968), since uncertainty will never be eliminated.

Iraola and Santos (2007) provide a model of technology adoption to analyze different channels of technological innovation that impact stock prices. The ration behind, is that the value of the stock market absorbs the option value of the emergence and adoption of the future technology.

The environment related to emerging technologies must also be accounted for in the form of obsolescence risk. Competitive advantages of firms with new technology may replace traditional firms, emerging with a dominant market share, which may result in initially signaling to the market competing traditional firm stocks being negatively impacted. This scenario may suggest that investors in traditional firms, will go toward a long-term strategy to overcome volatility that may be induced by initial competition entering the market. Thus, the demand for long-term investment increases. Evidence indicates, for example, that the average maturity of US corporate bonds increased from 9.5 years in 1996 to more than 15 years in 2017 (SIFMA, 2022) and the average European ten-year bond yield, dropped from 10.78% January 1993 to 5.73% in January 2000 and 1.15% in January 2019 (European Central Bank, 2021) followed by a negative yield scenario afterwards, this suggest and overall scenario away from short term volatility toward long term safety.

This may also be linked to several aspects of the digital era and comprehensive the emergence of technology waves. The flagship technologies of the most recent waves were brought into the market mainly by small, and young firms. This suggests that the narrative of the IT revolution is about entrance, and since entrance survival rates are low and may take decades to grow (O'Reilly III & Tushman, 2011; Stubbart & Knight, 2006), it might also sum to the uncertainty nature of emerging technologies. Corporate longevity is declining, according to Innosight's biennial corporate longevity reports (Viguerie, Calder, & Hindo, 2021). As the economy transitions from the industrial age to the digital age, firms will survive for shorter periods (Berente, Lee, Potts, & Srinivasan, 2020).

Investors additionally must incorporate the regulatory uncertainty in their evaluation of new technologies and opportunities. Governments are still exploring how to regulate the fast-growing emerging technology environment. However, at this point, it is unclear if technology-driven firms will self-regulate or as traditionally, imposed by a regulatory entity (PGIM, 2018). Emerging technologies themselves could facilitate regulatory compliance and supervision as RegTech alternatives, smart regulation which incorporates traditional regulators objectives, with boarding decentralized ledger or crypto economics incentives to implement the rule – based protocols.

To sum up, we reviewed the difference of uncertainty and risk, indicated that emerging technologies are naturally uncertain due to various circumstances.

First, evidence from the past is limited or inexistent. It is not possible to perform a solid risk analysis, preventing to get light into the future outcome of an emerging technology and its associated investment. Second, emerging technologies nature can be associated to bubble like pattern, obsolescence risk that comes along with any emerging technology by displacing traditional ones, and regulatory risk, since emerging technology will be regulated by governments, however it is not clear, yet which structural approach will be the usual frame implemented. Considering the foregoing, investors may look to overcome the increase volatility facing in the short-term, adjusting their portfolios to the more safety long-term horizons.

2.3.2 Greater complexity for calculating fundamental values

There are still questions to be asked as to how new technology may relate to macroeconomic factors and sources of uncertainty that could explain asset market phenomena such as driving the risk premia.

Short-term volatility among stock markets is well recognized, whereby firms seek to optimize investment opportunities (Pyka & Butghof, 2013) driven by the short-term pressure on them to generate economic returns for their investors (Hopkins, Crane, Nightingale, & Baden-Fuller, 2013; Martin & Scott, 2000; Salter & Martin, 2001) while monitoring their fundamentals in quarterly reporting (Aggarwal & Hsu, 2014; Manso, 2011; Noda & Bower, 1996).

With this rational, it seems difficult to link short term stock market fluctuation with long term economic theory, since the market value of a stock should be explained by fundamentals such as profit, dividend and output growth, these doses do not fluctuate as much (Peralta-Alva, 2007). Some literature, for example (Kydland & Prescott, 1982), has proposed technology shocks that impact the macroeconomy, channeled by the stock market, as an explanation for short-term fluctuations. Jovanovic and Rosseau (2002) associate fluctuations in the stock market with three technological revolutions: Electricity, World War II, and IT. These authors document long lags in the operation and diffusion of new technologies. During radical technological changes, excess volatility peaks associated to the related uncertainty (Shiller, 2000), and therefore, fundamental information is less useful for making estimations about future values (Tushman & O'Reilly III, 1996).

However, to better understand how technological shocks might be channeled and translated into stock market fluctuations, it is insightful to recall such a basic financial concept as the notion that asset prices should equal expected discounted cashflows. 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. Therefore, stock prices may also reflect the expectations regarding the emerging technology, since expected cashflows for investors in emerging technologies will also be considered.

The common component and forward-looking feature of asset valuation are the interest or growth rates that are used to discount the future payoffs. However, when looking at the fluctuations in those rates, stock valuation models are expected to imply a significant volatility driven by those economic components. The perception of an economic slowdown in this regard is enough to generate big changes in stock market prices (Peralta-Alva, 2007). Some literature shows that real stock price indexes move much more than the present value of the corresponding real dividend series and that the present value seems to behave much more like a trend over time (Shiller, 1981a; Shiller, 1981b; Leroy & Porter, 1981; West, 1984; Mankiw, Romer & Shapiro, 1985; Brooks & Katsaris, 2003;

Capelle-Blancard & Raymond, 2004). In the efficient-market literature, the valuation error is explained by “anomalies”, otherwise known as “small” departures from market efficiency. For an integral discussion on the topic of discount rates (see Cochrane (2011)).

Meanwhile, psychology and perceptions are being recovered that attribute most price variations to the field of behavioral finance, (see Kahneman and Tversky (1979), Bovi (2009), Sahni (2012); Tauni, Fang, and Iqbal (2016), Riccardi and Simon (2000)). The recent line of argument is that long-term behavior of stock prices is consistent with fundamentals, while their short-run evolution reflects unobserved behavioral factors (Gallagher & Taylor, 2001; Manzan, 2007; Coakley & Fuertes, 2006).

A different discussion in this area is the contradiction between the astonishingly growth of new technologies, versus a slowdown of productivity in recent decades. Brynjolfsson et al. (2019) studied this Modern Productivity Paradox applied to artificial intelligence technology and highlight that a mismeasurement of output and productivity may be prevailing due to a pessimistic reading of the empirical past, rather than optimism about the future, implying that productivity has already absorbed the benefits of new technologies but has yet to be accurately measured (e.g., Mokyr, 2014; Feldstein, 2015).

One factor may be the availability of new predictive technologies to evaluate investment opportunities. Allen (2012) finds empirical evidence suggesting that financial innovation often increases the complexity of transactions. More data availability and more complex predictive analytics techniques increase the chances of data mining, whereby spurious patterns are observed when, in fact, there are none (Siegel, 2021). Data mining is easier than ever now that computing power has become so cheap (Lo & Mackinlay, 1990).

Recapturing, financial analysis is forward looking, starting by the notion that the present value of an asset equals the future value of their future cash flows discounted. Emerging technologies bear greater complexity to identifying or calculating the fundamental values. Radical new technologies inventions are identified only by their ex-post impact on technological development (Ahuja & Morris Lampert, 2001; Schoenmakers and Duysters, 2010), product performance (Leifer, O'Connor & Rice, 2001) or market structure (Mascitelli, 2000), making it much more difficult to integrate associated features in financial forward-looking value frame.

2.3.3 Overenthusiastic and novice investors

Stock markets and market volatility cannot only be driven by stock and associated firm fundamental information. Significant market volatility is impacted by different factors that shape investors decisions, as for example overreaction and underreaction, irrational exuberance, overconfidence, bandwagon effect trend chasing, regretting and fear of missing out, among others.

Investors may induce volatility into the market by interpreting arriving stochastic information and noise trading. Several behavioral biases direct investors toward its decisions.

Investment in emerging technology provide more space for behavioral biases due to the uncertainty there are surrounded and more complexity of objectively value financial information as discussed in previous section The future of the unknown, and potential surprise effect or outcome that may result from an emerging technology, is particularly attractive for certain investor profiles. In the case of new emerging technologies, no past references or historical reference is available to be used as a guideline to follow, not only in terms of development, market acceptance, also on financial market behavior and investor profiling. As stated by Kucharavy and Guio (2008), forecasting emerging technologies with no past is difficult since they have not passed the infant mortality threshold. when the S-shaped curve is applied to forecast their trajectory.

Thus, and recalling the notion, that stock prices are formed based on the expected optimal forecast on available information, we can argue that the expectations about future profits from an emerging technology will also be reflected, including expectation, and signaling from overenthusiastic and novice investors.

Investment in new emerging technology may increase overenthusiasm and the influx of novice investors, who are more likely to be influenced by external and subjective factors. 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, decoupling the temporary price from its fundamental valuation.

To understand better the linkage between emerging technologies, stock return volatility and investors profiling, we may recall the context of new technologies and the rationale of bubble patterns.

Behavioral biases significantly influence the emergence of bubbles. Anderson (1787) as early as more than two centuries ago argued that investment will increase by potentials gains, resulting in a assets price appreciation, while attracting new investors, leading to further price and so on, creating a certain buckle driven by greed and profit seeking attitude.

The financial press commonly endorsed the view that individual investors as being largely responsible for the technology bubbles. When investors are inexperienced and less financially literate, they may be guided by opportunities that are new and seem exciting, as is often the situation with new technologies (Goldfarb & Kirsch, 2019). New emerging technology, that may be associated to a surprise effect of emergence, makes this problem more impactful.

As indicated by Griffin, Harris, Shu, and Topaloglu (2011) there are three theoretical models in the bubble literature that target investor interaction and that can be linked with specific new technology investment scenarios. The first is the rational market view that states that sophisticated traders (arbitrageurs) quickly trade against irrational agents, eliminating deviation from the economic value as represented by Friedman (1953) and Fama (1965). The second argument states that changes in economic value is driven by noise traders, preventing sophisticated traders to eliminate deviations from the fundamental value. The third, argues that rational speculators may drive a bubble, whereby arbitrageurs, knowing that the market is overvalued, maximize profits by riding the bubble (Abreu & Markus, 2002; Abreu & Brunnermeier, 2003). As a result, market prices may be self-driven based on prophecies (Merton, 1948), also known as 'rational bubbles' (Froot & Obstfeld, 1991).

From a more empirical perspective, Frehen, Goetzmann, & Rouwenhorst (2013) revisit the first global financial bubbles that occurred in 1720 in France, Great Britain, and the Netherlands and found evidence against irrational exuberance and in favor of speculation about fundamental financial and economic innovations in the European economy (Prendergast & Stole, 1996). Whereby young managers hope to acquire a reputation for quick learning, their tend to exaggerate their own information and via their attitude and trading behaviour, impact market. Benner and Ranganathan (2013), study the reactions of securities analysts as important sources of institutional pressure on firms to respond to industry convergence through relevant technological change, such as that between wireline telecom and cable industries. They found that analysts' reactions depend on investor preferences, which are more positive or negative toward "growth" and "margin" preferences respectively. Harrison, Scheinkman, & Xiong (2008), found that young managers intentionally assume excessive positions regarding technology stocks to signal to smart investors that they understand the new technology, as opposed to old managers. Griffin et al. (2011) examines the daily trading behavior of different investor groups and evidenced that institutional investors drove and burst the technology bubble. Greenwood and Nagel (2009) observe that during the technology bubble, young managers increased their technology holdings during the run-up and decreased them during the downturn. Furthermore, young managers, exhibit trend-chasing behavior in their technology stock investments. Also, during the run-up to the technology bubble, venture capital rose from a 10% to a 40% share of investment, as calculated by Goldfarb and Kirsch (2019). On the other hand, Zuckerman and Rao (2004) found that co-movement among internet and other stock categories is less common during periods of price appreciation than of erosion, what may suggest that the endogenous driven mechanism being driven by the buckle of price appreciation.

During the technology bubble between 1997 and 2000, technology stock rose more than five times and institutional investors reportedly bought more than individual investors (Griffin et al., 2011). Lewellen (2003) detected that almost all internet stocks in March 2000 had extremely high price to sale ratios, compared with other stocks, indicating that investors were more likely to pay more for internet stock compared to others. Corbet (2021) documented that companies who use "crypto-exuberant" naming practices become more volatile and offer substantial and persistent stock market premiums. Greenwood and Nagel (2009) claim that younger managers outperformed before the peak in March 2000, and significantly underperformed after the peak, averaging out to about zero. Siegel (2021) adds that the failure of analysts to adapt their earnings forecasts to the technology sector despite the negative views of the industry was particularly pronounced among analysts in the Internet sector. Dealing with news that does not correspond to one's worldview creates what is called cognitive dissonance. The distinguished paper by Cooper, Dimitrov, and Rau (2001) found that during the period of the internet hype from the late 1990s into the 2000s, there was a tendency among investors to bid up the stock prices just for changing domain names to ".com". In contrast, the paper by Lee (2001) related the event to a potential of misinterpretation of the fundamentals. Brunnermeier and Nagel (2004) documents that hedge funds, considered among the most sophisticated investors, did not exert a correcting force on stock prices during the technology bubble. Instead, they were heavily invested in technology stocks.

Recapturing, overall sentiments or feelings are experienced constantly on the markets. The excitement or overenthusiasm of something new and potential outcome of a surprise, as an emerging technology, impact market via decision take by overenthusiastic investors. Young and less experienced investors are more likely to follow behavioral biases. In hence it makes sense that enthusiastic and novice investors will bid up the stock price, since the future course of an emerging technology will be especially impacted by investors' expectations. From a different point of view, investors will learn from the past and the newer emerging technologies there are available to invest in, the greater leeway there is for risk diversification, even among the same sectors.

2.3.4 The idiosyncratic attribute of emerging technologies

Volatility can be categorized as market and firm-specific or idiosyncratic volatility. Idiosyncratic volatility (Campbell et al., 2001; Kearney & Potì, 2008) is attributed by some literature to the IT revolution (Campbell et al., 2001; Mazzucato, 2002; Mazzucato & Tancioni, 2008a) and that the economy is increasingly induced by intangible assets (Bagella, Becchetti, & Adriani, 2005; Kearney & Potì, 2008; Chan, Lakonishok, & Sougiannis, 2001).

As stated by Cao, Timothy, & Zhao (2008) much of the literature has attempted to characterize the rising trend in idiosyncratic risk. First, idiosyncratic risk may be related profitability level and variance (Pástor & Veronesi, 2003; Wei & Zhang, 2006). Second, it is positively related to expected earnings growth and institutional ownership (Xu & Malkiel, 2003). Third, idiosyncratic risk is negatively related to firm age (Pástor & Veronesi, 2003). Fourth, it is negatively related to expected returns in the cross-section (Ang, Hodrick, Xing, & Zhang, 2006; Ang, Hodrick, Xing, & Zhang, 2009). Fifth, it is correlated with the business cycle (Brown & Ferreira, 2004) and sixth, it is a stronger predictor of cross-section of return than of liquidity (Spiegel &Wang, 2005).

A large body of the literature provides evidence that innovative sectors are more exposed to idiosyncratic risk than traditional markets do (Chan et al., 2001; Schwert, 2002; Domanski, 2003) thus emerging technology. Technology, and specifically new technology developing sectors, have a unique setting that is systematically different from that of traditional firms. A broad range of industry participants, including public research organizations, entrants, and incumbent firms, contribute to the advancement of emerging technologies ecosystem (Kapoor & Klueter, 2020; Powell, Koput, & Smith-Doerr, 1996; Rosenberg & Nelson, 1994).

The flagship technologies of the most recent waves were mainly brought into the market by small, young firms, which may explain the overall uncertainty related to emerging technologies and be aligned (Pástor & Veronesi, 2003) with the notion that idiosyncratic risk is negatively related to firm age which we already reviewed in previous section.

Often these firms are defined as knowledge-based organizations since they are non-vertically integrated and human capital intense (Ahmed & Alhadab, 2020), which entails a higher level of unreported assets compared to traditional firms (Brown et al., 2017; Junttila, Kallunki, Kärja, & Martikainen, 2005; Kwon & Yin, 2006; Kwon & Yin, 2015; Lim, 2015; Watanabe, Hur & Lei, 2006).

Net assets of a form should be reflected by the stock market value of the firm. However, its more complicated in a firm with a relevant share of intangible assets as R&D. Explaining the real asset base of a companies by including soft assets or intangible assets and being able to explain asset valuation of tech giants and loss-making unicorns is still controversial and as expect, leading to a certain level of uncertainty. The last decades an increase in R&D expenditures. While predictable earnings and returns in highly innovative tech firms are generated by intangible assets, they are associated with a higher degree of uncertainty (Chan et al., 2001; Kothari, Laguerre, & Leone, 2002), whereby earnings volatility related to R&D expenditure is three times larger than earnings volatility associated to tangible assets. The positive relationship between the share of intangible assets (as a proxy for IT-related changes) and the increase in idiosyncratic risk in the 1990s is consistent with the view that IT increases uncertainty with respect to firm valuation (Domanski, 2003).

Since intangible assets are highly transferable, as for example qualified scientific knowledge, these firms are more exposed to underinvestment (Hall, 2002), since the possibility to retain its value is less secure, which provoke higher risk levels (Borah, Pan, Chul Park, & Shao, 2018). Thus, it makes sense that it is more complicated for these firms or projects to obtain external funding specially form risk adverse investment profiles, for their R&R activities. Small-cap stock outperform large-cap stocks based on the size effect and value stocks, stock with low market value relative to it fundamentals, outperform the market in the long run as the value effects states. Yu, Liu, Fung, and Kin (2020) state that R&D intensity in firms adds another important dimension to the size and value effects market anomalies, when describing stock returns, especially for small technology firms.

At the stock level, highly innovative stocks are growth stocks but are also considered riskier because they do not typically offer dividends. For example, Tesla stated in their dividend policy that there is a non-dividend-paying stock. One big reason is technology firms generally need to keep growing by adopting the best and brightest new innovations. If Alphabet, Amazon, and Facebook along with Berkshire Hatway, would pay shareholder dividends it would increase the S&P index's overall yield by 7.6 percent (Inbert, 2017). Aboody and Lev (2000) on the other hand, show that insiders in high-tech firms make more generous profits then their colleagues. Additionally, technology companies, are known as growth stocks, stocks that demonstrate to gain better than average earnings and with market expectation to deliver relevant profit growth. The momentum of growth stocks may be higher (Bagella et al., 2005) as the inertia of a price trend continues for a particular length in time.

A wide range of literature (see Greenwood & Jovanovic, 1999; Hobjin & Jovanovic, 2001; Laitner and Stolyarov, 2003; Peralta-Alva, 2007), studied the effects of technology on the values of old or traditional and new companies. Lin, Palazzo, & Yang (2017) found that higher risk and higher expected returns are reported by firms that operate with old capital, since old capital firms are more likely to upgrade soon and are therefore more exposed to shocks resulting from competing frontier technologies. Rubera and Kirca (2012) found that the effect of firm innovativeness is stronger on market position for firms with innovativeness output and radical innovation.

Projects, and projects related to emerging technologies, can generate greater degree of asymmetric information, since managers have the insights and more knowledge about the state of the outcome (Blazenko, 1987), resulting in an increased, stock return volatility. Particularly High-tech firms, suffer from the asymmetric information problem (Gharbi et al., 2014; Gu & Li, 2007; Gu & Wang, 2005; Barron, Byard, Kile, & Riedl, 2002). Idiosyncratic volatility can be used as an alternate measure or proxy of information asymmetry as it measures the amount price volatility due to firm−specific information (Abdul-Baki, 2013).

R&D intensity can be linked to asymmetric information in explaining volatility. Gharbi et al. (2014) show how firm generates information asymmetry with regard to a its firm's prospect. Duqi, Jaafar, & Torluccio (2015) state that mispricing can occur if investors are unable to correctly estimate long-term benefits of R&D investment or whether determine if R&D firms are riskier than others. On the downside, stocks listed on markets in continental Europe and operating in high-tech sectors are more prone to undervaluation due to information asymmetries that are more severe in bank-based countries. Technology firms with the objective to close the gap of lacking information, hold conference calls and provide the public with additional information about financial conditions (Tasker, 1998; Dell'Acqua, Perrini, & Caselli, 2010). Dell'Acqua et al. (2010) additionally found that these actions made by technology firms can decrease idiosyncratic volatility. This can be strategic for firms to overcome the initial burden of high idiosyncratic risk by launching emerging technologies. Another shade is external expert criterions about firm performance. Barron et al. (2002) studied analysts' forecasts consensus and found that it is negatively associated to firm's intangible asset share. On the other hand, lower levels of analyst consensus are associated with high-technology manufacturing companies. Arenas and Gil Lafuente (2021a) found that the price return of high−tech Exchange Traded Funds (ETFs) is negatively associated to idiosyncratic risk in high volatility regimes and positively related in low volatility regimes. These results suggests that idiosyncratic risk can penalize or reward investors investment in emerging technologies based on certain circumstances. Darby, Liu, & Zucker (2004) suggests that knowledge capital intensity explains price jumps of underlying knowledge base firm stocks, since firms with two standard deviations more in knowledge capital, are valued by 10−50% in excess. Resuming, the different shades of the idiosyncratic nature of emerging technologies, idiosyncratic risk increased in last decades and an overall argument suggest that this increase od idiosyncratic risk, is relate to the new economy as driving force of economic growth.

Technology firms are holding more idiosyncratic risk, then other sectors, due to asymmetric information related to invention and developments, to their knowledge intensity and high level of R&D expenditures, since these features are highly transferable, complex to measure and difficult to integrate into contemporaneous valuation frameworks, adding uncertainty. Nevertheless, idiosyncratic risk is conditional or time-varying in it proportions zooming into the emergence of new technologies. During technological revolutions, the nature of this uncertainty quantified by risk, shifts from being idiosyncratic, to become systemic, as the likelihood of a large−scale adoption is increasing in time.

2.4 Certain properties of emerging technologies

Financial time series comprehend features known as stylized factors, as volatility clustering, heteroscedastic variance, non-normal leptokurtic distribution, and the leverage effect. Stylized factors are originated in financial time series by 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 a perceived operational timescale (Stock, 1988). Stylized factors are related to technological change and often associated to bubble−like patterns during technological revolutions attributing more irrationality to the market (Shiller, 2000; Pérez, 2003).

The trajectory of the progress of an emerging technology has been studied by e.g., Anderson and Tushman (2018), Dosi (1982), Sahal (1985). A stylized description for an emerging technology is that there is slow but gradual improvement in the technology's performance, as reflected by the canonical S-shaped pattern (Dosi, 1982; Foster, 1986; Henderson, 1995; Sahal, 1985; Stoneman, 2002). The S-shape curve depicts the normal evolution of a system in accordance with the laws of natural growth over a period. It begins with slow change, followed by rapid change, and ends with slow change again until the asymptote is reached. These phases can be interpreted as periods of birth, growth, maturity, decline and death for any system and represent the characteristic features of the pattern followed by an emerging technology. The S-shape represents cumulative growth whereas a bell-shaped curve is usually applied to represent the rate of growth within a time span.

The idea of paradigms and trajectories can account for the observable phenomenon of cumulativeness of technical advances (within an established trajectory), also defined as the cumulative feature of the progress upon a technological trajectory and detailed by Dosi (1982) as the probability of future advances related to the position of firms or countries. The previous description coincides with the presentation of technical progress by Nelson and Winter, which applied Markovian chains at firm and industry level (Nelson & Winter, 1975). The advantages of Markovian chains are that if one knows the current state of the process, then no additional information on its past states is needed to make the best possible prediction of its future, which make sense for the study of emerging technology patterns. Multiple technological trajectories, for different digital technologies and applications, can develop, clash, and evolve over time, and at different speed, industry dependent (Martinelli, Mina, & Moggi, 2021).

The diffusion of an emerging technology may be also considered in the evolutionary context. Rogers (1995) defines diffusion as a process in which innovations are spread among the members of a social system over time. From this perspective, diffusion is defined as the process by which innovations, new products, new processes, or new management methods spread within and across economies (Stoneman, 1986). In turn, adoption is a decision to implement innovations based on knowledge, and persuasion by individuals within a given system. On the other hand, social adoption, and contagion influences adoption. Adoptions of new technologies, fads, and many other human activities spread among individuals through social interactions (Goffman & Newill, 1964; Leskovec, Adamic, & Huberman, 2007).

Three theoretical approaches have been widely adopted to define the diffusion process and they are worth mentioning at this point. The first is known as the epidemic approach, which considers diffusion to result from the spread of information (Griliches, 1975; Mansfield, 1961; Mansfield, 1989; Mansfied, 1968). The second is the rank approach (Davies, 1979; Karshenas & Stoneman, 1993; Stoneman & Diederen, 1994), in which empirical Probit models are used to rank firms by their characteristics. Third is the game theory approach. Adoption is based on firms' strategic interactions, more precisely on order and stock effects (Reinganum, 1981a; Reinganum, 1981b; Stoneman, 1986; Fudenberg & Tirole, 1985). The rank and game theory approaches are based on the explicit treatment of the firm's adoption decision. However, technology diffusion also influences technology adoption due to complementarity effects between prevailing strategies, organization, and information technologies (Bocquet, 2007). For example, the introduction of low energy consumption to sensors, and their declining costs, drove their diffusion; advanced machine learning and deep learning began to drive automation; cloud connectivity is delivering low-cost processing power and pervasive interconnection; and new ways to connect monitoring and management systems (so-called 'digital twins') (Martinelli et al., 2021). Several studies (see Berman, Bound, & Machin, 1998; Greenan & Guellec, 1998; Brynjolfsson & Hitt, 2000; Brynjolfsson & Hitt, 2003; Bresnahan Brynolfsson, & Hitt, 2002) have highlighted the fact that since the information technology (IT) revolution, the mere adoption of IT may no longer be enough to gain competitiveness, which also requires a cluster of related innovations in the organization, new customer and supplier relationships and new product designs.

The complementarity perspective suggests that the adoption of a new technology only generates better firm performance if its fits with other complementary choices made by the firm. Empirical studies have shown that the adoption of a new technology is strongly linked to firms' strategies, to their organizational practices and to their competitive environments (Bocquet, 2007). Therefore, diffusion should be analyzed from a multivariate and multipartite perspective, as stated by Grübler (1991).

When a technology is subject to increasing returns, this sets the scenario for a distinctive pattern of diffusion. Pezzoni, Veugelers, & Visentini (2019) provided new evidence on technological diffusion and found that the highest-impact novel technologies need longer to be legitimized, particularly the riskier types of new inventions involving new combinations of dissimilar, unfamiliar, and science-based components. One feature of diffusion may be driven by positive feedback loops in terms of adoption and the associated "bandwagon" effects (Abrahamson & Rosenkopf, 1997; Arthur, 1996; Shapiro & Varian 1998; Fichman, 2000), also known as irrational exuberance in the context of investors in stock markets, and which refers to the tendency to adopt a certain attitude simply because everyone else is doing it (Schmitt-Beck, 2015).

The bandwagon phenomenon can be viewed as a bull market situation and emergence of bubbles. See, for example, the IPO of SNAP Inc. in 2017, which led to appreciation among technology companies driven by the technology rally and evidenced the existence of an inherent correlation apparatus, which can be understood as emerging technologies self-organizing their growth. In the context of a technology evolution, the trajectory is linked to the autonomous momentum (Dosi, 1982), which is the momentum that seems to be maintained by its own (Nelson & Winter, 1975; Rosenberg, 1976) technical progress or trajectory. However, from the stock market perspective, momentum commonly related to investor irrationality (Daniel, Hirshleifer, & Subrahmanyam, 1997; Barberis, Shleifer, & Vishny, 1998) since investors miss to integrate new arriving information thus underreact. Nevertheless, also perfectly rational investors may follow momentum (Crombez, 2001). High/tech firms generate greater momentum as shown by Ahmed and Alhadab (2020), notwithstanding this response is asymmetric for low-tech stocks. Jaggia and Thosar (2004) found similar evidence as the momentum is important, while fundamental have at best weak explanatory power on the medium-term in emerging tech US IPOs. The industrial evolution is revealed as a stochastic process, meaning that its evolution follows a succession of random variables that evolve in function of other variables, generally time. The rate of change of this succession has similar shades as of a complex system dynamic. Heavy tails, for example, are increasingly related dynamics originating from innovation and are viewed as evidence of lumpy growth, suggesting the absence of a single rational expectation (Dosi, 2005). Instead, it suggests the occurrence of extreme events due to greater probabilities for dynamic innovation (Axtell, 2001).

While many studies have looked at innovation and the adoption of technologies separately, they are linked. Advances (and expected advances) in a single technology should affect both its adoption rate and the adoption of alternative technologies.

Gold, Peirce, & Rosegger (1970) find that the rate of adoption is relatively slow, and that technologies for which it is slow take off as standard technologies. Recent surveys show that although the rate of adoption for many digital technologies is relatively low and skewed toward larger firms, it has a hierarchical pattern in which the most sophisticated technologies are most frequently accepted only after more basic applications (Zolas et al., 2021). The direction of change in adoption can also be affected by unexpected events, as highlighted and exemplified by Ciarli, Kenney, Massini, & Piscitello (2021) for the COVID-19 pandemic that, in a very short time, forced in-person events to go online and in a matter of weeks fostered the use of digitalization in such fields as telemedicine, which had previously only had limited impact (Mann, Chen, Chunara, Testa, & Nov, 2020). Changes that might have taken years to be adopted were accelerated by an unexpected event (Ciarli et al., 2021).

Significant heterogeneity is seen in the recombination and development of emerging technologies that cannot be fully explained by adoption. For example, many firms develop their digital technologies in-house for their own use (Montobbio, Staccioli, Virgillito, & Vivarelli, 2022).

The persistence over time is also being addressed in the literature as a distinct feature of innovation dynamics (Alfranca, Rama, & von Tunzelmann, 2002; Cefis, 2003; Malerba, Orsenigo & Peretto, 1997; Dosi, 2005). Technologies mature (Christensen, 1992) and firms that have invested in innovative technologies in the past are more probable to continue in this line, investing in the future (Cohen & Levinthal, 1989), as an endogenous pattern. This procyclical and endogenous pattern is consistent with the cyclical patterns of diffusion. Since new technologies take time to catch on, the cyclical response to news shocks is highly persistent (Comin, 2009). High persistence in a process may be related or exemplified by a random walk, which recalling certain numerical properties refers to an I(1) process, where the series in level is not weakly dependent (iid) but its first difference is.

Also, the establishment of extensive new technological trajectories might explain a "clustering" of new technological innovations and their economic impact in time (Dosi, 1982), forming the evolutionary curve of the emerging technology. However, evidence exists that a certain clustering of innovations can apparently be identified at a statistically significant level (Kleinknecht, 1987) and returns (Arenas & Gil Lafuente, 2021a) and that the clustering effect is more focused on the end of the diffusion life cycle also known as "season of saturations" (Grübler, 1991). Dosi (2005) attributed mentioned heterogeneous to differences capability to innovate and adopt innovation, developed elsewhere due to differentiation.

Discontinuity in technological change can be associated to the emergence of extraordinary innovative and radical technology (Dosi, 1982) that induces major discontinuities in the statistics that describe structures (Dosi, 1995), particularly (i) different organizational arrangements and (ii) different production efficiencies. Since the work by Mensch (1975), the debate on the discontinuous nature of technological change has been dominated by discussion of the Schumpeterian hypothesis of the discontinuous rate of the appearance of innovations. There has been under debate that the evolution of emerging technologies does not cohere to a smooth pattern of cumulative progress but is, often disorderly and punctuated by episodes of setbacks (Freeman, 2013; Kapoor & Klueter, 2020; Kline & Rosenberg, 1986; Rotolo et al., 2015). A setback is defined as a reversal or check in progress and is a relatively common feature of technology emergence, as detailed and exemplified by Kapoor and Klueter (2020) and made evident by such examples as ballpoint pens (Cooper & Smith, 1992), biogas (Geels & Raven, 2006), electric cars (Garud & Gehman, 2012), fuel cells (Bakker, 2010) and semiconductor lithography equipment (Adner & Kapoor, 2016).

2.5 Recent empirical evidence

Recent empirical evidence of the link between stock prices, stock price returns and stock return volatility are still lacking in order to provide further insight into the little-known intersection between economic and financial measures. However, below some articles that shed some light on different nuances related to the constellation of emerging technologies and the stock market are reviewed.

FinTech developments, for example, can be seen as disruptive innovations, and particularly automation of financial services, providing alternatives for traditional financing and trading. In the context of disruptive technologies and stock market returns, recent studies have attempted to provide evidence on the value creation side due to FinTech. Navaretti, Calzolari, Mansilla-Fernande and Pozzolo (2018) found that FinTech increases liquidity demand uncertainty in the financial market, which may augment market volatility and, per se, additional return to compensate. Majid, Sultana, Abid, and Elahi (2021) studied the impact of innovation over the S&P100 firms and found that innovation is a resource enabler to obtain positive abnormal returns for firms, remaining steady under noise trading and investor biasedness. Low and Wong (2021) studied the varying effects of disruptive FinTech growth across six ASEAN countries on incumbent banks' stock returns and found that the results vary across respective geographical areas and may be considered when studying the impact of innovation on stock market performance.

AI is transforming the way financial services are delivered to customers and almost daily new developments are being deployed, from research and new libraries for Python, R, Julia and others. Lui, Lee, and Ngai (2022) studied the impact of 119 AI related announcements on 62 listed firms that have invested in AI. The result indicates a 1.77% decline in firms' stock prices. However, negative impact was observed for firms with weak information technology capabilities or low credit ratings. Setiawan et al. (2021) found, that artificial intelligence programs led to a greater financial performance for the banking industry.

The World Economic Forum (2016) identified Bitcoin-based Blockchain technology as among the top 10 emerging technologies. A relevant concern here is volatility spillovers in the cryptocurrency market spreading to the financial system. Some researchers as Baek and Elbeck (2015) and Glaser, Zimmermann, Haferkorn, Weber and Siering (2014) claim that Bitcoin is mainly used as a speculative vehicle due to its volatility. Hassani, Huang and Silva (2018) argued that a ‘stable coin’ have low price volatility since there are being tied to some underlying fiat currency. Andersson and Styf (2020) identified a slight increase in systematic risk on 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. Based on 175 firm announcements between 2015 and 2019, Klöckner, Schmidt and Wagner (2022) conducted an international study to estimate the impact of blockchain initiatives on the market value of firms and found that engagement in a blockchain project attenuates a positive stock market reaction. Akyildirim, Corbet, Lucey and Sensoy (2020a) studied the link between a range of cryptocurrencies and the implied volatility of both United States and European financial markets as measured by the VIX and VSTOXX respectively. The results indicated the existence of a varying positive interrelationship between the conditional correlations of cryptocurrencies and financial market stress, which increases during periods of high stress because of contagion from the market to cryptocurrencies. Umar, Rizvi, and Naqvi (2021) examine risk, return and volatility spillovers originated from the cryptocurrency market that is transmitted into the global financial system using Baba-Engle-Kraft-Kroner (BEKK) methodology. The result show that that in the case of shock emitted by the crypto market, spillover effect is channeled to the financial markets; while form the contrarian perspective, does not hold. Omce the shock is incorporated or absorbed, equity and high yield hedged bond markets persistent to the subsequent volatility spillovers originating from the crypto market.

Cloud computing is powerful extensive and will continue to grow in the future since it is extremely cost-effective. Mahmood, Arslan, Dandu, and Udo (2014) study how the public business is impacted by Cloud Computing adoption in terms of stock performance and found that the impact results in a positive cumulative abnormal return at the time of an event announcement. This study also highlights that cloud adopting and non-cloud adopting companies suffer from higher stock risk during the announcement, but the risk is not statistically significant. Parameswaran, Venkatesan, Gupta, Sharman, and Rao (2011) studied cloud computing announcements regarding stocks listed in the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ and found that they have a significant positive impact on stock price, albeit a few days later than the day of announcement. The same results are found by Son, Lee, Lee and Bong (2014), who also observe that market reactions to cloud computing initiatives depend on three key characteristics of the latter, namely firm-specific, resource-specific, and vendor-specific factors. Parameswaran, Venkatesan and Gupta (2013) study this topic from the perspective of the competitor and find that cloud security breach announcements have a significant negative impact on the stock value both of firms and of their competitors. Nicholas-Donald, Mahmood and Trevino (2018) used a resource-based view, the efficient market hypothesis, to analyze 136 companies that adopted cloud computing and are listed in one of the US stock exchanges and found that cloud computing announcements increase the trading volume and risk of these companies.

IoT is another technology that has become widespread. Tang, Huang, and Wang (2018) found positive impacts of this on firms' Tobin's q and financial performance, particularly in terms of improving return on assets (ROA).

Ba, Lisic, Liu and Stallaert (2013) found that the stock market reacted positively to announcements of global green vehicle innovation and that overall green product development decisions, such as innovation type and market segment choices, exert a direct influence on a firm's market value.

Arenas and Gil Lafuente (2021b) investigated 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.

The study by Agrawal, Bharath, and Viswanathan (2004) shows that there is a significant increase in idiosyncratic and total stock return volatility when a firm initiates ecommerce, accompanied by positive abnormal returns of stock prices.

2.6 Conclusion

The chapter presents a review of research to provide new insights on the linkage of emerging technology and stock price and stock return volatility. The chapter takes the form of an agenda and is based on secondary information.

The baseline notion for this review is that emerging technologies should be examined in the context of stock return and stock return volatility. Risk is commonly used as a proxy for uncertainty, and innovation is an example of true uncertainty (Knight, 1921) thus emerging technology should be studied under the lens of stock return and stock return volatility.

After offering a general overview in section 1, the concept of emerging technology is discussed in section 2. In section 3, some key areas to shed some light on the link between emerging technologies and stock volatility are examined. Section 4 defined certain properties of emerging technology, such as diffusive, persistent, heterogeneous, and momentum-oriented are defined, which brought us back to the historical considerations of technology bubbles, booms, and busts. In section 5 recent empirical evidence on FinTech, AI, Blockchain, Cloud Computing and other technologies are reviewed. One important implication of this review is that similar terms are used in the literature to refer to emerging technology.

The main conclusion is that emerging technologies increase systemically stock return and stock return volatility. After reviewing theoretical arguments on economic growth, and how these arguments relate and link to stock market fluctuations and irrational expectations, we observe a connection within the framework of the New Economy. Since emerging technologies can be interpreted as being derived from radical innovation and may be consolidated within what Carlota Perez introduced as the "techno-economic paradigm" (Pérez, 1983), the stock market will reflect the economic conditions, which are ultimately related to technological change.

Risk is mainly generated by uncertain individual events concerning emerging technology, whose overall aggregated impact generates stock market volatility. The main drivers of risk in the presented scenario are the uncertain nature of emerging technologies, greater difficulty to calculate fundamental values, over-enthusiastic novice investors and the idiosyncratic nature of emerging technologies being driven by intangible assets. Emerging technologies can be defined as diffusive, persistent, heterogeneous, and momentum-oriented, which can be regarded as the natural pattern those systems evolve.

The premise brings us back to the historical implications of technology bubbles, idiosyncratic risk and indeed the fact that the overall risk resulting from the emerging technology environment is conditional or time-variant, initially mostly idiosyncratic nature later becomes more systematic as large-scale adoption and the effects of social contagion take place. The review of recent empirical evidence supports the premise that there is a link between emerging technology dynamics and stock return and volatility. However, direction and tertiary circumstances must be considered, from a unique perspective as are still not able to deliver a generalized statement.

3 Regime Switching in High-Tech ETFs: Idiosyncratic Volatility and Return

Abstract. The volatility of asset returns can be classified into market and firm-specific volatility, otherwise known as idiosyncratic volatility. Idiosyncratic volatility is increasing over time with some literature attributing this to the IT revolution. An understanding of the relationship between idiosyncratic risk and return is indeed relevant for idiosyncratic risk pricing and asset allocation, in a context of emerging technologies. The case of high-tech exchange traded funds (ETFs) is especially interesting, since ETFs introduce new noise to the market due to arbitrage activities and high frequency trading. This article examines the relevance of idiosyncratic risk in explaining the return of nine high-tech ETFs. The Markov regime-switching (MRS) methodology for heteroscedastic regimes has been applied. We found that high-tech ETF returns are negatively related to idiosyncratic risk during the high volatility regime and positively related to idiosyncratic risk during the low volatility regime. These results suggest that idiosyncratic volatility matters in high-tech ETF pricing, and that the effects are driven by volatility regimes, leading to changes across them.

Keywords: Idiosyncratic risk; stock market return and volatility; Markov regime switching.

3.1 Introduction

The role of idiosyncratic volatility in asset pricing has not received much attention since, under the Capital Asset Pricing Model (CAPM), it is only the non-diversifiable systematic risk that matters (Sharpe, 1964; Lintner, 1965; Black, 1972). According to modern portfolio theory, idiosyncratic risk can be completely diversified away. However, several studies (Tinic & West, 1986; Goyal & Santa Clara, 2003: Fu, 2009) have observed that portfolios of common stocks with higher idiosyncratic volatility record higher average returns. In other words, there is a positive relationship between idiosyncratic risk and their returns, providing empirical support for Merton’s (Merton, 1987) argument that in a world of incomplete information, under-diversified investors are compensated for not holding diversified portfolios.

Recently, an opposing scenario was reported by Ang et al. (2006, 2009) in which a negative price of idiosyncratic risk was found. In general, the existing literature is not clear about the relationship between idiosyncratic risk and return.

This topic has become even more important in the light of recent evidence that idiosyncratic volatility has increased overall (Campbell at al. 2001; Kearney & Potì, 2008); which some literature attributes to the IT revolution (Campbell at al. 2001, Kearney & Potì, 2008; Mazzucato, 2008) and to the fact that the economy is increasingly driven by intangible assets (Bagella at al., 2005; Chan et al., 2001).

Innovation is leading to changes to goods and services, leading businesses to restructure their IT models. It therefore makes sense for the purchase of emerging technology stocks to be part of a company’s strategy to ensure smooth adaption to the innovation driven environment.

Firms in the high-tech sector exhibit high stock return volatility (Schwert, 2002), and it is unclear whether IT is more volatile because of the market perceptions or whether this is due to new forms of firm management. Gharbi et al. (2014) state that high-tech industries exhibit high stock return because R&D activities involve information asymmetry in terms of firms’ expectations and thus make their stock riskier. When more closely examining IT elements in the context of the rising idiosyncratic risk and considering their potential to simultaneously affect a wide range of industries inside and outside of the IT sector (Domanski, 2003), it becomes clear why IT is considered a relevant factor.

The case of exchange traded funds (ETFs) is especially interesting, since some studies reveal that ETFs introduce new noise to the market due to arbitrage activities and high frequency trading (Ben-David, Franzoni, & Moussawi, 2012; Ben-David, Franzoni, & Moussawi, 2018). It is therefore important to improve our understanding of volatility patterns among high-tech specified ETFs. For instance, like common stock prices, ETF prices can fluctuate throughout the day and can be traded on margin or sold short. Arbitrage activities only occur if the deviation of the ETF price and the underlying index price is relevant. When the price of an ETF is below the underlying portfolio value, arbitrageurs' step in to buy the cheap ETF and usually hedge their risk by selling the basket of the underlying index. Hence, arbitrage activity moves ETF prices back up, aligning them with their underlying index. ETFs also report economically large momentum profits (Li, Teo, & Yang, 2019).

We investigate the relationship between idiosyncratic volatility and excess return among nine high-tech exchange traded funds (ETFs) using daily data for the period from 12/01/2017 to 1/31/2020. Markov regime-switching (MRS) modeling involving time series analysis was deemed suitable for this study since idiosyncratic volatility and excess return series are not constant in time.

In contrast to previous studies, this article not only looks in depth at the relationship between idiosyncratic risk and return, but also considers it in the IT related environment under a specific ETF scheme.

We found a negative relationship between idiosyncratic risk and return for the nine high-tech ETFs during the high volatility regime and a positive relationship for eight of the nine high-tech ETFs during the low volatility regime. These results suggest that idiosyncratic volatility matters in high-tech ETF pricing, suggesting that firm-specific risk may matter in high-tech ETF pricing and can lead to under-diversification of portfolios. The explanatory power of idiosyncratic risk is shown to be robust when we control for two volatility regimes, one high and one low.

The remainder of the article is structured as follows. Section 2 reviews the related studies in the literature to provide relevant background for our research design. Section 3 describes the methodology. Section 4 presents the data, Section 5 presents the empirical results, and Section 6 summarizes the conclusions and provides certain directions for future research.

Our objective is to investigate whether the patterns of returns in the high-tech specific sector are indeed linked to idiosyncratic volatility in ETF pricing.

This article contributes to the idiosyncratic volatility literature in the following ways: First, it documents a significant relationship between idiosyncratic risk and return, contrary to the fundamental theory of investment, which states that idiosyncratic risk should not be priced since it can be eliminated through diversification. Second, it provides evidence that idiosyncratic risk is priced negatively or positively depending on volatility regimes in the context of an IT related environment. Third, the results highlight how investors do not diversify the risk rationally under certain market circumstances.

This article also provides insights into the role of pricing of managed funds, especially for funds exposed to equity investment, and has other important implications for investors and international institutions that include high-tech investments in their portfolios. In order to diversify investment in the high-tech sector, idiosyncratic risk can play an important role in terms of idiosyncratic volatility and return since the effects are not constant but driven by regimes, leading to changes across the two volatility regimes.

3.2 Literature

3.2.1 IT Revolution and Increasing Idiosyncratic Risk

The world economy has shifted from a tangible to an intangible asset driven one (Bagella, 2005; Chan et al., 2001). More than 50% of the GDP of most advanced economies is attributed to high-tech industries (Borah, 2018). Recent studies attribute this to economy-wide factors, such as the role of the IT revolution (Campbell at al. 2001, Kearney & Potì, 2008; Mazzucato & Tancioni, 2008a). Fornari and Pericoli (2001) revealed that small portfolios of IT- and non-IT equities are more sensitive to technology shocks. However, a large body of the literature has reviewed the spectrum of innovative firms in the new technology market and provided evidence that innovative sectors are riskier and involve more idiosyncratic or firm-specific risk than traditional markets do (Chan et al., 2001; Schwert, 2002; Domanski, 2003). For example, Schwert (2002) finds that NASDAQ, a particularly high-tech stocks index, is more volatile than the S&P index, concluding that such unusual volatility is better explained by technology than such other factors as firm size or immaturity.

This study considers high-tech sectors to be a unique setting that is systematically different to that of traditional firms. High-tech firms are defined as knowledge-based organizations since they are non-vertically integrated and human capital intense (Ahmed & Alhadab, 2020), which entails a higher level of unreported assets compared to traditional firms (Brown et al., 2017; Junttila et al., 2005; Kwon & Yin, 2006; Kwon & Yin, 2015; Lim, 2015; Watanabe et al., 2006). Predictable earnings and returns in high-tech firms are generated by intangible assets that are associated with a higher degree of uncertainty (Chan et al., 2001; Kothari et al., 2002). As reported by Kothari et al. (2002) earnings volatility related to R&D expenditure is three times larger than earnings volatility associated to tangible assets. The positive relationship between the share of intangible assets (as a proxy for IT-related changes) and the increase in idiosyncratic risk in the 1990s is consistent with the view that IT increases uncertainty with respect to firm valuation (Domanski, 2003). Since intangible assets are highly transferable, high-tech firms are more exposed to underinvestment (Hall, 2002), encounter higher risk levels (Borah et al., 2018), and find it harder to obtain external funding for their R&D activities (Upadhyay & Zeng, 2017). High-tech stocks are growth stocks but are also considered riskier because they do not typically offer dividends. For instance, Aboody and Lev (2000) show that insiders in high-tech firms make more generous profits. Additionally, the momentum of growth stocks may be higher (Bagella et al., 2005).

3.2.2 Idiosyncratic Risk and Return

Traditional CAPM theory states that only systematic risk matters for asset pricing because it is non-diversifiable, and that idiosyncratic risk should not be priced since it can be completely diversified (Sharpe, 1964; Lintner, 1965; Black, 1972). However, in a situation where more stocks are added to a portfolio, there needs to be a tradeoff between the profit obtained from diversification and the higher transaction cost, leading to a scenario in which investors do not have full information about all of the securities in the market. Merton (1987) postulated that idiosyncratic volatility is relevant to asset pricing, and agents will demand a premium for holding more idiosyncratically volatile assets if investors are not able to diversify the risk (Jones & Rhodes-Kropf, 2003; Lehmann, 1990). As suggested by Merton (1987), firms with greater firm-specific variance require higher returns to compensate investors for holding an imperfectly diversified portfolio.

Several early-stage studies, such as Lintner (1965); Tinic et al. (1986), Merton (1987) and Lehmann (1990), are consistent with recent studies supporting a significant positive relationship between idiosyncratic risk and expected stock returns, either at the aggregate level, or at the firm or portfolio level, supporting Merton's view of the relevance of idiosyncratic risk in asset pricing.

For the aggregate level, see Goyal and Santa-Clara (2003) and Jiang and Lee (2006), which also offers relevant insights into portfolio level, following Fu (2009), Malkiel and Xu (2002), Levy (1978), Spiegel and Wang (2005), Chua, Goh, & Zhang (2006). For instance, evidence for a significant positive effect of idiosyncratic volatility was found, the results being robust for various portfolios of different sized firms, sample periods, and measures of idiosyncratic risk (Jiang and Lee, 2006).

Spiegel and Wang (2005) find that stock returns are positively related with the level of idiosyncratic risk and negatively related to a stock's liquidity, the impact of idiosyncratic risk being significantly stronger and more explanatory than the impact of liquidity. Fu (2009) applied an exponential GARCH and found that idiosyncratic volatilities and cross-sectional returns are positively related, and that the idiosyncratic risk varies in time. Chua et al. (2006) used data from all common stocks traded at NYSE, AMEX, and NASDAQ to find that expected idiosyncratic volatility is significantly and positively related to expected returns, in addition to the fact that unexpected idiosyncratic volatility is positively related to unexpected returns. Switzer and Picard (2015) used a five-factor model to also conclude that idiosyncratic risk is positively related to month-ahead expected returns for many emerging markets. Mazzucato and Tancioni, 2008a delivered further insights based on industry level and firm level data showing that idiosyncratic risk has increased over time and found that R&D intensive firms are characterized by higher idiosyncratic risk profiles since innovation activity affects the uncertainty of expected future profits. Rachwalski and Wen (2016) found a short-lived negative relationship between idiosyncratic risk innovations and high idiosyncratic risk stocks earning persistently high returns. Behavioral models also support these theories regarding the positive relationship between idiosyncratic volatility and expected return. For example, see Rachwalski and Wen (2016).

However, Ang et al. (2006, 2009) found contrary results to the prevailing assumption that idiosyncratic risk is positively priced, indicating that stock prices with high idiosyncratic volatility yield exceptionally low returns, controlling for value, size, liquidity, volume, dispersion of analysts' forecasts, and momentum, although other studies (Bali & Cakici, 2008; Huang, Liu, Rhee, & Zhang, 2010; Han & Lesmond 2011, Bali, Cakici, & Whitelaw, 2011). Boyer, Mitton, & Vorkink, 2010; Nartea & Ward, 2017) considered these results weak since the findings could be attributed to liquidity or a skewed pattern of returns. Nartea and Wald (2017) studied this topic for the Philippine stock market and found that the average equal-weighted idiosyncratic volatility is negatively related to market returns, in stark contrast to the findings of Goyal and Santa-Clara (2003) for the US market who found no relationship between IV and abnormal returns, as opposed to the aforesaid findings of Ang et al. (2006), and Brockman and Yan (2008) for the US market.

This topic has gained further importance given the evidence that both firm-level volatility and the number of stocks needed to achieve a specific level of diversification have increased in the United States since the 1960′s (2001). Additional evidence as Barber and Odean (2000), Benartzi and Thaler (2001), and Falkenstein (1996) reports that not only are individual investors' portfolios undiversified, but mutual fund portfolios too. Therefore, idiosyncratic volatility should play a significant role in the pricing of managed funds, especially those with significant investments in equities (Di Iorio & Liu, 2015).

3.3 Methodology

3.3.1 ARMA

The ARMA (autoregressive moving average) refers to stationary structure and time discrete stochastic approach that is useful to identify past effects of the series themselves as well as the MA (moving average) effect that identifies signals sent by the error term. We can represent an ARMA(p, q) model as

$$Y_t = \alpha_o + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \cdots + \alpha_p Y_{t-p} + \beta_1 e_{t-1} + \beta_2 e_{t-2} + \ldots + \beta_q e_{t-q} + e_t \qquad (3.1)$$

where $(e_t) = 0$; $Var(e_t) = \sigma^2$; $Cov(e_t, e_{t-h}) = 0 \; \forall h \neq 0,$ p is number of lags of the dependent variable and q the number of lags of the error term.

3.3.2 ARCH

The autoregressive conditional heteroskedastic (ARCH) introduced by Engel (1982) has become a useful model to explain the behavior of asset return volatility over time, where the conditional variance can be represented as

$$Var(e_t) \equiv \sigma_t^2 = \theta_0 + \sum_{i=1}^{q} \theta_i \, e_{t-i}^2 \qquad (3.2)$$

where $E(e_t) = 0$; $Var(e_t) = \sigma^2$, $COV(e_t, e_{t-h}) = 0 \forall h \neq 0$, p represents the number of lags of the dependent variable and q represents the number of lags of the residuals.

3.3.3 GARCH

Bollerslev (1986) introduced the generalized ARCH (GARCH) model, an extension of the ARCH model. The conditional variance, as a function of its own lags, can be expressed as follows:

$$Var(e_t) \equiv \sigma_t^2 = \theta_0 + \sum_{i=1}^{q} \theta_i \, e_{t-i}^2 + \sum_{j=1}^{p} \pi_j \, \sigma_{t-j}^2 \tag{3.3}$$

where θ_0 > 0 and the GARCH (p, q) is covariance stationary only if $\sum_{i=1}^{q} \theta_i + \sum_{j=1}^{p} \pi_j$ <1.

3.3.4 Idiosyncratic Volatility Measure

Idiosyncratic risk is usually measured as the asset specific return volatility. For some examples of this, see Richards (1999). In this article we apply the market model approach to obtain the residuals that are utilized to calculate the idiosyncratic volatility measure, as also applied in Rachwalski and Wen (2016), Di Iorio and Liu (2015), Angelidis (2010), Hamao, Mei, & Xu (2003) under similar circumstances. The MSCI World index is used as a proxy for the market returns.

Idiosyncratic volatility is calculated as the 15-day moving standard deviation of the residuals resulting from the one-factor market model as presented below:

$$r_t = \alpha + \beta Mkt_t + e_t \tag{3.4}$$

where r_t is the excess return of the ETF, Mkt is the market excess return and e_t is the residuals. The GARCH approach as specified in Section 3.3. was utilized for this purpose.

3.3.5 Heteroscedastic MRS for Idiosyncratic Volatility and Return

Financial time series present several characteristics that are also known as stylized factors. These are volatility clustering, heteroscedastic variance, non-normal leptokurtic distribution, and leverage effect. These stylized factors lead to sudden changes in financial time series behavior. The underlying reason for this is related to the rate of information arriving in the market (Lamoureux & Lastrapes, 1999); errors in the learning processes of economic agents (Mizrach, 1996); and the artificial nature of a calendar timescale in lieu of a perceived operational timescale (Stock, 1988). Regime switching models are able capture those sudden changes in behavior Ang and Timmermann (2012).

Markov regime-switching (MRS) models assume that an observed process is motivated by an unobserved state process and are widely applied in finance and macroeconomics. Moreover, RS (regime switching) and MS (Markov switching) models are in themselves well-known examples of non-linear time series models. Evidence supports the idea that MRS modeling outperforms static mean-variance strategies overall (e.g., Ang and Bekaert (2004), Guidolin, & Timmermann (2008), Kritzman, Page, & Turkington (2012), and Dou, Gallagher, Schneider, & Walter (2014)) and specifically for ETFs (Jiang, Liu, & Tse, 2015).

The method for estimating a single switching point position for a lineal regression system was introduced by Quandt (1958) and the Markov switching model was presented by Goldfeld and Quandt (1973). Hamilton (1989) proposed a multivariate generalization of the univariate Markov switching process to model the U.S. business cycle.

Under the MRS approach, the universe of occurrence can be decomposed into m states, with $s_i, i = 1, \dots, m$, with m regimes. Y_t switches regime according to an unobserved s_t variable, where s_t=1 and s_t=2 represent how the process is in regime 1 at time t and in regime 2 at time t, respectively. The state variable follows a Markov process with the probability distribution of state t depending on state $t-1$ only, as represented by the following expression:

$$P[a < Y_t \leq b|\, y_1, y_2, \dots, y_{t-1}] = P[a < y_t \leq b|\, y_{t-1}] \quad (3.5)$$

The process captures changes in the mean and in the variance among states. Consider a first order Markov process with an unobserved state variable, then:

$$\begin{gathered} P[s_t = 1|s_{t-1} = 1] = p_{11} \\ P[s_t = 2|s_{t-1} = 1] = 1 - p_{11} \\ P[s_t = 2|s_{t-1} = 2] = p_{22} \\ P[s_t = 1|s_{t-1} = 2] = 1 - p_{22} \end{gathered} \quad (3.6)$$

where p_{11} and p_{22} are the probabilities of being in regime 1 given that the process was previously in regime 1 and the probability of being in regime 2 given that the process was previously in regime 2, respectively. Further, $1 - p_{11}$ and $1 - p_{22}$ are the probabilities that the process will switch from state 1 in period $t-1$ to state 2 in t and from state 2 in period $t-1$ to state 1 in t. In this context the observed series can be represented as

$$P[a < Y_t \leq b|\, y_1, y_2, \dots, y_{t-1}] = P[a < y_t \leq b|\, y_{t-1}] \quad (3.7)$$

where $e_t \sim N(0,1)$. The mean and variance are α_1, $\alpha_1 + \alpha_2$ and σ_1^2, $\sigma_1^2 + \theta$ in state 1 and in state 2, respectively. Maximum likelihood is used to estimate the unknown parameters.

Because the objective of our paper is to analyze the relationship between idiosyncratic volatility and excess return under different market circumstances, we estimate the following MRS specification for all individual ETFs:

$$\hat{r}_t = \begin{cases} \alpha_{o,s_t} + \delta_1 IR_t + e_{t,}s_t = h \\ \alpha_{o,s_t} + \delta_1 IR_t + e_{t,}s_t = l, \end{cases} \quad (3.8)$$

where $\hat{r}_t$ is the ETF excess return, IR the ETF idiosyncratic volatility measure, α_{o,s_t} and $e_{t,}s_t$ are the constant and residuals in the presence of the unobserved state variable s respectively and δ_1 is the coefficient related to the idiosyncratic volatility measure, in high volatility regime h and in low volatility regime l.

3.4 Data

This article studies the following nine high-tech ETFs: First Trust NASDAQ Cybersecurity ETF (CIBR), Global X FinTech Thematic ETF (FINX), Fidelity MSCI Information Technology Index ETF (FTE), ETFMG Prime Cyber Security ETF (HACK), iShares Expanded Tech-Software Sector ETF (IGV), VanEck Vectors Semiconductor ETF (SMH), iShares PHLX Semiconductor ETF (SOXX), SPDR S&P Semiconductor ETF (XSD), and SPDR S&P Software & Services ETF (XSW). Table A3.1 in the Appendix provides the specifications of each ETF.

The sample period is from 12/01/2017 to 1/31/2020. Daily price data is used in the form of log returns on the adjusted closing prices of the indices in US dollars and are calculated by the following formula:

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3.9}$$

where r_t is the log return, P_t the closing price and P_{t-1} the previous day closing price. We used the 13-week Treasury Bill as the risk-free rate to calculate the excess return as:

$$r_t = R_t - rf_t \tag{3.10}$$

where r_t is the excess return, R_t the previous calculated log return and rf_t the risk-free rate in time t. The data are available to the public at www.finance.yahoo.com (2020, November 15).

3.5 Empirical Results

3.5.1 Preliminary Data

In Table 3.1, all ETFs excess returns are slightly negative. The kurtosis values of the nine high-tech ETFs excess returns are higher than three, suggesting that the distribution of returns could be fat-tailed. As the skewness values are generally negative, they define the asymmetric tail, since the Jacque–Bera results are statistically significant and reject the null hypothesis of a normal distribution for all ETFs returns. Nonetheless, our analysis is robust, just as models are also usually robust in non-normal cases applying Huber–White robust standard errors.

Table 3.1: Summary statistics for daily excess returns of the nine exchange traded funds (ETFs).

	CIBR	FINX	FTE	HACK	IGV	SMH	SOXX	XSD	XSW
Mean	−0.0070	−0.0069	−0.0068	−0.0071	−0.0068	−0.0070	−0.0069	−0.0069	−0.0069
Median	−0.0062	−0.0053	−0.0061	−0.0060	−0.0057	−0.0057	−0.0057	−0.0058	−0.0054
Maximum	0.0345	0.0430	0.0490	0.0382	0.0539	0.0478	0.0491	0.0491	0.0367
Minimum	−0.0567	−0.0727	−0.0606	−0.0570	−0.0648	−0.0785	−0.0768	−0.0797	−0.0585
Std. Dev.	0.0123	0.0135	0.0131	0.0123	0.0139	0.0168	0.0169	0.0168	0.0124
Skewness	−0.6761	−0.8232	−0.6015	−0.5713	−0.4799	−0.4248	−0.3867	−0.4718	−0.7614
Kurtosis	4.3894	5.6211	5.3273	4.4956	4.9509	4.3395	4.2901	4.2864	4.9238
Jarque–Bera	85.2100	217.1676	155.5869	80.3041	107.1545	57.0417	51.2879	57.6976	136.4673
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sum	−3.8537	−3.7940	−3.7429	−3.8662	−3.7055	−3.8103	−3.8037	−3.7959	−3.7651
Sum Sq. Dev.	0.0821	0.0991	0.0932	0.0826	0.1061	0.1542	0.1553	0.1539	0.0835
Observations	544	544	544	544	544	544	544	544	544

Source: EViews 11 University Version.

Technology companies are known for their high profit margins, and explosive growth patterns resulting in significant capital gains. On the downside, the high valuation of such firms means that they are highly exposed to interest rate volatility; also, given the strong performance of these firms in the long run, investors tend to have high expectations.

Figure 3.1 plots the excess return of the nine high-tech ETFs. We can observe similar trends or an association between all high-tech ETFs, oscillating around zero, and highly volatile with larger spikes during the fourth quarter of 2018. Interestingly, all series retrieve high volatility in the fourth quarter of 2018, which can be linked to the general plunge in tech stocks in October due to concerns about the US–China trade war and rising interest rates.

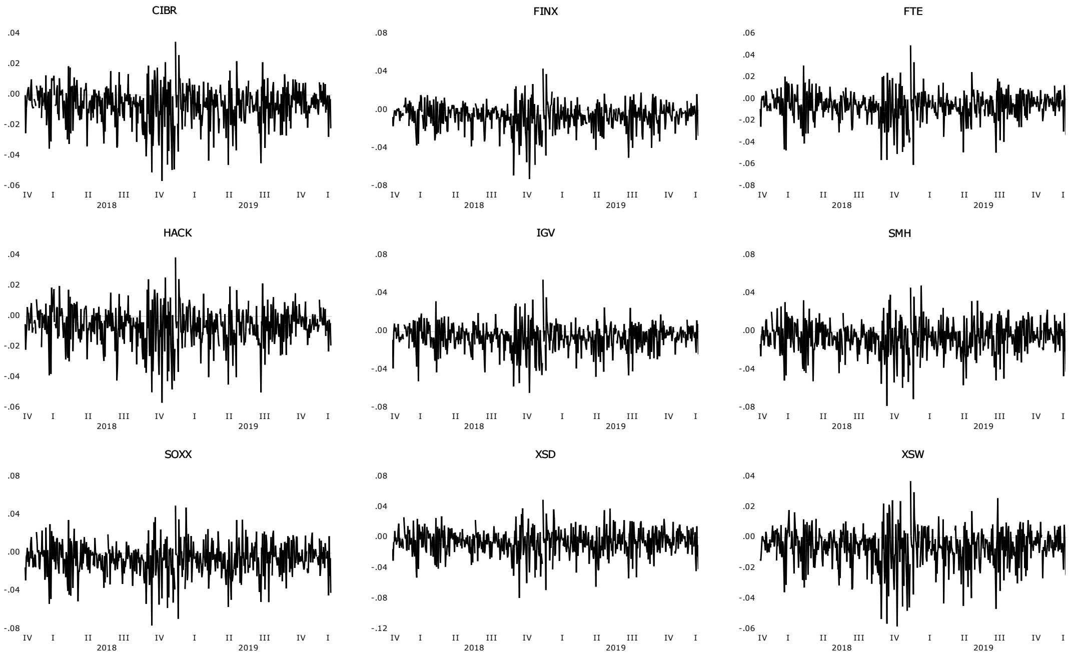

Figure 3.1.: Daily excess returns, high-tech ETFs (12/01/2017-1/31/2020).

The BDS test of Brock, Dechert, and Scheinkman was run to confirm the nonlinearity of the series as described in Brock and Dechert (1988) and Brock, Dechert, Scheinkman and LeBaron (1996). The results (see Table A3.2 in the Appendix) suggest that we can reject the hypothesis of linearity in this sense, while nonlinearity is confirmed.

We also determine whether the analyzed series are stationary by using the Augmented Dickey–Fuller (ADF) test, proposed by Dickey and Fuller (1981), and the Phillips–Perron (PP) test (Phillips & Perron, 1988). A stationary time series is mean-reverting and has a finite variance that guarantees that the process will never drift too far away from the mean. Table A3.3 in the Appendix shows the results of the ADF test and the PP test for the daily logarithmic returns. The hypothesis of a unit root is rejected for all the variables at 90%, 95%, and 99% of confidence, which implies that the excess returns of price levels are stationary.

3.5.2 Constructing the Idiosyncratic Volatility Measure

The idiosyncratic volatility measure was estimated as specified in Section 3.3.4. The results are available in Table A3.4 in the Appendix.

In Figure 3.2, where the resulting idiosyncratic volatility measures are plotted, we can observe similar trends or an association between all nine high-tech ETFs. High volatility occurred with greater spikes during the fourth quarter of 2018. A mean comparison for the idiosyncratic volatility measure was performed between the range of 2018 and 2019. The average mean for the studied high-tech ETFs reported for this measure in 2018 and 2019 is 0.0017 and 0.0014, respectively, implying a decrease of 13%.

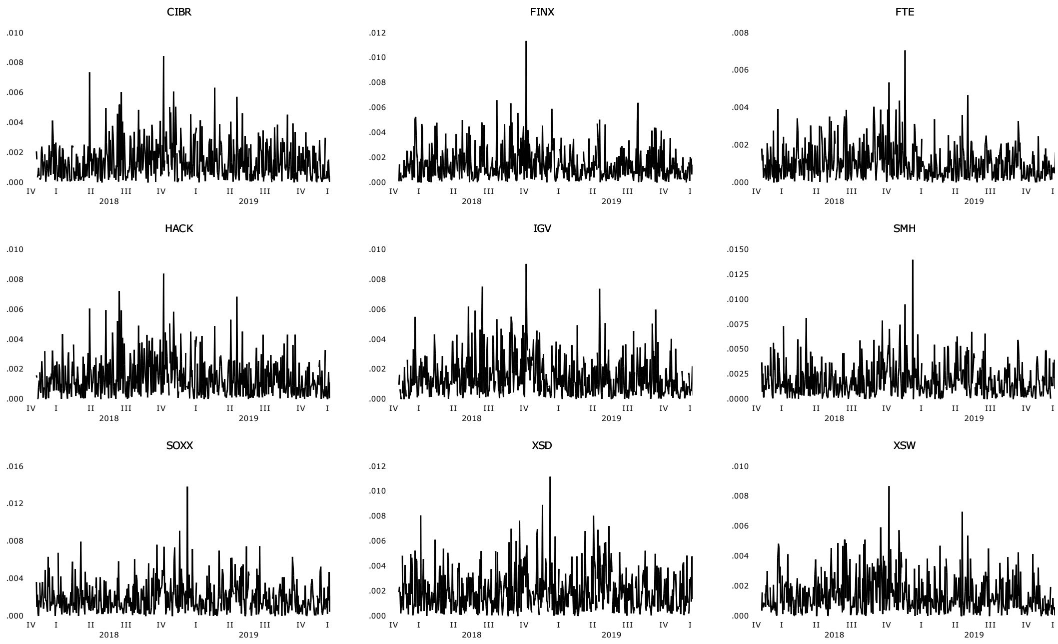

Figure 3.2.: Daily excess returns, high-tech ETFs (12/01/2017-1/31/2020).

Having estimated the one-factor market model structure and confirmed the robustness of the model, we proceed by using the constructed idiosyncratic volatility measure in our MRS model to measure the relationship between the expected excess return and the constructed idiosyncratic volatility of the ETFs.

3.5.3 Heteroscedastic MRS (1,1) for Idiosyncratic Volatility and Return

In this section we present the results of the Heteroscedastic MRS model to analyze the relationship between idiosyncratic and excess return in the context of emerging technologies.

Multiple breakpoint Bai–Perron tests of 1 to M globally determined breaks was executed. For four of the nine ETFs the test indicated the existence of 1 break. The results can be consulted in Appendix Table A3.5. For simplicity, we assume that the nine ETFs present a high and a low volatility regime. The results of the Heteroscedastic MRS model are shown in Table 3.2.

The Wald Test is performed for the model coefficient associated to idiosyncratic risk, to test the null hypothesis, which states that the mean idiosyncratic risk in both regimes combined equals zero. The null hypothesis can be rejected for all associated coefficients for the nine models. The results are shown in Table A3.6 in the Appendix. The Wald Test was also run to test equality between the idiosyncratic risk, Log(Sigma) and the mean coefficient in the high volatility regime versus the low volatility regime. The null hypothesis can be rejected for all nine models for idiosyncratic volatility and Log(Sigma) coefficient, as reported in Tables A3.7 and A3.8 in the Appendix. The equality test for the mean can be rejected for only two models as shown in Table A3.9 in the Appendix.

For comparative purposes, the same idiosyncratic risk and excess return structure was modelled with a GARCH(1,1) in order to check the goodness of fit. The GARCH(1,1) model output is shown in Table A3.10 in the Appendix and the root mean square error (RMSE) measure, log likelihood statistic and Akaike information criterion (AIC) are shown for comparative purposes in Table A3.11 in the Appendix. The results indicate that the Heteroscedastic MRS model is preferable than the GARCH model.

Table 3.2.: Heteroscedastic Markov regime-switching (MRS) for high-tech ETFs excess returns, individual idiosyncratic risk, and excess return in two regimes.

		Intercept	IR	Log (Sigma)	Sigma	Ph,h	Ph,l	Pl,l	Pl,h	Exp. Duration (Q)	Log Likelihood	Akaike	Schwarz	Hanna Quinn
CIBR	*High Vol. Regime*	−0.0048	−4.9323	−4.4399	0.0118	0.5857	0.4142	0.5766	0.4233	2.4139	1644.9480	−6.1771	−6.1126	−6.1519
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
	Low Vol. Regime	−0.0063	3.4830	−4.9991	0.0067					2.3623				
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
FINX	*High Vol. Regime*	−0.0048	−4.5206	−4.2604	0.0141	0.6450	0.3549	0.6651	0.3348	2.8171	1600.0300	−6.0076	−5.9431	−5.9824
		*(0.0005)****	*(0.0000)****	*(0.0000)****										
	Low Vol. Regime	−0.0073	4.4245	−4.9727	0.0069					2.9861				
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
FTE	*High Vol. Regime*	−0.0060	−3.1016	−3.9775	0.0187	0.9343	0.0656	0.9622	0.0377	15.2408	1619.0880	−6.0795	−6.0150	−6.0543
		*(0.0060)****	*(0.0613)**	*(0.0000)****										
	Low Vol. Regime	−0.0046	−0.4947	−4.8792	0.0076					26.4839				
		*(0.0000)****	*(0.6215)*	*(0.0000)****										
HACK	*High Vol. Regime*	−0.0054	−4.9121	−4.5288	0.0107	0.5595	0.4404	0.5951	0.4048	2.2703	1648.0110	−6.1887	−6.1242	−6.1634
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
	Low Vol. Regime	−0.0073	4.1498	−4.8982	0.0074					2.4700				
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
IGV	*High Vol. Regime*	−0.0046	−4.9083	−4.4079	0.0121	0.5168	0.4831	0.4307	0.5692	2.0697	1571.2560	−5.8990	−5.8345	−5.8738
		*(0.0008)****	*(0.0000)****	*(0.0000)****										
	Low Vol. Regime	−0.0066	4.6013	−4.4079	0.0121					1.7566				
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
SMH	*High Vol. Regime*	−0.0030	−4.7351	−4.1279	0.0161	0.7310	0.2689	0.6044	0.3955	3.7179	1470.7400	−5.5197	−5.4552	−5.4945
		*(0.0634)**	*(0.0000)****	*(0.0000)****										
	Low Vol. Regime	−0.0078	4.6414	−4.7704	0.0084					2.5278				
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
SOXX	*High Vol. Regime*	−0.0032	−4.6259	−4.1229	0.0162	0.7176	0.2823	0.5957	0.4042	3.5411	1468.5520	−5.5115	−5.4470	−5.4862
		*(0.0468)***	*(0.0000)****	*(0.0000)****										
	Low Vol. Regime	−0.0078	4.6143	−4.7642	0.0085					2.4738				
		*(0.0000)****	*(0.0000)****	*(0.0000)****										

XSD	*High Vol. Regime*	−0.0043	−4.8695	−4.1484	0.0157	0.6197	0.3802	0.6054	0.3945	2.6295	1467.3570	−5.5070	−5.4425	−5.4817
		*(0.0277)***	*(0.0000)****	*(0.0000)****										
	Low Vol. Regime	−0.0073	4.0436	−4.6202	0.0098					2.5345				
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
XSW	*High Vol. Regime*	−0.0060	−5.3904	−4.5516	0.0105	0.4420	0.5579	0.5873	0.4126	1.7922	1646.9700	−6.1847	−6.1203	−6.1595
		*(0.0000)****	*(0.0000)****	*(0.0000)****										
	Low Vol. Regime	−0.0053	3.0578	−4.8818	0.0075					2.42361				
		*(0.0000)****	*(0.0000)****	*(0.0000)****										

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

A heteroscedastic MRS model was estimated to analyze the relationship between idiosyncratic risk and excess return in the context of emerging technologies.

Idiosyncratic volatility and excess return are not constant in time, for they are regime dependent. MRS involving time series analysis was therefore suitable for this study. The coefficient of interest is related to the independent idiosyncratic risk variable that explains the excess return for each individual high-tech ETF.

For all nine ETFs, a high volatility and a low volatility regime were identified. From the estimated heteroscedastic MRS model we can observe that the coefficients related to the idiosyncratic risk are statistically significant at 99% confidence, indicating that idiosyncratic risk matters for ETF excess returns. The standard deviation for the high volatility regime is 0.0140 and for the low volatility regime is 0.0084.

In the high volatility regime, the estimated coefficients are negative and in the low volatility regime the estimated coefficients are positive for eight of the nine ETFs. For the remaining one, FTE ETF, the associated coefficient is negative in the low volatility regime, but not statistically significant.

These findings indicate that idiosyncratic risk is relevant in explaining returns in the context of high-tech ETFs and that the sign of the relationship is volatility dependent, having a negative relationship in high volatility periods and a positive relationship in low volatility periods.

Higher idiosyncratic risk hence leads to lower excess return during high volatility and to higher excess returns during low volatility and higher excess returns for the studied ETFs during low volatility regimes.

The Markov-chain transition probability shows how ETF prices fluctuate across the regimes. We observed that the probabilities of transiting from one state to another are lower than the probabilities of remaining in the same regime.

The average probabilities of the nine high-tech ETFs staying in the high and low volatility regimes are 64% and 62%, respectively. The probabilities of transit from the high volatility regime to the low volatility regime and vice versa are 36% and 37%, respectively.

The likelihood of each regime remaining in the same regime interval demonstrates the presence of a moderate volatility clustering among the excess returns of ETFs. In other words, a high volatility observation is preceded by a low volatility observation, and vice versa; also, no re-estimation of the two-regime heteroscedastic MRS model with restrictions on the transition matrix was required since none of the transition probabilities have near-zero values.

Regarding the expected duration of regimes, the average for the high volatility regime is four days and for the low volatility regime is five days, which is aligned with the behavior of the high-tech sector subject to short-term noise across stock markets.

Overall, the results indicate that the heteroscedastic MRS models for the nine high-tech ETFs identify and distinguish between several sources of volatility clustering, where regime persistence implies that if the unconditional variance is high in one regime, then the phases of high volatility tend to cluster together due to that regime persistence (Gray, 1996). This shows that volatility clustering is moderately caused by the persistence of the high volatility regime.

Figures 3.3–3.11 show the filtered and smooth probability plots for the nine high-tech ETFs. The heteroscedastic MRS (1,1) models cause switching between regimes for all nine high-tech ETFs, which are consistent with the probabilities of staying and switching. Hence, association between regimes can be crucial to capture volatility clustering. Figures 3.3–3.11 also indicate similar patterns across the nine high-tech ETFs where, as expected, the probability of the ETF price return is slightly higher in a low volatility regime than in a high volatility regime, indicating that ETFs can be used to a certain extent as hedging tools.

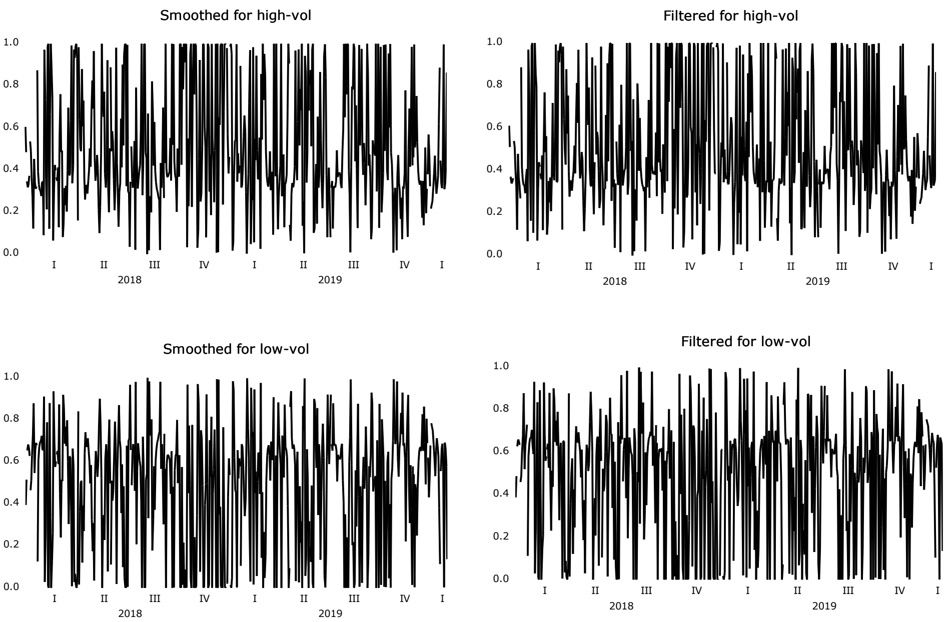

Figure 3.3.: Computed smoothed probabilities and filtered conditional volatilities for CIBR.

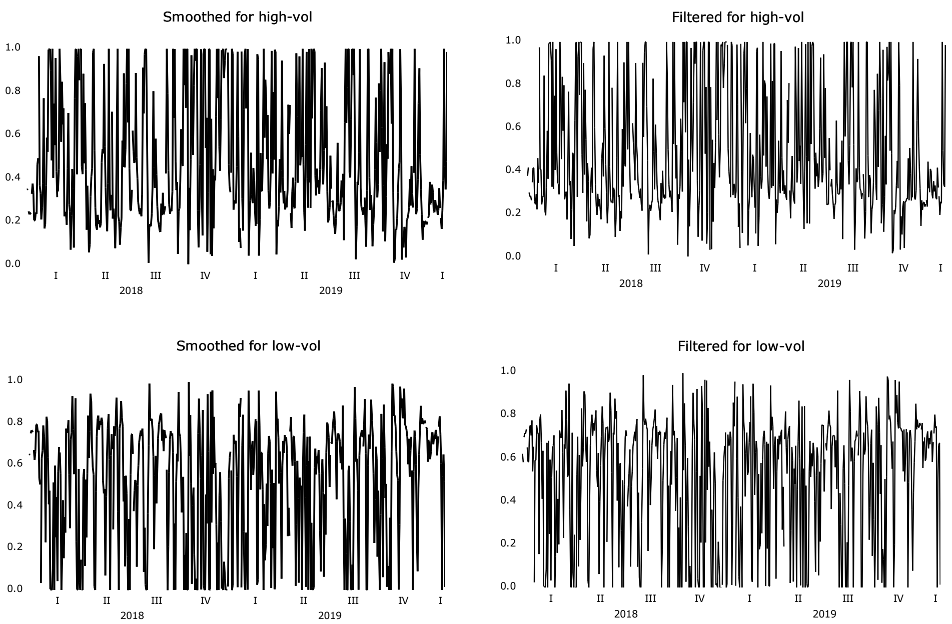

Figure 3.4.: Computed smoothed probabilities and filtered conditional volatilities for FINX.

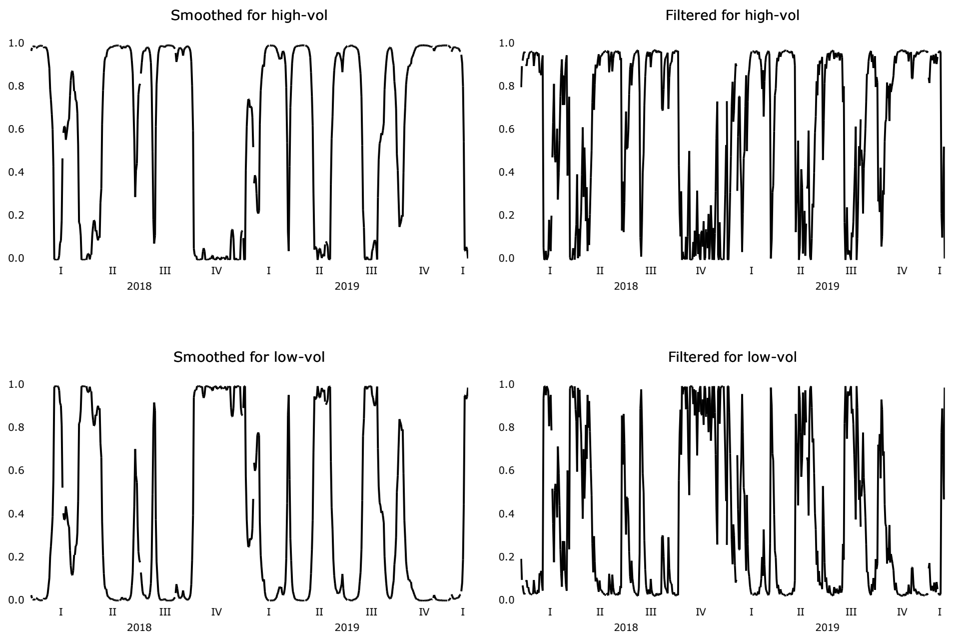

Figure 3.5.: Computed smoothed probabilities and filtered conditional volatilities for FTE.

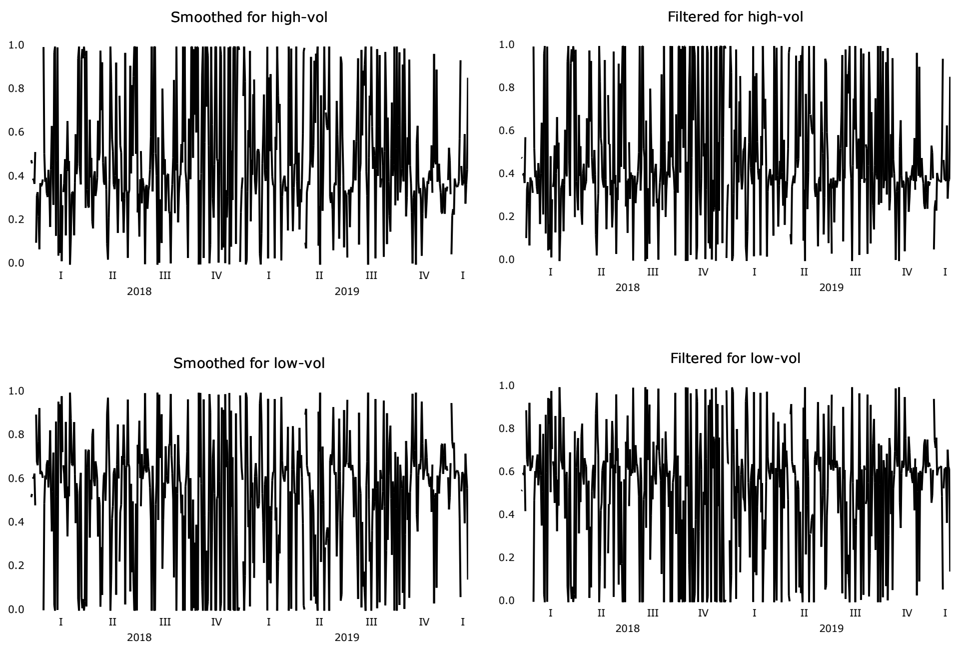

Figure 3.6.: Computed smoothed probabilities and filtered conditional volatilities for HACK.

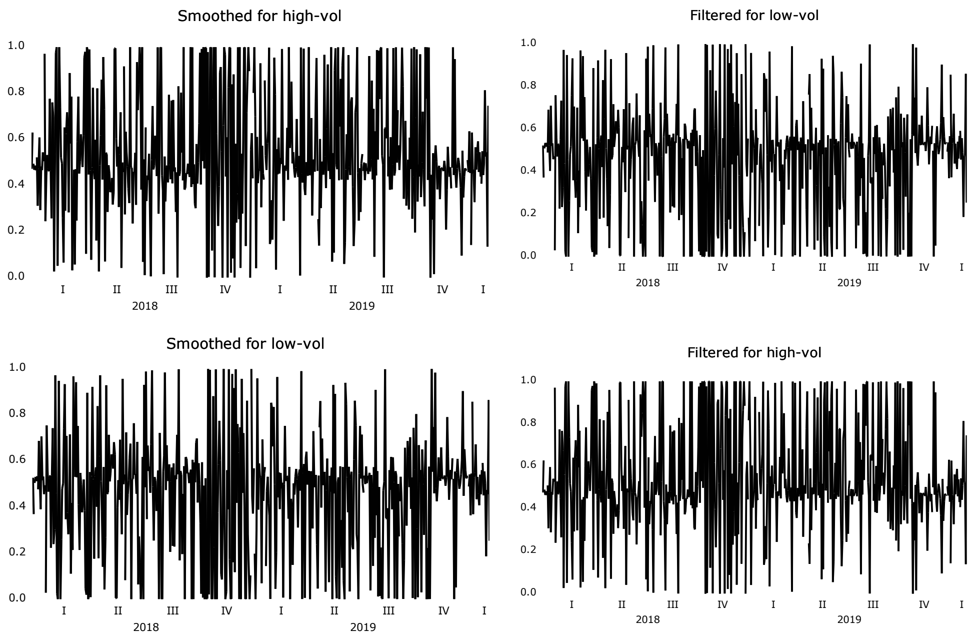

Figure 3.7.: Computed smoothed probabilities and filtered conditional volatilities for IGV.

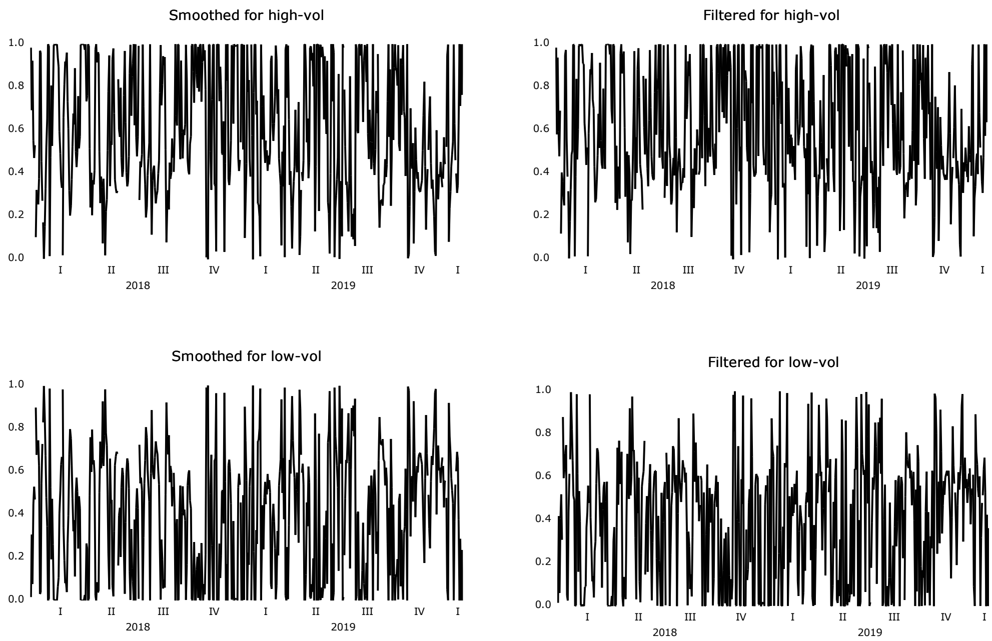

Figure 3.8.: Computed smoothed probabilities and filtered conditional volatilities for SMH.

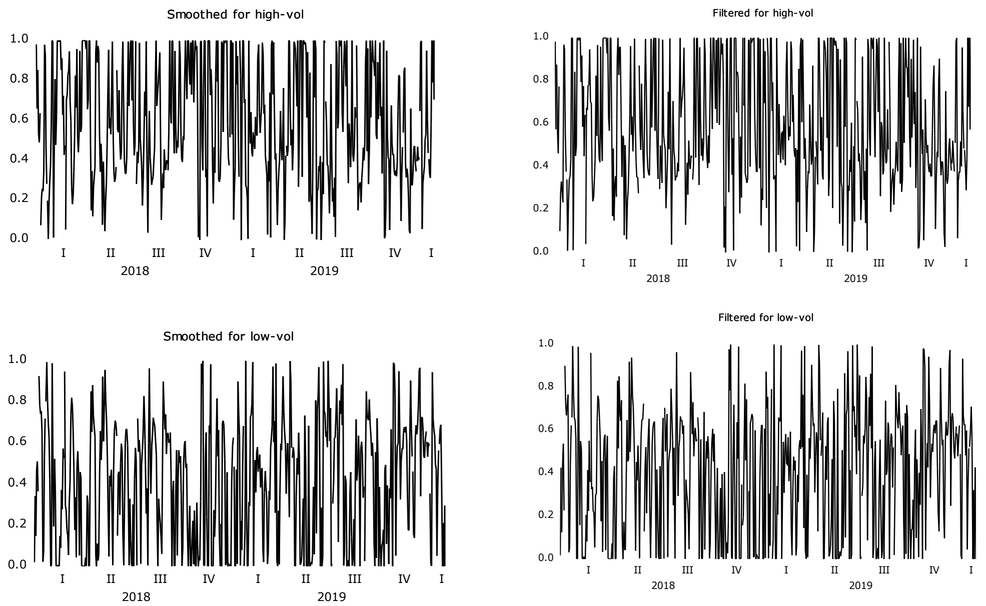

Figure 3.9.: Computed smoothed probabilities and filtered conditional volatilities for SOXX.

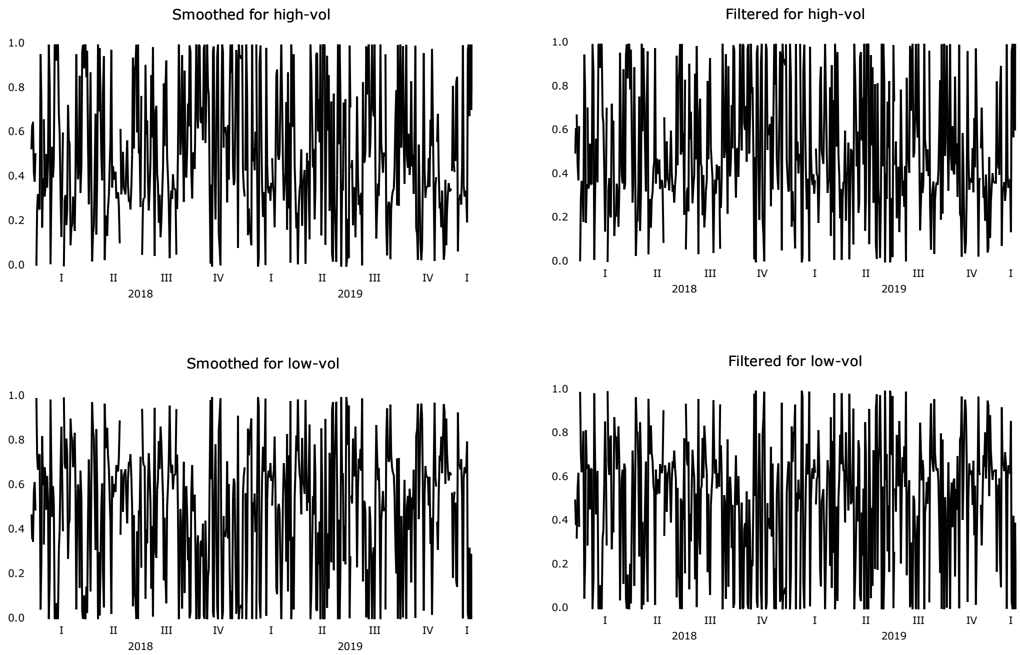

Figure 3.10.: Computed smoothed probabilities and filtered conditional volatilities for XSD.

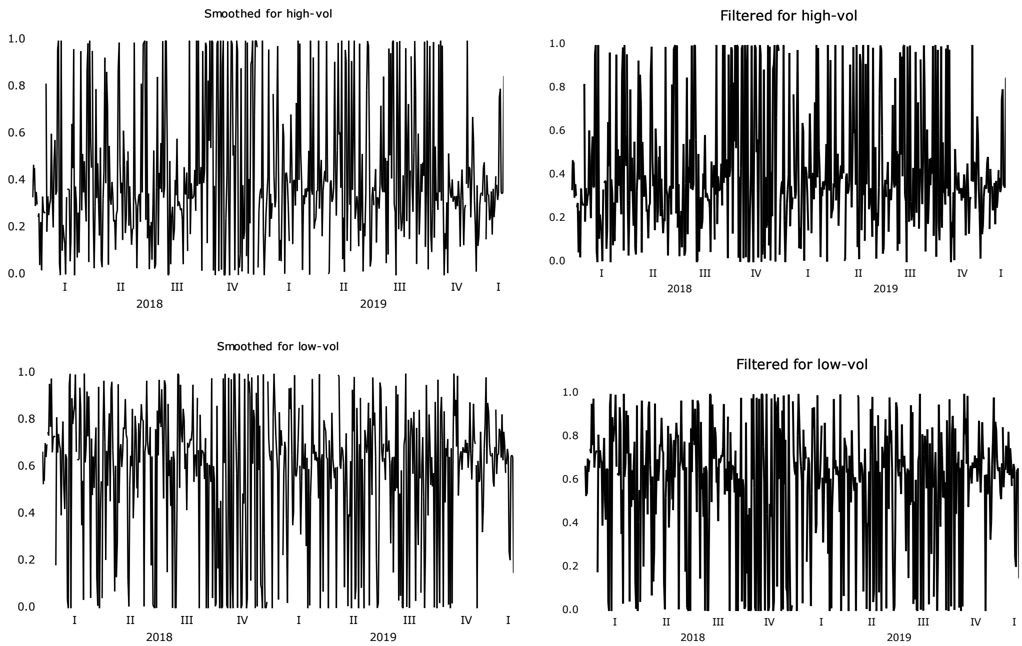

Figure 3.11.: Computed smoothed probabilities and filtered conditional volatilities for XSW.

In These results provide empirical support for the idea that under-diversified investors are not compensated for not holding diversified portfolios in high volatility regimes, as opposed to low volatility regimes, where compensation for not holding a diversified portfolio does occur. The benefits of diversification vary across the studied period, which also implies that the number of stocks required for a specific diversification level also varies.

These facts suggest that investors do not rationally diversify the risk under certain market conditions in the context of the emerging technology sector. One area requiring further examination is the role of information arriving in the market. Excess volatility peaks precisely during periods associated to uncertainty (Barron et al., 2002), such as radical technological changes, and therefore the resulting fundamental information is less useful for making predictions about future values (Barron et al., 2002). Moreover, high-tech firms suffer from the asymmetric information problem (Gharbi et al., 2014; Gu & Li, 2007; Gu & Wang, 2005), which may also explain why investors do not seem to necessarily diversify their portfolios rationally under certain market conditions.

3.6 Conclusions

We investigate the relationship between idiosyncratic risk and return among nine high-tech ETFs using daily return data for the 12/01/2017–1/31/2020 period using idiosyncratic volatility as a proxy for idiosyncratic risk. According to the fundamental theory, idiosyncratic risks can be eliminated through diversification and hence should not be priced, though the empirical evidence is mixed.

To further investigate these relationships, time series analysis and a heteroscedastic MRS model were used because the results obtained are not constant over time. Two regimes were identified, namely those of high and low volatility.

By studying the relationship between excess return and idiosyncratic volatility we found that a negative relationship between idiosyncratic risk and return prevails during the high volatility regime, while in low volatility regimes a positive relationship is identified for eight of the nine high-tech ETFs.

The results are partially aligned with the predominant theory that idiosyncratic risk is priced positively and suggest that firm-specific risk matters for ETF pricing and indeed for the underlying index pricing of the high-tech sector. High-tech investment therefore seems to entail a higher or lower idiosyncratic risk and a negative or positive effect on the high-tech ETF returns during different regimes.

This indicates that investors do require a greater risk premium for being more exposed to idiosyncratic risk during low volatility in the high-tech sector. However, during high volatility periods, compensation for such exposure does not occur.

There are relevant implications for investors. In the high-tech sector, the return and idiosyncratic risk can play an important role in risk diversification and allocation, thus leading to changes across volatility regimes. However, idiosyncratic risk might not necessarily reflect a risk premium and lead to inconclusive price inference. The adjustment of returns by idiosyncratic risk should be considered when evaluating performance with benchmarks. If portfolio managers ignore idiosyncratic risk, this may lead to under-diversification of those portfolios, and given the recent evidence that idiosyncratic risk and the number of stocks needed to achieve a specific level of diversification have increased, those implications require even greater attention.

The results also indicate that the idiosyncratic component impacts market returns and drives the predictability of the expected returns of high-tech companies. Adding ETFs from the high-tech sector to a portfolio does not necessarily lead to risk reduction, since the patterns between idiosyncratic volatility and return are similar, and regime dependent.

This article makes the following new contributions to the idiosyncratic volatility literature: First, it documents a significant relationship between idiosyncratic risk and return in the high-tech sector, contrary to the fundamental theory of investment that generally states that idiosyncratic risk should not be priced since it can be eliminated through diversification. Second, it provides evidence that idiosyncratic risk is priced negatively or positively depending on volatility regimes in the IT context. Third, the results highlight how investors do not diversify the risk rationally under certain market circumstances.

This article also provides insights into the role of pricing of managed funds, especially for funds exposed to equity investment, and has important implications for investors and international institutions that include high-tech investment portfolios in their decision-making. This paper is merely the first step towards determining the scope of excess return and idiosyncratic volatility for purposes of asset pricing in the high-tech sector, and its conclusions are therefore tentative.

Future work will cover the analyzed sectors in a broader manner, including a comparative view of ETFs versus underlying assets, and will improve the database by extending the sample over time. Areas for further research include the actual portfolio implications of changes in idiosyncratic risk and return.

Appendix

Table A3.1.: ETF Specifications.

	ETF	Underlying Index	Description of the Index
1	First Trust NASDAQ Cybersecurity ETF (CIBR)	Nasdaq CTA Cybersecurity IndexSM	The equity index includes securities of companies classified by the CTA as “cyber security” companies.
2	Global X FinTech Thematic ETF (FINX)	Indxx Global FinTech Thematic Index	The equity index seeks to invest in companies on the cutting edge of the emerging financial technology sector, which encompasses a range of innovations helping to transform established industries like insurance, investment, fundraising, and third-party lending through unique mobile and digital solutions.
3	Fidelity MSCI Information Technology Index ETF (FTE)	MSCI USA IMI Information Technology Index	The equity index includes securities classified in the Information Technology sector as per the Global Industry Classification Standard (GICS®).
4	ETFMG Prime Cyber Security ETF (HACK)	ISE Cyber SecurityTM Index.	The equity index is designed to track companies that are actively involved in providing cyber security technology and services.
5	iShares Expanded Tech-Software Sector ETF (IGV)	S&P North American Expanded Technology Software Index	The equity index includes securities in the GICS® application software, systems software, and home entertainment software sub-industries as well as applicable supplementary stocks.
6	VanEck Vectors Semiconductor ETF (SMH)	Market Vectors US Listed Semiconductor 25 Index	The equity index is intended to track the overall performance of companies involved in semiconductor production and equipment.
7	iShares PHLX Semiconductor ETF (SOXX)	PHLX Semiconductor (^SOX)	The equity index is designed to track companies that produce semiconductors, a crucial part of modern computing.
8	SPDR S&P Semiconductor ETF (XSD)	S&P® Semiconductor Select IndustryTM Index.	The equity index includes companies that produce semiconductors, a crucial part of modern computing.
9	SPDR S&P Software & Services ETF (XSW)	S&P Software & Services Select Industry Index	The equity index seeks to provide exposure to the software and services segment of the S&P TMI, which comprises the following sub-industries: Application Software, Data Processing & Outsourced Services, Interactive Home Entertainment, IT Consulting & Other Services, and Systems Software.

Table A3.2.: BDS Test for Nonlinearity for ETF excess return.

BDS Statistic (*p*-Value)					
Dimension	**2**	**3**	**4**	**5**	6
CIBR	0.0147	0.0315	0.0468	0.0566	0.0596
	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
FINX	0.0174	0.0431	0.0607	0.0695	0.0734
	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
FTE	0.0246	0.0528	0.0734	0.0849	0.0908
	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
HACK	0.0145	0.0321	0.0480	0.0570	0.0602
	*(0.0001)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
IGV	0.0131	0.0328	0.0493	0.0591	0.0641
	*(0.0007)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
SMH	0.0105	0.0244	0.0318	0.0359	0.0360
	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
SOXX	0.0091	0.0227	0.0296	0.0340	0.0343
	*(0.0099)****	*(0.0001)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
XSD	0.0089	0.0228	0.0299	0.0339	0.0342
	*(0.0087)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
XSW	0.0128	0.0301	0.0450	0.0540	0.0589
	*(0.0008)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.3.: Unit Root Test for ETF excess return.

	Augmented Dickey-Fuller	**Phillips-Perron test statistic**
CIBR	−4.3073	−22.3895
	*(0.0000)****	*(0.0000)****
FINX	−6.4614	−21.3114
	*(0.0000)****	*(0.0000)****
FTE	−4.1479	−23.7799
	*(0.0000)****	*(0.0000)****
HACK	−4.3231	−21.8960
	*(0.0000)****	*(0.0000)****
IGV	−4.6865	−23.1261
	*(0.0000)****	*(0.0000)****
SMH	−7.8672	−23.9443
	*(0.0000)****	*(0.0000)****
SOXX	−7.9550	−23.7026
	*(0.0000)****	*(0.0000)****
XSD	−7.9897	−23.3733
	*(0.0000)****	*(0.0000)****
XSW	−4.3068	−22.2330
	*(0.0000)****	*(0.0000)****

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.4.: Generalized autoregressive conditional heteroskedastic (GARCH) (1,1) one-factor model for constructing the idiosyncratic volatility measure.

Coefficient *(p-Value)*	***Mean Equation***	**Intercept**	**Market**	**R**	***Variance Equation***	**Intercept**	**ARCH(1)**	**GARCH(1)**	**Log Likelihood**	**Akaike**	**Schwarz**	**Hanna Quinn**	**ARCH−LM**
CIBR		0.0010	1.0900	0.6121		0.00000	0.0237	0.9551	1881.5160	−6.8989	−6.8594	−6.8835	0.3220
		*(0.0130)***	*(0.0000)****			*(0.5641)*	*(0.0212)***	*(0.0000)****					*(0.5704)*
FINX		0.0021	1.2188	0.6513		0.00000	0.0687	0.8867	1866.3450	−6.8431	−6.8036	−6.8277	0.0115
		*(0.0001)****	*(0.0000)****			*(0.5035)*	*(0.3356)*	*(0.0000)****					*(0.9144)*
FTE		0.0031	1.3379	0.8056		0.00000	0.0488	0.9245	2043.6840	−7.4951	−7.4556	−7.4797	0.9316
		*(0.0000)****	*(0.0000)****			*(0.0000)****	*(0.00000)****	*(0.0000)****					*(0.3344)*
HACK		0.0008	1.0737	0.5977		0.00000	0.0228	0.9712	1876.5110	−6.8805	−6.8410	−6.8651	0.6791
		*(0.0460)***	*(0.0000)****			*(0.5111)*	*(0.0062)****	*(0.0000)****					*(0.4099)*
IGV		0.0028	1.2944	0.6531		0.00001	0.0696	0.8303	1848.6300	−6.7780	−6.7385	−6.7626	0.0726
		*(0.0000)****	*(0.0000)****			*(0.0676)**	*(0.0153)***	*(0.0000)****					*(0.7876)*
SMH		0.0045	1.5566	0.6258		0.00000	0.0304	0.9414	1722.3690	−6.3138	−6.2743	−6.2984	0.0272
		*(0.0000)****	*(0.0000)****			*(0.1990)*	*(0.0433)***	*(0.0000)****					*(0.8688)*
SOXX		0.0045	1.5522	0.6201		0.00000	0.0261	0.9424	1714.8760	−6.2863	−6.2468	−6.2708	0.0230
		*(0.0000)****	*(0.0000)****			*(0.3867)*	*(0.0664)**	*(0.0000)****					*(0.8793)*
XSD		0.0043	1.5297	0.6112		0.00000	0.0288	0.9371	1710.9350	−6.2718	−6.2323	−6.2563	0.1081
		*(0.0000)****	*(0.0000)****			*(0.1781)*	*(0.0101)***	*(0.0000)****					*(0.7423)*
XSW		0.0012	1.1030	0.6212		0.00000	0.0544	0.9254	1895.1790	−6.9491	−6.9096	−6.9337	0.2347
		*(0.0000)****	*(0.0000)****			*(0.0000)****	*(0.0000)****	*(0.0000)****					*(0.6280)*

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.5.: Multiple breakpoint Bai–Perron tests for ETF excess return. (2A5)

	Breaks	F-Statistic	Scaled F-Statistic	Weighted F-Statistic	Critical Value
CIBR	1 *	7.1116	7.1116	7.1116	7.0400
FINX	1	5.7116	5.7116	5.7116	7.0400
FTE	1 *	10.1444	10.1444	10.1444	7.0400
HACK	1 *	8.1440	8.1440	8.1440	7.0400
IGV	1 *	7.8399	7.8399	7.8399	7.0400
SMH	1	4.2834	4.2834	4.2834	7.0400
SOXX	1	3.6054	3.6054	3.6054	7.0400
XSD	1	3.5319	3.5319	3.5319	7.0400
XSW	1	6.3070	6.3070	6.3070	7.0400

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.6.: WALD Test for idiosyncratic risk coefficient combined.

	CIBR	FINX	FTE	HACK	IGV	SMH	SOXX	XSD	XSW
F-statistic	75.8130	27.5418	3.5432	95.0712	66.6255	98.0683	101.3735	71.8535	73.1399
	*(0.0000)****	*(0.0000)****	*(0.0296)***	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
Chi-square	151.6261	55.083	7.0865	190.1424	133.2511	196.1366	202.7471	143.7070	146.2799
	*(0.0000)****	*(0.0000)****	*(0.0289)***	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.7.: WALD Test for the idiosyncratic risk coefficient.

	CIBR	FINX	FTE	HACK	IGV	SMH	SOXX	XSD	XSW
F-statistic	151.6142	49.1907	1.4761	184.4640	122.8236	161.3711	158.6597	38.9602	127.7079
	*(0.0000)****	*(0.0000)****	*(0.2249)*	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****
Chi-square	151.6142	49.1907	1.4761	184.4640	122.8236	161.3711	158.6597	38.9602	127.7079
	*(0.0000)****	*(0.0000)****	*(0.2244)*	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****	*(0.0000)****

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.8.: WALD Test for the LOG(SIGM) coefficient.

	CIBR	FINX	FTE	HACK	IGV	SMH	SOXX	XSD	XSW
F-statistic	9.88669	20.37216	131.90750	6.79993	7.08012	33.33429	31.86846	16.18007	4.07243
	*(0.0018)****	*(0.0000)****	*(0.0000)****	*(0.0094)****	*(0.0080)****	*(0.0000)****	*(0.0000)****	*(0.0001)****	*(0.0441)*
Chi- square	9.88669	20.37216	131.90750	6.79993	7.08012	33.33429	31.86846	16.18007	4.07243
	*(0.0007)****	*(0.0000)****	*(0.0000)****	*(0.0091)****	*(0.0078)****	*(0.0000)****	*(0.0000)****	*(0.0001)****	*(0.0436)***

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.9.: WALD Test for the mean.

	CIBR	FINX	FTE	HACK	IGV	SMH	SOXX	XSD	XSW
F-statistic	81.16899	1.66628	0.33594	1.72741	0.84624	3.79511	3.54408	1.07838	0.27057
	(0.3381)	*0.1973)*	*(0.5624)*	*(0.1893)*	*(0.3580)*	*(0.0519)**	*(0.0603)**	*(0.2995)*	*(0.6032)*
Chi-square	81.16899	1.66628	0.33594	1.72741	0.84624	3.79511	3.54408	1.07838	0.27057
	(0.3376)	*(0.1968)*	*(0.5622)*	*(0.1887)*	*(0.3576)*	*(0.0514)**	*(0.0598)**	*(0.2991)*	*(0.6029)*

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.10.: GARCH (1,1) model of ETF idiosyncratic risk and excess return.

Coefficient *(p-Value)*	***Mean Equation***	**Intercept**	**IR**	**R**	***Variance Equation***	**Intercept**	**ARCH(1)**	**GARCH(1)**	**Log Likelihood**	**Akaike**	**Schwarz**	**Hanna Quinn**	**ARCH−LM**
CIBR		−0.0036	−1.9901	0.0399		0.0000	0.1189	0.8331	1625.1420	−6.1137	−6.0734	−6.0979	0.4540
		*(0.0000)****	*(0.0001)****			*(0.0062)****	*(0.0001)****	*(0.0000)****					*(0.5004)*
FINX		−0.0028	−2.3639	0.0490		0.0000	0.1369	0.8235	1588.3300	−5.9748	−5.9345	−5.9590	0.7841
		*(0.0001)****	*(0.0000)****			*(0.0028)****	*(0.0001)****	*(0.0000)****					*(0.3759)*
FTE		−0.0042	−1.6216	0.0201		0.0000	0.1971	0.7624	1608.6160	−6.0513	−6.0110	−6.0356	0.0004
		*(0.0000)****	*(0.0002)****			*(0.0002)****	*(0.0000)****	*(0.0000)****					*(0.9832)*
HACK		−0.0041	−1.5515	0.0259		0.0000	0.1236	0.8243	1619.3950	−6.0920	−6.0517	−6.0762	0.7684
		*(0.0000)****	*(0.0026)****			*(0.0110)***	*(0.0003)****	*(0.0000)****					*(0.3807)*
IGV		−0.0032	−1.9129	0.0259		0.0000	0.1670	0.7846	1565.0040	−5.8868	−5.8465	−5.8710	1.0602
		*(0.0002)****	*(0.0000)****			*(0.0041)****	*(0.0000)****	*(0.0000)****					*(0.3031)*
SMH		−0.0056	−0.4415	0.0034		0.0000	0.0990	0.8473	1428.9160	−5.3732	−5.3329	−5.3574	0.2148
		*(0.0000)****	*(0.4891)*			*(0.0098)****	*(0.0002)****	*(0.0000)****					*(0.6430)*
SOXX		−0.0060	−0.1841	0.0002		0.0000	0.1038	0.8440	1426.9620	−5.3658	−5.3255	−5.3501	0.1491
		*(0.0000)****	*(0.7626)*			*(0.0101)***	*(0.0002)****	*(0.0000)****					*(0.6994)*
XSD		−0.0058	−0.2016	−0.0002		0.0000	0.1034	0.8456	1428.6320	−5.3722	−5.3318	−5.3564	0.1942
		*(0.0000)****	*(0.7247)*			*(0.0179)***	*(0.0002)****	*(0.0000)****					*(0.6594)*
XSW		−0.0030	−2.2535	0.0410		0.0000	0.1443	0.8140	1626.6820	−6.1195	−6.0792	−6.1037	0.4298

		*(0.0000)****	*(0.0000)****			*(0.0019)****	*(0.0001)****	*(0.0000)****					*(0.5121)*

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

Table A3.11.: Comparing GARCH vs. Heteroscedastic MRS, root mean square error (RMSE), Log Likelihood, AIC for Idiosyncratic Risk vs. Return.

	RMSE		**Log Likelihood**		**AIC**	
	GARCH	MRS	GARCH	MRS	GARCH	MRS
CIBR	0.0121	0.0122	1625.1420	1644.9480	−6.1137	−6.1771
FINX	0.0133	0.0137	1588.3300	1600.0300	−5.9748	−6.0076
FTE	0.0130	0.0130	1608.6160	1619.0880	−6.0513	−6.0795
HACK	0.0122	0.0123	1619.3950	1648.0110	−6.0920	−6.1887
IGV	0.0138	0.0139	1565.0040	1571.2560	−5.8868	−5.8990
SMH	0.0169	0.0169	1428.9160	1470.7400	−5.3732	−5.5197
SOXX	0.0170	0.0170	1426.9620	1468.5520	−5.3658	−5.5115
XSD	0.0169	0.0169	1428.6320	1467.3570	−5.3722	−5.5070
XSW	0.0122	0.0124	1626.6820	1646.9700	−6.1195	−6.1847

Source: EViews 11 University Version. Note 1: * significant at level of 10%, ** significant at level of 5%, *** significant at level of 1%.

4 Impact of emerging technologies in banking and finance in Europe: A volatility spillover and contagion approach

Abstract. The empirical evidence suggests that stock returns in the emerging technology environment exhibit high stock return volatility. The fundamental aim of the article is to investigate the dynamic, time series properties of the correlations between daily log returns and magnitude of the volatility transmissions from the emerging technologies environment to the Spanish banking sector, the Spanish market portfolio, and the finance industry in the EU area. Using daily log returns for the performance variables and an equally weighted index was constructed as proxy to represent the emerging technology phenomena covering a period from the 7th of July of 2015 to the 20th of September of 2019. The study applies generalized autoregressive conditional heteroskedasticity GARCH followed by the diagonal BEKK approach. One key finding is that the emerging technology environment is important in capturing volatility of Spanish banking sector, the Spanish market portfolio, and the finance industry in the EU area through significant volatility clustering, volatility spillover and volatility persistence. Results exhibit very large GARCH and relatively low ARCH effects indicating a long persistence of resulting shocks over volatility. Broadly, the Spanish banking sector seems to be the most exposed to volatility spillover. Nevertheless, it is the finance industry across the EU which is more affected by the volatility persistence from emerging technology shocks in terms of volatility and cross – volatility point of view. Additionally, high volatility periods provide insights about an increased integration and volatility spillover. From an investor perspective, one important implication is that adding stocks from different emerging technologies to a portfolio does not necessarily lead to risk reduction.

Keywords: Emerging Technologies; Volatility Spillovers; Volatility Persistence; GARCH; Multivariate GARCH.

4.1 Introduction

Since the crisis in 2008, the financial industry has been exponentially reaching for innovation to increase stability, improve quality of services and to rebuild trust, suggesting that the demand of innovation is driven by the financial stability. Besides, works from a different perspective have assumed that the New Economy, or the ‘information age’, has affected the stability of the market valuation process, and in so, doing increased volatility across stock markets (Campbell et al., 2001; Kearney & Potì, 2008). This article (Campbell et al., 2001) indicates that the increases generalized volatility might be due to new technologies, especially those related to the ‘IT ’revolution.

In this context, “emerging technologies” can be absorbed under the framework of the possibility to lead a dramatic change and impact on socio-economic systems (Rotolo et al., 2015) and this context is extensively connected to innovation management (Cozzens et al., 2010).

Additionally, since stock prices are expected to reflect expectations about future profits (Pástor & Veronesi, 2005; Mazzucato, 2006), it makes sense that expectations about the outcome of a technological innovation also will be reflected by the stock prices and its return volatility.

Previous empirical work has focused on studying the relationship of technological innovation and stock prices over the industry life cycle and the linkage between market value, profits, and patents as proxy for innovation. Despite the recognized importance of emerging technologies phenomena in descriptive literature, there have been surprisingly few empirical studies. This investigation provides several contemporaneous extensions.

The goal of this work is to empirically analyze the dynamic, time series properties of the correlations between daily log returns and magnitude of the volatility transmissions due to emerging technology to the to the Spanish banking sector, the Spanish market portfolio, and the finance industry in the EU area as the performance variables.

First, we investigate the link between changes in emerging technologies and market proxies at mean and volatility terms. The Generalized autoregressive conditional heteroskedasticity GARCH methodology is used followed by a diagonal BEKK approach.

Second, we investigate the link between the emerging technologies for to the Spanish banking sector, the Spanish market portfolio, and the finance industry in the EU area.

Finally, we expect that volatility of the performance variable should be affected by emerging technology phenomena as an uncertain investment. By reason, since volatility is commonly perceived as a proxy for uncertainty (Pástor & Veronesi, 2005) and innovation is a perfect example of true Knightian uncertainty (Knight, 1921), we interpret the relationship between the emerging technologies under the innovation context and volatility (Mazzucato & Tancioni, 2012).

Furthermore, we suggest that our results are useful for researchers studying the emerging technology phenomena and implications for market evolution and participants and what does suggest for the current regularity framework.

From the investor's perspective, insights from the risk -return trade-off will be provided through the emerging technology -return trade-off since innovation is used as a sound proxy for risk.

Besides, the exploring feature of this work is aligned with the suggestions raised by some experts (Wiener, 2004; Guo & Liang, 2016; Zetzsche, Buckley, Barberis, & Arner, 2017), stating that more experiments are needed to understand the phenomena of the emerging technologies (ECB, 2019; Schwab, 2017; Coeckelbergh, 2016) and possible novel viable approaches for financial regulation.

The remainder of the article is structured as follows. Section 2 reviews the literature on the theoretical as well as the empirical association between technology and emerging technology and finance industry. Section 3 describes the data set. Section 4 presents the empirical results and section 5 develops the conclusion and provides certain directions for future research.

4.2 Literature Review

A new wave of innovation and changes can be observed. Over the last two decades, the financial industry and particularly the banking sector, have been significantly affected by rapid and intense progress in information and communication technology (ICT) (Ratten, 2008; Rishi & Saxena, 2004; Campanella, Della Peruta, & Del Giudice, 2017) or in other words, highly exposed to technological innovation.

Technological change is viewed as endogenous and persistence by endogenous growth models in Romer (1990) and Lucas (1988). However, in most orthodox macroeconomic models, technological change is introduced as an exogenous stochastic shock (Castellacci, 2008). In order to provide a notion, as quoted by Freeman and colleagues (1995) growth on technical innovation resembles better to a series of explosions rather than a gentle and incessant transformation.

Recent literature is focusing on the impact of the technological change and innovation on stock return volatility in order to better understand the IT Revolution or New Economy phenomena.

The rational expectation hypothesis states that the current price of a stock is equal to the rational expectations as identically to optimal forecast (the best guess of the future) using all available information (Mishkin, 2016). Since stock prices are expected to reflect expectations about (discounted) future profits, it makes sense that expectations about the outcome of a technological innovation to also be reflected by the stock prices (Pástor & Veronesi, 2005; Mazzucato, 2006).

Widely used under a similar approach by the literature to investigate the role of technological change and stock prices and returns, is the efficient market hypothesis, which assumes that the price traded in the market reflects all available information stated by Fama (1965) and Malakian and Fama (1970) and hence, the real firm's innovation potential. The efficient market hypothesis is associated extensively with the idea of a "random walk." Financial markets use often random walk to model fat tail distributions like those in the high frequency data. In the present context, heavy tails are increasingly related to innovation dynamics and evidence to lumpy growth (Dosi, 2005) suggesting the absence of a solely rational expectation. Additionally, heavy tails indicated the occurrence of extreme events due to greater market opportunities for innovation dynamic (Axtell, 2001).

Persistence (i.e. correlation) over time from innovation dynamics is also recognized by the literature as a distinct feature (Malerba et at., 1997; Alfranca, et al., 2002; Cefis, 2003). Technologies mature with time (Christensen, 1992) and firms, which have invested in innovation in the past, are more likely to innovate in the future due to the perceived positive feedback (Cohen & Levinthal, 1989). This endogenous and procyclical movement of adoption is consistent with the cyclical patterns of diffusion. Since diffusion of new technologies takes time, the cyclical response to news shock is highly persistent (Comin, 2009). Numerical experiment and time series approaches provide the tools to study implications for the entrance of new technologies to the stock markets (Iraola & Santos, 2007; Pástor & Veronesi, 2009).

Uncertainty and risk have been widely adopted. In any case, in the frame of this paper the interplay between them is strictly conceptually so that the frame of mind can be further nuanced.

Commonly, uncertainty is defined as the situation with unknown information about the environment (Merigó, Gil Lafuente, & Gil Lafuente, 2016) and risk derives from uncertainty by the intention to quantify. In other words, in this sense conceptually risk can be considered as a proxy for uncertainty. Innovation is an uncertain process where the outcomes are uncertain as well. This premise is not new and was already recognized by Knight (1921) and Keynes (1973), as stated in Mazzucato's study (2006). Both economists used the concept of technological innovation as an example of true uncertainty. Based on this assumption, empirical works show that technology changes and period of technological changes lead to increased uncertainty and therefore to increased stock return volatility (Shiller, 2000; Campbell et al., 2001; Mazzucato, 2006). Technological innovations play a major role in explaining the long-term volatility observed in stock markets (Iraola & Santos, 2007). Excess volatility peaks precisely during periods associated to uncertainty (Shiller, 2000), such as radical technological changes and therefore the fundamental information is less useful for making prediction about future values (Tushman & O'Reilly III, 1996). This entails to less information available and leads the market trend to be driven by other speculative investors heading them to "follow the crowd" instead of using their own fundamental data. This phenomenon is also known as "herd effect" and over-reaction (Campbell & Shiller, 1988).

In addition, the asymmetric information problem is studied within the innovation process context. All type of projects and certainly the ones related to new technology can generate a greater degree of asymmetric information, since managers have more knowledge about the state of the outcome compared to the outside (Blazenko, 1987), as a result, stock return volatility increases. Especially high-tech firms suffer under the asymmetric information problem (Gharbi et al., 2014; Gu & Li, 2007; Gu & Wang, 2005; Barron et al., 2002). To offset the lack of information, high- tech firms organize conference calls and provide additional information about financial conditions to the public (Tasker, 1998).

Another body of literature is the firm's approach level on high tech firms or frontier technologies firms in this frame of reference, which exhibit unjustifiably high stock return and volatility (Pástor & Veronesi, 2006; Gharbi et al., 2014; Schwert, 2002). Evidence exists that return volatility is 2.21 percent higher for R&D intense firms compared to no R&D investing firms (Chan et al., 2001) and that the beta is twice higher for companies with intensive R&D investment (Lantz & Sahut, 2005). This makes sense in order to compensate the additional risk due to intensive R&D exposure leading to a significant premium (Wedig, 1990).

To briefly recapitulate the goal of this article, we intend to empirically analyze the dynamic, time series properties of the correlations between daily log returns and the magnitude of the volatility transmissions from the emerging technologies to the representative indexes for the Spanish banking sector, the overall Spanish market, and the finance industry in the EU area level.

As highlighted by Demirel and Mazzucato (2013), new research must focus on understating time series behaviors of innovation performance as well as considering the heterogeneous nature of technological innovation and performance variables.

To summarize, it is reasonable to explore the impact of emerging technologies on the Spanish banking sector, the Spanish market portfolio and the finance industry in the EU area volatility using a time series approach, given the volatility interpretation for innovation and dynamic processes under uncertainty and evaluating this relationship from the defined perspectives.

4.3 Data and Methodology

Since profits and growth rates are mainly used as reference for economic performance, then industry specific and a general market performance can be extrapolated through stock prices and financial market proxies in levels and returns.

4.3.1 Data

4.3.1.1 Dependent performance variables

This study utilizes a constructed BANK index (BANK) as proxy for the Spanish banking sector, the IBEX35 (IBEX) index as proxy for the overall Spanish market performance and the MSCI Europe

Finance index (MSCI_EUR_FIN) as proxies for the financial industry in the Europe Area.

BANK is a reconstructed index that was calculated as proxy for the banking sector in Spain selecting the most representatives' Spanish banks in terms of Market Cap, and these are Banco de Sabadell, S.A. (SAB.MC), Banco Bilbao Vizcaya Argentaria, S.A. (BBVA.MC), Bankia, S.A. (BKIA.MC), Bankinter, S.A. (BKT.MC), CaixaBank, S.A. (CABK.MC) and Banco Santander, S.A. (SAN.MC). The expected price is calculated as a weighted sum of the individual assets' prices (Ross, Westerfield, & Jaffe, 2002).

Information for the construction of the BANK index and IBEX was obtained from yahoo finance webpage (2022). Information for the MSCI_EUR_FIN was retrieved from Investing webpage.

4.3.1.2 Independent variables

An equally weighted index was constructed denominates as TECH index which contains the ROBO Global Robotics & Automation Index ETF (ROBO) and First Trust NASDAQ Cybersecurity ETF (CIBR) as proxy to represent the emerging technology phenomena. In order to capture aside the emerging technology phenomena, associated risks and cyber risk awareness should also be tackled since Cybersecurity concerns financial institutions and can threaten the stability of financial markets (Johnson, 2015). Weighting the CIBR ETF and the ROBO ETF would provide additional deepness that contributes.

As Credit default swap (CDS), the ITRAXX Europe index was selected as independent variable to expose the model against economic performance (Augustin, Subrahmanyam, Tang, & Wang, 2014, Augustin, Subrahmanyam, Tang, & Wang, 2016; Arce, Mayordomo, & Peña, 2013). Information was obtained from Bloomberg.

The indices have been selected based on the completeness of data covering a sample period is from 8 July 2015 to 20 September 2019. Daily data utilized is in the form of log returns on the price indices, the returns are in US dollars as calculated by the following formula:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{4.1}$$

Information for the exchange rate USD vs EUR was obtained from Macrotrend webpage.

4.3.2 Methodology

The first methodology an GARCH modeling in order to determine volatility clustering. The ARCH model was the first of the GARCH family introduced by Engle in 1982. Furthermore, many extensions were developed such as the GARCH, EGARCH, IGARCH among others, these models being highly useful to estimate volatility.

The second stage evaluates the contagion of volatility between the dependent variables or proxies for the finance industry and the emerging technologies, through a multivariate GARCH as diagonal BEKK, to verify the results.

4.3.2.1 ARMA

The ARMA (autoregressive and moving average) stands for stationary structure and time discrete stochastic approach. This structure is useful to identify effects of the past of the series themselves as well as the MA effect that identifies signals send by the error term. We can represent an ARMA(p, q) model as:

$$Y_t = \alpha_o + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \cdots + \alpha_p Y_{t-p} + \beta_1 e_{t-1} + \beta_2 e_{t-2} + \dots + \beta_q e_{t-q} + e_t \tag{4.2}$$

where $(e_t) = 0$; $Var(e_t) = \sigma^2$; $Cov(e_t, e_{t-h}) = 0 \ \forall h \neq 0, p$ is number of lags of the dependent variable and q the number of lags of the error term.

4.3.2.2 ARCH

Autoregressive conditional heteroskedastic (ARCH) introduced by Engel (1982) has become a useful model to explain the behavior of asset return volatility over time, where the conditional variance can be represented as:

$$Var_{e_t} \equiv \sigma_t^2 = \theta_0 + \sum_{i=1}^{q} \theta_i e_{t-i}^2 \tag{4.3}$$

where q refers to the lag order of the squared error term include in the model. Under the consideration of the present analysis, in order to test the existence of an ARCH structure, the following set of the hypothesis will be tested:

$$H_0: \theta_1 = \theta_2 = \cdots = \theta_q = 0$$
$$H_1: At\ least\ one\ \theta \neq 0$$

If the null hypothesis is rejected, this would imply that there is a structure for the volatility of the log price return. On the other hand, if the null is not rejected, that would imply stability for the volatility of the log prices returns.

4.3.2.3 GARCH

Bollerslev (1986) introduced the generalized ARCH (GARCH) model, an extension of the ARCH model. The conditional variance, in function of its own lags, is given by:

$$Var_{e_t} \equiv \sigma_t^2 = \theta_0 + \sum_{i=1}^{q} \theta_i e_{t-i}^2 + \sum_{j=1}^{p} \pi_j \sigma_{t-j}^2 \tag{4.4}$$

where $\theta_0 > 0$ and GARCH(p, q) is covariance stationary only if $\sum_{i=1}^{q} \theta_\mathrm{i} + \sum_{j=1}^{p} \pi_j < 1$. It is important to notice that this is the structures used to model the volatility cluster once the dynamic of the variables was modelled with an ARMA structure.

4.3.2.4 Diagonal BEKK

The second stage evaluate the contagion of volatility between the dependent variables or proxies for the finance industry and the emerging technologies through the GARCH multivariate model.
Among the different possible specifications for the model, the BEKK specification, developed by Baba, Engle, Kraft and Kroner, which can be found in the study by Engle and Kroner (1995) seems to fit best the multivariate extension of univariate GARCH for this purpose (Chang, McAleer, &Zuo, 2017; Chang & McAleer, 2018; Chang & McAleer, 2019). The diagonal BEKK model is given as

$$H_t = WW' + Ae_{t-1}'A' + BQ_{t-1}B' \text{ (xx)} \tag{4.5}$$

where A, and B are N x N matrices of parameter W is an upper triangular matrix of parameters. The Diagonal BEKK model is given as:

$$Ht{=}WW'{+}diagaet{-}1diaga{+}diag\ (b)'Qt{-}1diag(b) \tag{4.6}$$

$$H_t = W'W + (aa')^{\circ}e_{t-1}e_{\prime t-1} + (bb')^{\circ}H_{t-1} \tag{4.7}$$

Aiming to reduce the number of parameters in the BEKK model, it is possible to apply a BEKK diagonal model, in which the matrices A and B are diagonal. By reducing the number of parameters estimated by the model and since it is one of the most used in the literature for contagion overflow volatility (Vartanian, 2018) the diagonal BEKK specification was the application selected for this analysis.

McAleer, Chan, Hoti, & Lieberman (2008) proved that the Quasi-Maximum Likelihood Estimators (QMLE) of the parameters of the diagonal or scalar BEKK models were consistent and asymptotically normal, so that standard statistical inference for testing hypotheses is valid.

4.4 Empirical Results

4.4.1 Data Preliminaries

Descriptive statistics for each log return between 7 July 2015 and 20 September 2019 are reported in Table A4.1 in the Appendix. Plots of daily prices and log returns for each variable are illustrated in Figure 4.1 and Figure 4.2. All return series display volatility clustering and leverage effects, making ARCH models applicable.

4.4.1.1 Levels

From Figure 4.1, where the involved series as represented at levels, we can observe similar trends or an association between BANK, IBEX and MSCI_EU_FIN. On the other hand, the CIBR Index and the Robo Index seems to follow and incremental trend.

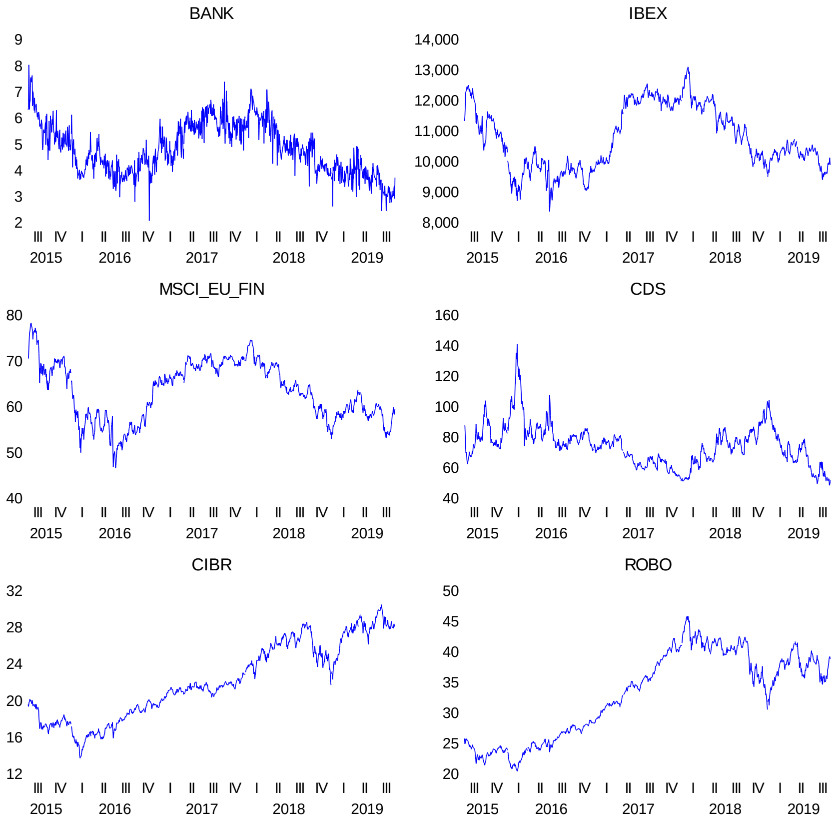

Figure 4.1.: BANK, IBEX, MSCI_EU_FIN, CDS, ROBO, CIBR at levels in the period 7 July 2015 to 20 September 2019.

4.4.1.2 Logarithmic Returns

From Figure 4.2, where the involved series are represented by logarithmic return level, two volatility clusters can be observed commonly during the period 2015 – 2016 and 2018 – 2019. Interestingly we can appreciate that during the first period, the most immediate impacted variable are MSCI_EU_FIN and IBEX and a lagged impacted over BANK. On the other hand, TECH is the most impacted varietal form the second volatility period. From Figure 4.2, we can observe volatility clustering specially during the 2015 – 2016 period for MSCI_EU_FIN. Interestingly all series retrieve an outlier during 2016 which can be linked to the rise of political risk driven by nationalism in 2016 around Europe as for example the Catalonian independence movement, the Brexit announcement among other events.

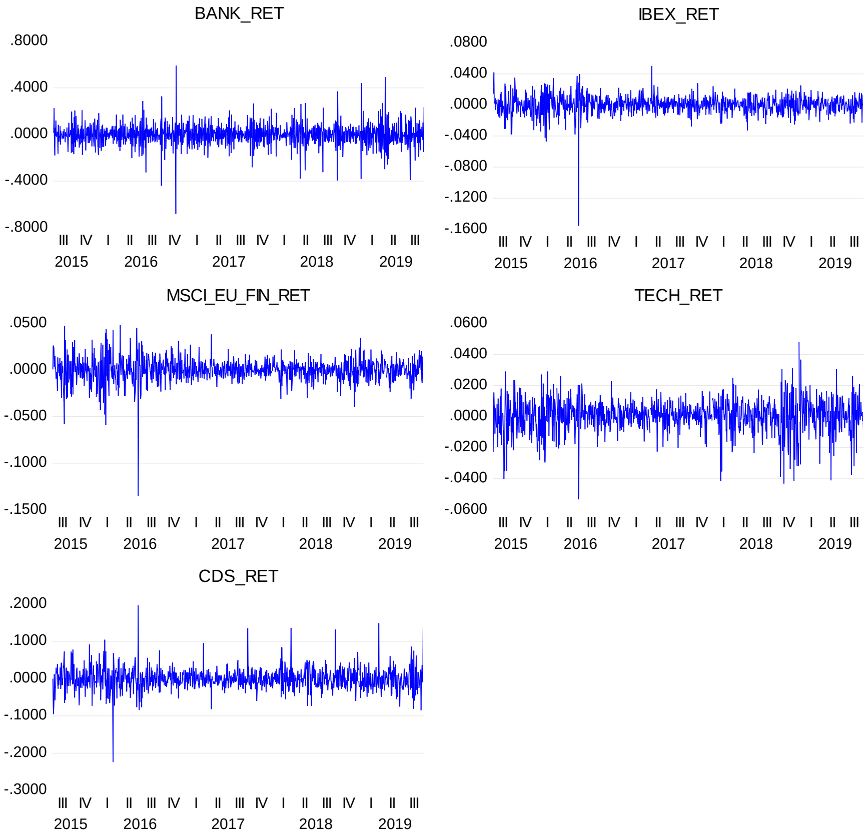

Figure 4.2.: Logarithmic returns of BANK, IBEX35, MSCI_EU_FIN and TECH in the period 8 July 2015 to 20 September 2019.

The logarithmic returns stay around zero as we can observe from Figure 4.2. The largest negative mean return (−0.0483%) is for BANK whereas the IBEX has the lowest negative mean return (−0.0111%). The kurtosis values of all index's returns are higher than three, thus the returns distribution could be fat-tailed. As the skewness values are negative, the skewness values are the asymmetric tail. Since the Jacque-Bera results are statistically significant and reject the null hypothesis of a normal distribution for all indices returns.

Nonetheless, our analysis is robust as models are usually robust as well in non-normal cases.

The correlation among the variables in its logarithmic return expression is reported in Table A4.2 in the Appendix. IBEX and MSCI_EUR_FIN have high correlations around 0.7900. Interestingly our depended variables indicate differentiated correlation with TECH. Highest correlation between MSCI_EU_FIN and TECH with 0.52 and lowest with BANK with TECH at 0.0995.

4.4.2 Unit Root Test

We determined whether the analyzed series are stationary, employing the Augmented Dickey-Fuller (ADF) test, proposed by Dickey and Fuller, (1981) and the Phillips-Perron (PP) test, developed by Perron (1997). A stationary time series is mean-reverting and has a finite variance that guarantees that the process will never drift too far away from the mean.

Table 4.1 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 variables at 90%, 95% and 99% of confidence, which implies that the logarithmic returns of prices levels are stationary.

Table 4.1: Null hypothesis: Log return of indices.

Variable	Augmented Dickey-Fuller test statistics (p-value)	Phillips-Perron test statistics (p-value)
BANK	−26.05192 ***(0.0000)	−110.2503***(0.0001)
IBEX	−32.22969 ***(0.0000)	−32.43474***(0.0000)
MSCI_EU_FIN	−30.82986***(0.0000)	−30.77527***(0.0000)
TECH	−31.33133***(0.0000)	−31.33320***(0.0000)
CDS	−30.28771***(0.0000)	−30.25784***(0.0000)

Source: EViews 10 University Version.

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

Once we have determined that the variables are stationary, it is necessary to model their stochastic dynamics through ARMA structures. The results of modelling the stochastic dynamics of the different log returns through ARMA structures are presented in the following section.

4.4.3 ARCH GARCH

As indicated in the methodology GARCH model are estimated in order to capture volatility clustering among the performance variables for banking (BANK), overall Spanish market (IBEX) and finance industry in Europe (MSCI_EU_FIN) respectively as dependent variable from emerging technologies (TECH). To fulfill the structure for the mean equation, CDS spread independent variable were included as proxy for economic performance. The results are represented in Table 4.2.

4.4.3.1 Mean Equation

First step is the mean equation model the coefficient for of TECH impacting on BANK is a positive significant 0.7560, for IBEX is positive significant 0.2347 and for MSCI_EU_FIN is 0.2498, indicating that there is a generalized positive impact from TECH on the performance variables all significant at 99% confidence. Nevertheless, it is interesting that coefficient of BANK is much higher, indicating that the Spanish banking sector is more impacted by the emerging technologies than the Spanish market as an overall. The associated coefficient of the CDS spread, widely used as an economic control variable, is slightly negative for all the three cases and shows to be consistent with the literature (Collin-Dufresn, Goldstein, & Martin, 2001; Aunon-Nerin, Cossin, Hricko, & Huang, 2002; Blanco, Brennan, & Marsh, 2004) since CDS market seems to lead the stock market (Apergis & Andreas, 2010).

4.4.3.2 Variance Equation

For the performance variables BANK, IBEX and MSCI_EU_FIN, presence of ARCH and GARCH effects are identified and in accordance with the literature (Comin, 2009; Campbell et al., 2001; Pástor & Veronesi, 2005). A large sum of these coefficients implies that a large positive or a large negative logarithmic return will lead future forecasts of the variance to be high for a protracted period. The individual conditional variance coefficients are also as one would expect. The variance intercept is very small, own-volatility spillovers (ARCH effects) are relatively low while the coefficients on the lagged conditional variance or ‘GARCH term’ are large and significant at 99%

confidence. The ARCH effect is higher for IBEX (0.1614) followed by MSCI_EU_FIN (0.1340) and for IBEX (0.147482) than for BANK (0.083350).

The GARCH coefficients suggest a positive impact from the volatility of TECH on the performance variables. The lagged own-volatility persistence (GARCH effects) is BANK (0.8144), IBEX (0.7477) and MSCI_EU_FIN (0.8173). These results suggest that BANK, IBEX and MSCI_EU_FIN derive their volatility persistence more from themselves. In other words, the large values GARCH effect for BANK, IBEX and MSCI_EU_FIN mean that large changes in the volatility will affect future volatility, and that volatilizes for a long period of time since the decay is slower. IBEX, compared to BANK and MSCI_EU_FIN, has a lower GARCH coefficient; in other words, the Spanish banking sector and the finance industry within the EU area will revert to equilibrium relatively slowly in the long run due to a shock in its volatilities perceived by a shock coming from emerging technology environment. On the other hand, IBEX can decay faster to its mean, which has interesting implication for an investor perspective. From the investor's perspective and in this context, this suggests what was expected regarding risk reduction purpose; an overall market indexes would be more recommended due to its diversified portfolio nature across industries. Moreover, the own volatility persistence effects for the performance variables modeled are within a tight range.

Additionally, the long-run average variance per day implied by the models is 0.0067 for BANK, 8.8552E-05 for IBEX and 9.8194E-05 for MSCI_EU_FIN. This corresponds to a total volatility per day is 8.20% for BANK, 0.99% for IBEX and 0.99% for MSCI_EU_FIN.

Table 4.2.: Model results for the estimated GARCH model for BANK, IBEX, MSCI_EU_FIN.

		BANK	IBEX	MSCI_EU_FIN
		Coefficient (p-value)	*Coefficient (p-value)*	*Coefficient (p-value)*
ARMA Model				
Intercept				
TECH		***0.756059 (0.0010)****	***0.234705 (0.0000)****	***0.249820 (0.0000)****
TECH(-1)		-	0.148736 (0.0000)***	-
CDS		−0.194540 (0.0402)**	−0.145700 (0.0000)***	−0.200061 (0.0000)***
AR(1)		−0.591045 (0.0000)***	−0.075173 (0.0185)**	
AR(2)		−0.378099 (0.0000)***		
AR(3)		−0.296768 (0.0000)***		
AR(4)		−0.129661 (0.0000)***		
R		0.295545	0.378976	0.469274
Variance equation				
Intercept		0.000687 (0.0000)***	8.94E-0.6 (0.0000)***	4.77-06 (0.0000)***
ARCH(1)		0.083350 (0.0000)***	0.161469 (0.0000)***	0.134063 (0.0000)***
GARCH(1)		***0.814474 (0.0000)****	***0.747786 (0.0000)****	***0.817362 (0.0000)****
Log Likelihood		1216.256	3556.996	3598.450
Akaike		−2.248150	−6.592379	−6.666884
Schwarz		−2.206425	−6.559998	−6.643772

Hanna Quinn		−2.232347	−6.580116	−6.658132
ARCH-LM		0.203783 (0.9951)	0.006157 (0.9375)	1.228455 (0.2677)

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

4.4.3.3 Diagonal BEKK

The analysis of volatility series and volatility spillovers (contagion effect) in the context of the diagonal BEKK model is performed using the behavior of the conditional variance, conditional covariance and especially the conditional correlation.

This then provides us with estimates of the dynamic, also denominated time-varying co-movements between logarithmic returns of the variables. Table A4.3, A4.4 and A4.5 in Appendix reports the estimates of the Mean Equation and Diagonal BEKK.

Table 4.3.: Model results for the estimated diagonal BEKK for BANK in the period 8 July 2015 to 20 September 2019.

Matrix	*Coefficient (p-value)*	Standard error
M(1,1)	0.000960 (0.0000)***	0.000328
M(1,2)	8.56E-06 (0.0000)***	5.71E-06
M(2,2)	4.87E-06 (0.0000)***	1.68E-06
A1(1,1)	0.281344 (0.0000)***	0.042790
A1(2,2)	0.360802 (0.0000)***	0.038163
B1(1,1)	0.869175 (0.0000)***	0.039692
B1(2,2)	0.916845 (0.0000)***	0.017646

Source: Eviews 10 University Version.
Notes: *significant at level of 10%, **significant at level of 5%, *** significant at level of 1%.
Notes: GARCH = M + A1*e t-1* e t-1'*A1 + B1*GARCH t-1B1, where M is an undefined matrix and A1 and B1 are diagonal matrices.
GARCH (BANK) = M(1,1) + A1(1,1) 2* (e BANK t-1)2 + B1(1,1) 2 *GARCH BANK t-1
GARCH (TECH) = M(2,2) + A1(2,2) 2 *(e TECH t-1)2 + B1(2,2)2 *GARCH TECH t-1
COV (BANK, TECH) = M(1,2) + A1(1,1)*A1(2,2)* (e BANK t-1)* (e TECH t-1)+ B1(1,1)*B1(2,2)* (BANK, TECH) t-1

Table 4.4.: Model results for the estimated diagonal BEKK for IBEX in the period 8 July 2015 to 20 September 2019.

Matrix	*Coefficient (p-value)*	Standard error
M(1,1)	1.48E-05 (0.0001)***	3.76E-06
M (1,2)	3.60E-06 (0.0010)***	1.09E-06
M(2,2)	5.06E-06	1.48E-06

	(0.0006)***	
A1(1,1)	0.135591 (0.0000)***	0.028242
A1(2,2)	0.088030 (0.0000)***	0.019270
B1(1,1)	0.115897 (0.0000)***	0.021885
EB1(2,2)	0.738018 (0.0000)***	0.048311

Source: Eviews 10 University Version.
Notes: *significant at level of 10%, **significant at level of 5%, *** significant at level of 1%.
Notes: GARCH = M + A1*e t-1* e t-1'*A1 + B1*GARCH t-1B1, where M is an undefined matrix and A1 and B1 are diagonal matrices.
GARCH (IBEX) = M(1,1) + A1(1,1) 2* (e IBEX t-1)2 + B1(1,1) 2 *GARCH IBEX t-1
GARCH (TECH) = M(2,2) + A1(2,2) 2 *(e TECH t-1)2 + B1(2,2)2 *GARCH TECH t-1
COV (IBEX, TECH) = M(1,2) + A1(1,1)*A1(2,2)* (e IBEX t-1)* (e TECH t-1)+ B1(1,1)*B1(2,2)* (IBEX, TECH) t-1

Table 4.5.: Model results for the estimated diagonal BEKK for MSCI_EU_FIN in the period 8 July 2015 to 20 September 2019.

Matrix	*Coefficient (p-value)*	Standard error
M(1,1)	5.26E-06 (0.0000)***	9.94E-07
M (1,2)	1.73E-06 (0.0001)***	4.51E-07
M(2,2)	3.51E-06 (0.0001)***	8.83E-07
A1(1,1)	0.324464 (0.0000)***	0.015612
A1(2,2)	0.325214 (0.0000)***	0.019274
B1(1,1)	0.928118 (0.0000)***	0.008194
B1(2,2)	0.929163 (0.0000)***	0.009556

Source: Eviews 10 University Version.
Notes: *significant at level of 10%, **significant at level of 5%, *** significant at level of 1%.
Notes: GARCH = M + A1*e t-1* e t-1'*A1 + B1*GARCH t-1B1, where M is an undefined matrix and A1 and B1 are diagonal matrices.
GARCH (MSCI_EUROPE_FIN) = M(1,1) + A1(1,1) 2* (e MSCI_EUROPE_FIN t-1)2 + B1(1,1) 2 *GARCH MSCI_EU_FIN t-1
GARCH (TECH) = M(2,2) + A1(2,2) 2 *(e TECH t-1)2 + B1(2,2)2 *GARCH TECH t-1
COV (MSCI_EU_FIN, TECH) = M(1,2) + A1(1,1)*A1(2,2)* (e MSCI_EU_FIN t-1)* (e TECH t-1)+ B1(1,1)*B1(2,2)* (MSCI_EU_FIN, TECH) t-1

Wald Test is performed for the coefficient associated to TECH, to test the null hypothesis, which states that mean spillovers from TECH equal zero. The null can be rejected for all associated coefficient for the three models. In the context of the diagonal BEKK model, the analysis of the conditional covariance and conditional correlation between two or more assets effectively allows the evaluation of the contagion effect.

Conditional variance-covariance equations effectively capture the volatility and cross volatility because most coefficients are statistically significant (see Table A4.1 in the Appendix). The conditional variances-covariances implied by the Diagonal BEKK Specification are presented below.

$$hBANK_t = 0.0009 + 0.0791eBANK_{t-12} + 0.7554hBANK_{t-1} \tag{4.8}$$

$$hBANK_t = 4.8672e - 06 + 0.1301eTECH_{t-12} + 0.08406hTECH_{t-1} \tag{4.9}$$

$$hBANK,TECH_t = 8.5635e - 05 + 0.11015eBANK_{t-1}eTECH_{t-1} + 0.7968hBANK,TECH_{t-1} \tag{4.10}$$

$$hIBEX_t = 1.4779e - 05 + 0.1355eIBEX_{t-12} + 0.7380hIBEX_{t-1} \tag{4.11}$$

$$hTECH_t = 5.0620e - 06 + 0.01158eTECH_{t-12} + 0.8663hTECH_{t-1} \tag{4.12}$$

$$hIBEX_t = 1.4779e - 05 + 0.1344eIBEX_{t-12} + 0.7380hIBEX_{t-1} \tag{4.13}$$

$$hMSCI\_EU\_FIN_t = 5.2551e - 06 + 0.1052eMSCI\_EU\_FIN_{t-12} + 0.8614hMSCI\_EU\_FIM_{t-1} \tag{4.14}$$

$$hTECH_t = 3.5147e - 06 + 0.1057eTECH_{t-12} + 0.8633hTECH_{t-1} \tag{4.15}$$

$$\begin{aligned} hMSCI\_EU\_FIN,TECH_t \\ &= 1.17321e - 06 + 0.1055eMSCI_{EU_{FIN}\,t-1}eTECH_{t-1} \\ &+ 0.8623hMSCI\_EU\_FIN,TECH_{t-1} \end{aligned} \tag{4.16}$$

From these empirical results we conclude strong evidence of GARCH effect and the presence of a weaker ARCH effect, results that are in line with the previous methodology applied.

Results of conditional mean return show a statistically significant covariation in shocks, which depends more on its lags than on past errors. Consequently, the shocks for the Spanish banking sector, Spanish market and MSCI_EU_FIN are influenced by past information. These coefficients show the volatility persistence for each dependent variable in terms of its own past errors. Equations show a statistically significant covariation in shocks, which depends more on its lags than on past errors.

In terms of cross-volatility spillover (ARCH) is less then cross-volatility persistence (GARCH) and in lines with the results obtained with the previous methodology. TECH have the greatest ARCH effect for BANK (0.1101) followed by IBEX (0.0880) and MSCI_EU_FIN (0.1055), even though the coefficient is relatively close.

Cross-volatility persistence as past volatility shocks in TECH have large effects on the future volatility of MSCI_EU_FIN (0.8623) followed by IBEX (0.8200) and BANK (0.7968); nevertheless, for BANK the associated coefficient is lower.

It is an important finding here that although cross-volatility spillover and cross-volatility persistence are relatively close across the three performance variables.

The plots for the conditional variances-covariances estimated by the Diagonal BEKK Model are illustrated in Figure 4.3, Figure 4.4, and Figure 4.5. They suggest that the movements display an extremely volatile trend for the study period.

Moreover, from Figure 4.6 we can observe that the conditional correlations show sharp increases at some point during 2015 − 2016 and period during 2018 − 2019 for each pair of variables. Known exogenous factors have shown to be the root causes. The first period of high volatility is related to political risk driven by nationalism in 2016 around Europe. The highest peak was experienced by IBEX and MSCI_EU_FIN during the first period of high volatility with a conditional correlation of 0.8107 and 0.9370 respectively, as maximum values presented over the entire studied period. BANK experienced a maximum conditional correlation of 0.6730. The results are aligned with political risk across Europe as the caused uncertainty with continuously cause high instability in key financial markets. The second period of high volatility be investor to weight the prospect of global trade tensions and excessive debt.

This provides evidence that the linkages between examined dependent variables with the emerging technology phenomena highly integrated and that volatility spillovers rise during period of high volatility.

The Ljung-Box Q statistics show no evidence of autocorrelation in the standardized residuals (see Table A4.6, Table A4.7 and Table A4.8 in Appendix). It can be concluded that the conditional mean return equations are correctly specified with the diagonal BEKK GARCH model.

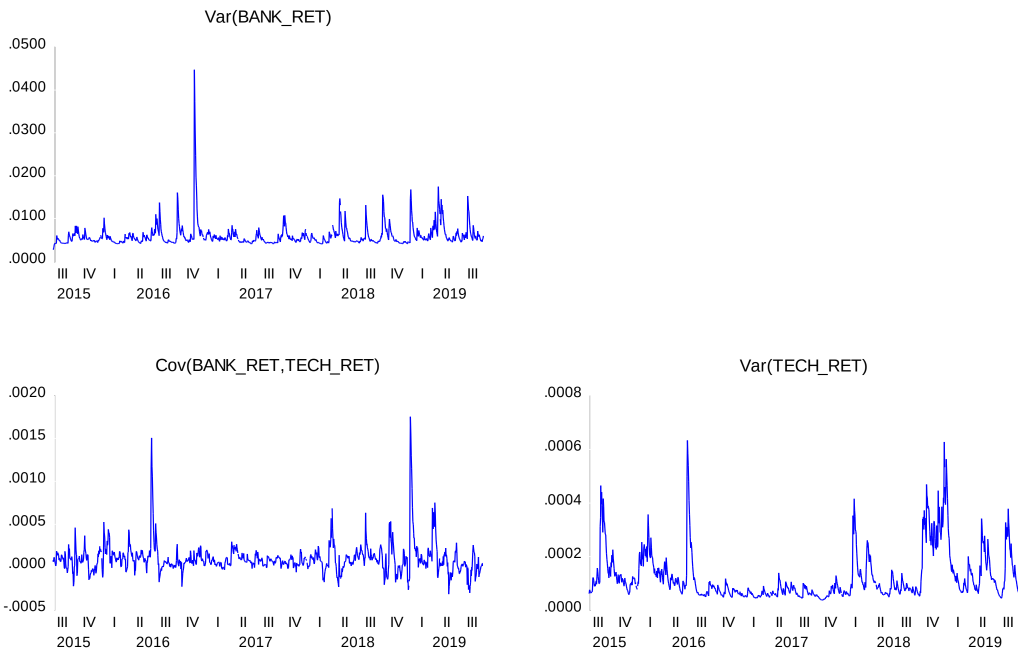

Figure 4.3.: Variance and Conditional Covariance for logarithmic returns for BANK and TECH in the period 8 July 2015 to 20 September 2019.

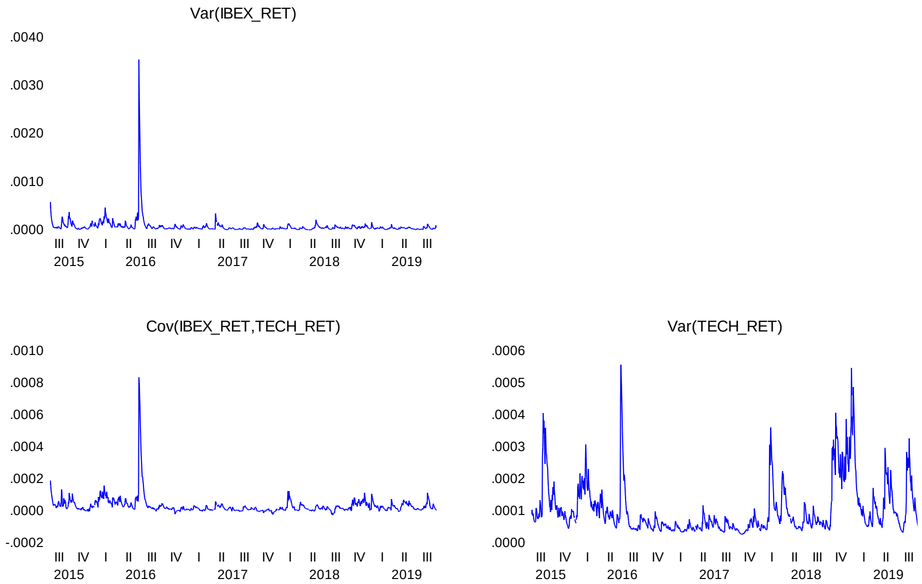

Figure 4.4.: Variance and Conditional Covariance for logarithmic returns for IBEX and TECH in the period 8 July 2015 to 20 September 2019.

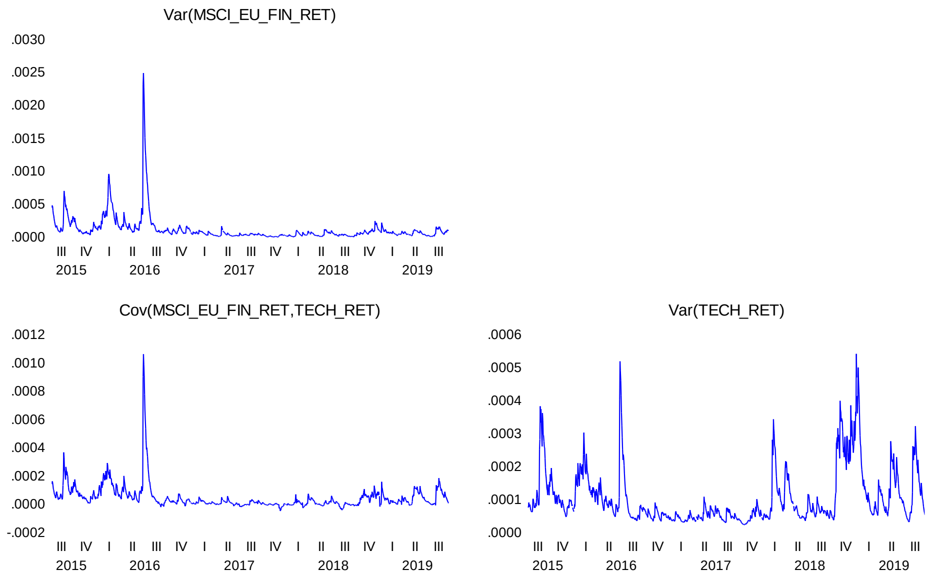

Figure 4.5.: Variance and Conditional Covariance for logarithmic returns for MSCI_EU_FIN and TECH in the period 8 July 2015 to 20 September 2019.

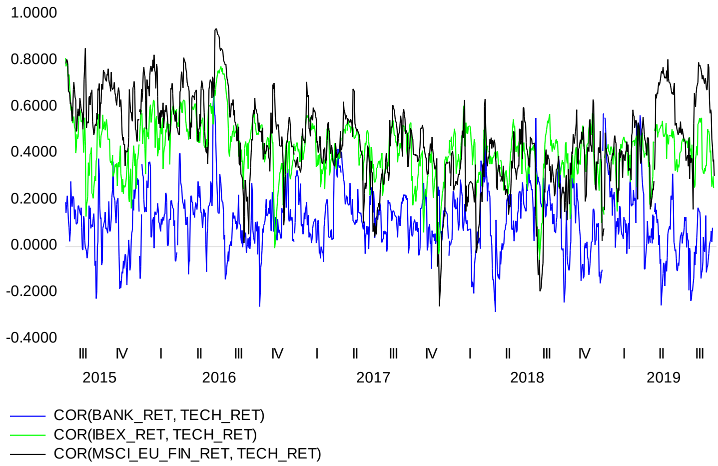

Figure 4.6.: Conditional Correlation of the logarithmic returns of BANK and TECH, IBEX and TECH and MSCI_EU_FIN and TECH in the period 8 July 2015 to 20 September 2019.

4.5 Conclusion

This article investigates the dynamic, time series properties of the correlations, volatility cluster, spillover and persistence for daily log returns as for three performance variables and emerging technology phenomena with the objective to study the impact on Spanish banking sector (BANK), the Spanish market portfolio (IBEX) and the finance industry in the European Union Area (MSCI_EUR_FIN). An equally weighted index was constructed as proxy to represent the emerging technology phenomena using the ROBO Global Robotics & Automation Index ETF (ROBO) and First Trust NASDAQ Cybersecurity ETF (CIBR). Credit default swap (CDS) as proxy was incorporated to control for the economy-wide risk. The indices have been selected based on the completeness of data covering a sample period from 7 July 2015 to 20 September 2019. Daily log returns were calculated. The generalized autoregressive conditional heteroskedasticity GARCH methodology was applied followed by a diagonal BEKK approach. Descriptive statistics of our series showed stationary nature as confirmed by the Dickey and Fuller (1981), and the Phillips-Perron test (1997) which implies that the logarithmic returns of prices levels are stationary. Also, volatility clustering where identified. In this sense the proposed methodologies seem to fit most for this purpose.

Broadly, the results confirm that emerging technology environment is important in capturing the level of risk for the three performance variables return and volatility context. The results of the estimated models within the mentioned methodologies are in line.

Resulting from the first methodology applied, the associated coefficient for the emerging technology is positive and statistically significant for all three performance variables. The magnitude indicates that the Spanish banking sector (BANK) is much more impacted by the emerging technologies (TECH) than the Spanish market as an overall (IBEX). These results suggest that an increase in log returns of the Spanish banking sector is significantly associates with the performance of emerging technology phenomena.

The variance equation provide insight about the volatility dynamics. The ARCH effect is relatively low compared to GARCH for the performance variables, indicating that they will recover its equilibrium volatility level slowly after a shock from emerging technology environment was perceived. However, the ARCH is slightly higher for Spanish market index, suggesting that they decay faster to its equilibrium volatility level compared to the Spanish banking sector and the finance industry in the EU area.

In the context of the diagonal BEKK model, the analysis of the conditional covariance and conditional correlation between two or more variables effectively allows the evaluation of the contagion effect. In term of cross volatility conditions, the ARCH effect is relatively low compared to GARCH, tough a slow decay and slow regression toward the mean is perceived. The results indicate that contagion from the emerging technology environment (TECH) to the performance variable exists through cross-volatilities spillover and cross-volatilities persistence. The contagion of shocks emitted from the technology phenomena are relatively similar among the performance variables, being the Spanish banking sector slightly more impacted, regardless with the ability to revert faster to its cross-volatilities equilibrium compared to the other performance variables. The Spanish banking sector and the finance industry at regional EU level will revert to its cross-volatilities equilibrium relatively slowly given a shock coming from emerging technology environment (TECH). Shock from emerging technology will most persist at the finance industry at EU area level. These results provide interesting implication for an investor perspective and confirms the need to further explore the impact of emerging technologies in different sectors and industries.

Additionally, two volatility clustering periods where identified withing an sharp increase in conditional variance-covariance estimated by the diagonal BEKK model. This provides evidence that the linkages between examined performance variables with the emerging technology phenomena is highly integrated and that volatility spillovers rise during period of high volatility.

One important implication of this study is that adding stocks from the performance variables will not diversify necessarily the portfolio risk away. Investors must diversify their portfolios towards different risk profile components. The results also evidence that for risk reduction purpose an overall market standpoint would be more recommended due to is diversified portfolio nature across industries.

The work reviews in this article provide results on correlations, volatility spillover and persistence effects between emerging technologies and performance variables that must be considered. Sector, industry and market specific features must be contemplated and can result in heterogeneous insights about the relationship between emerging technology phenomena and performance variables.

The need to understand the time series behavior is highlighted at this stage and opens a key area for future research as a feature of persistence and diffusion nature of innovation and emerging technology context. This, in fact, implies that more work needs to be delimited by the gap between the concept of risk and uncertainty in order to apply more suitable numerical approaches.

Appendix

Table A4.1.: Descriptive statistics of the logarithmic returns of BANK, IBEX, MSCI_EUR_FIN and TECH in the period 8 July 2015 to 20 September 2019.

	BANK	*IBEX_*	*MSCI_EU_FIN*	*TECH*
Mean	−0.000483	−0.000111	−0.000157	0.000348
Median	−1.49E-05	0.000299	0.000000	0.001019
Maximum	0.591772	0.049841	0.047936	0.047870
Minimum	−0.679932	−0.155674	-0.135393	−0.053353
Std. Dev.	0.094927	0.012035	0.012951	0.010755
Skewness	-0.150312	−2.036759	−1.262044	−0.636995
Kurtosis	9.158410	29.12856	16.13983	5.418643
Jarque-Bera	1707.570	31410.02	8041.256	335.6571
Probability	0.000000	0.000000	0.000000	0.000000
Sum	−0.520426	−0.119318	−0.168939	0.374945
Sum Sq. Dev.	9.704950	0.156003	0.180635	0.124572
Observations	1078	1078	1078	1078

Table A4.2.: Correlation analysis of the logarithmic returns of BANK, IBEX, MSCI_EUR_FIN and TECH in the period 8 July 2015 to 20 September 2019.

	BANK	*IBEX*	*MSCI_EU_FIN*	*TECH*
BANK	1.000000	0.183201	0.163659	0.099557
IBEX_	0.183201	1.000000	0.790043	0.469432
MSCI_EU_FIN	0.163659	0.790043	1.000000	0.521006
TECH	0.099557	0.469432	0.521006	1.000000

Table A4.3.: Report the estimates of the Mean Equation and Diagonal BEKK for BANK.

	BANK	TECH
	Coefficient *(p-value)* *[Std error]*	*Coefficient* *(p-value)* *[Std error]*
Intercept		0.000986 (0.0001)*** *[0.000250]*
TECH $_{t-1}$	0.372708 (0.0946)* *[0.222995]*	
CDS $_{t-1}$	−0.118810 (0.1445)	
BANK $_{t-1}$	−0.596974 (0.0000)*** *[0.081412]*	
BANK $_{t-2}$	−0.368099 (0.0000)*** *[0.032600]*	
BANK $_{t-3}$	−0.276393 (0.0000)*** *[0.030414]*	
BANK $_{t-4}$	−0.144721 (0.0000)*** *[0.027340]*	

Source: EViews 10 University Version.
Notes: *significant at level of 10%, **significant at level of 5%, *** significant at level of 1%.
Notes: BANK $_{t\,=}$ *TECH* $_{t-1}$ + +CDS $_{t-1}$ + BANK $_{t\,-1}$ + BANK $_{t\,-2}$ + BANK $_{t\,-3}$ + BANK $_{t\,-4}$
TECH $_{t\,=}$ C

Table A4.4.: Report the estimates of the Mean Equation and Diagonal BEKK for IBEX.

	IBEX	*TECH*
	Coefficient *(p-value)* *[Std error]*	*Coefficient* *(p-value)* *[Std error]*
Intercept		0.000973 (0.0000)*** [0.000233]
TECH $_{t-1}$	0.216567 (0.0000)*** *[0.029507]*	
TECH $_{t-2}$	0.005749 (0.8223) *[0.025604]*	
CDS $_{t-1}$	0.002731 (0.8159) *[0.011729]*	
IBEX $_{t-1}$	−0.108293 (0.0014)*** *[0.033812]*	

Source: EViews 10 University Version.
Notes: *significant at level of 10%, **significant at level of 5%, *** significant at level of 1%.
Notes: IBEX $_{t\,=}$ *TECH* $_{t-1\,+}$ *TECH* $_{t-2\,+}$ CDS $_{t-1\,+}$ IBEX $_{t-1}$; TECH $_{t\,=}$ C

Table A4.5.: Report the estimates of the Mean Equation and Diagonal BEKK for MSCI_EU_FIN.

	MSCI_EU_FIN	TECH
	Coefficient *(p-value)* *[Std error]*	*Coefficient* *(p-value)* *[Std error]*
Intercept		0.000755 (0.0012)*** *[0.000234]*
TECH $_{t-1}$	0.188977 (0.0000)*** *[0.022694]*	
CDS $_{t-1}$	0.018141 (0.0662)* *[0.009876]*	

Source: EViews 10 University Version.
Notes: *significant at level of 10%, **significant at level of 5%, *** significant at level of 1%.
Notes: MSCI_EU_FIN $_{t}$ = *TECH* $_{t-1}$ + CDS $_{t-1}$; TECH $_{t}$ = C

Table A4.6.: Portmanteau Test using Standard Residual Diagonal BEKK for BANK.

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	2.841841	0.5846	2.844489	0.5842	4
2	9.816734	0.2781	9.832395	0.2770	8
3	17.64521	0.1269	17.68280	0.1257	12
4	19.89488	0.2250	19.94088	0.2229	16
5	24.11002	0.2376	24.17573	0.2348	20
6	29.04144	0.2186	29.13486	0.2151	24
7	29.27136	0.3989	29.36629	0.3941	28
8	33.41052	0.3986	33.53651	0.3927	32
9	40.30240	0.2857	40.48663	0.2789	36
10	46.58130	0.2199	46.82454	0.2127	40
11	48.27149	0.3043	48.53222	0.2953	44
12	50.38766	0.3792	50.67231	0.3686	48

[1] Null hypothesis: No residual autocorrelation up to lag h.
[2] Orthogonalization: Cholesky (Lutkepohl).

Table A4.7.: Portmanteau Test using Standard Residual Diagonal BEKK for IBEX.

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	4.938825	0.2936	4.943419	0.2932	4
2	7.094931	0.5264	7.103540	0.5255	8
3	12.75354	0.3872	12.77798	0.3854	12
4	14.34874	0.5728	14.37912	0.5705	16
5	19.96216	0.4603	20.01875	0.4568	20
6	23.17875	0.5093	23.25338	0.5049	24
7	23.50290	0.7075	23.57965	0.7035	28
8	29.08135	0.6150	29.19988	0.6090	32
9	34.28518	0.5503	34.44760	0.5425	36
10	36.96452	0.6077	37.15208	0.5992	40
11	41.61325	0.5744	41.84883	0.5642	44
12	44.54866	0.6151	44.81734	0.6040	48

[1] Null hypothesis: No residual autocorrelation up to lag h.
[2] Orthogonalization: Cholesky (Lutkepohl).

Table A4.8.: Portmanteau Test using Standard Residual Diagonal BEKK for MSCI_EU_FIN.

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	7.572840	0.1085	7.579878	0.1082	4
2	9.241557	0.3223	9.251700	0.3215	8
3	15.91077	0.1954	15.93955	0.1940	12
4	19.02444	0.2674	19.06482	0.2653	16
5	21.99958	0.3405	22.05384	0.3376	20
6	26.88934	0.3096	26.97099	0.3058	24
7	28.04596	0.4620	28.13518	0.4573	28
8	29.67689	0.5846	29.77831	0.5794	32
9	36.31979	0.4538	36.47719	0.4465	36
10	37.63378	0.5773	37.80349	0.5696	40
11	43.07817	0.5110	43.30406	0.5013	44
12	45.30336	0.5840	45.55433	0.5736	48

[1] Null hypothesis: No residual autocorrelation up to lag h.
[2] Orthogonalization: Cholesky (Lutkepohl)

5 The impact of disruptive technology on banking under switching volatility regimes

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 summarize, 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.

5.1 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 and 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.

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, 2008b) and market spillover effects.

Spanish banking is making a major effort to keep up with new technologies, and this is also channeled 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 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 unfavorable 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 unfavorable 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.

5.2 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, Rodríguez-Ruiz, Rodríguez-Duarte, & Gómez-Martínez, 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 5.1) 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).

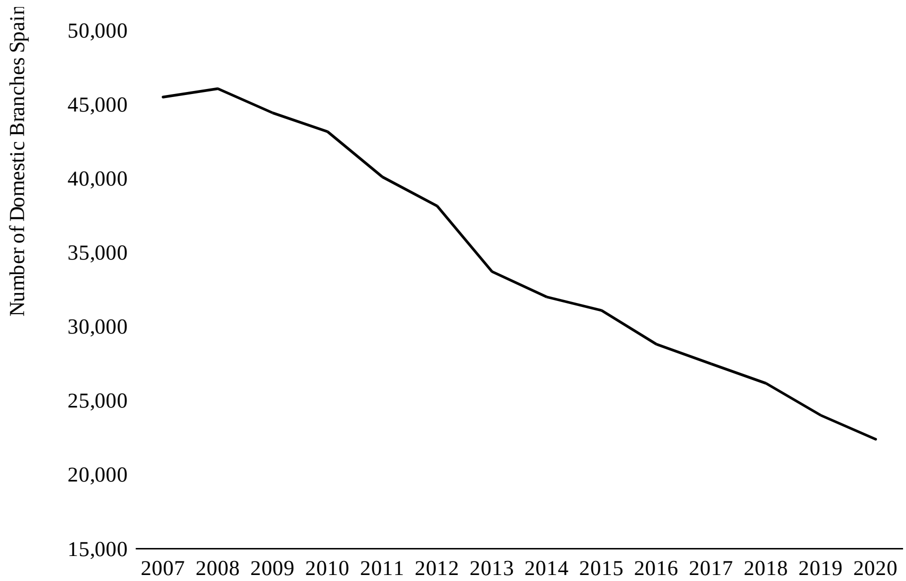

Figure 5.1.: ECB MFIs structural indicators of domestic branches in Spain (2007 to 2020). Data from Bloomberg.

In 2020, 50% of financial products were being sold online, and 6 out of 10 Spaniards had replaced physical banking with digital banking (KPMG, 2021), 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 5.2).

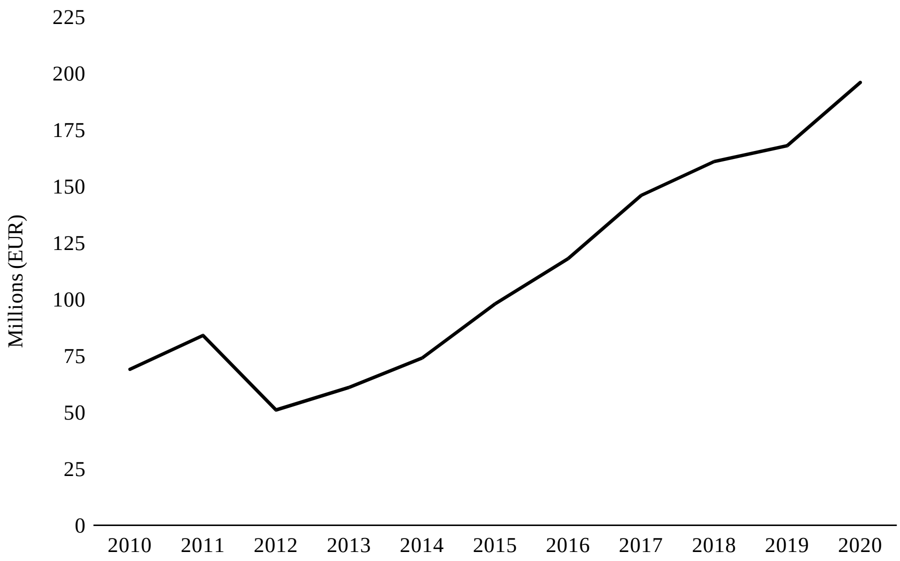

Figure 5.2.: Electronic money – Total reported by electronic money institutions in Spain (stock) (2014 to 2020). Data from ECB Statistic Datawarehouse (2021).

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 5.3) and the COVID-19 crisis have driven banks to accelerate their digitalization prospectuses.

Figure 5.3.: IMF Spain interbank money market rate (2007 to 2019). Data from Bloomberg.

In contrast, the non-performing loan ratio has been recovering since 2013 (see Figure 5.4) and the overall risk of the sector has been decreasing, as the BIS Ultimate Risk Total from Spain Banks shows (see Figure 5.5), 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.

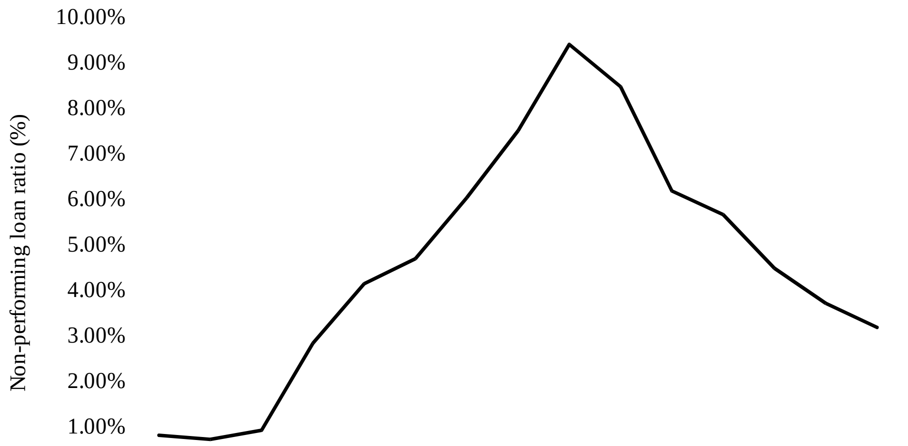

Figure 5.4.: Non-performing loan ratio (2005 to 2019). Data from Statista (2021, December 30).

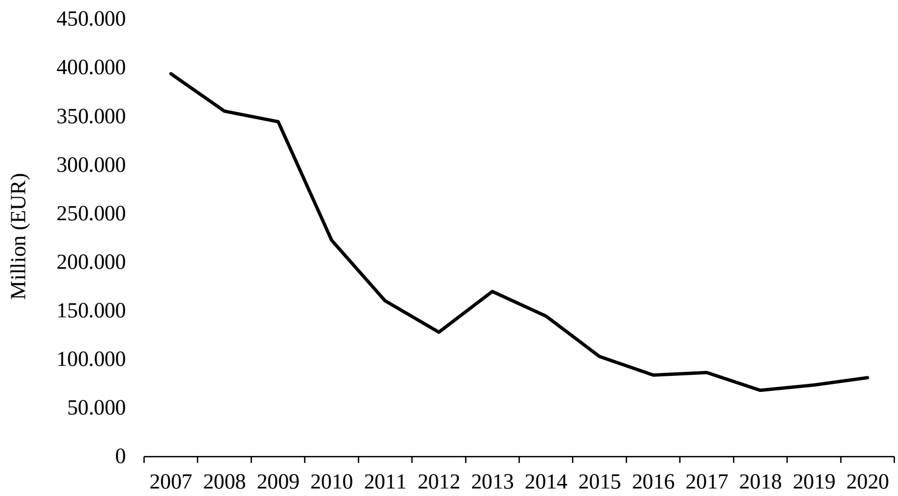

Figure 5.5.: BIS ultimate risk total from Spain banks (2007 to 2019). Data from Bloomberg.

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, September 15).

5.3 Literature

5.3.1 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, channeled by the stock market, might explain short-term fluctuations. Jovanovic and Rosseau (2002) 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 channeled 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.

5.3.2 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, Bharath, and Viswanathan (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, Corbet, Sensoy, & Yarovaya (2020b) 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. (2022) 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.

5.3.3 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, Matvos, Piskorski, & Seru, 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 (2021) 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, Spigt, and Swinkels (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, Narayan, Rahman, and Hutabarat (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, Yang, and Ma (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.

5.4 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, Purnanandam, & Zheng, 2017; Ho et al., 2020). A variety of methods to quantify bank risk have been proposed (e.g. Stiroh, 2006; Sawada, 2013; Anginer, Demirguc-Kunt, & Zhu, 2014; Bennett, Güntay, & Unal, 2015; Demirer, Diebold, Liu, & Yilmaz, 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, Guermat, & Tucker, 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,

$$E(R_i) = R_f + \beta_i(E(Rm) - R_f) , \tag{5.1}$$

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:

$$R_{it} = \alpha_i + \beta_i(Rm_t)+\gamma_i(DT_t) + e_{it}, \tag{5.2}$$

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:

$$R_{it} = \alpha_i + \beta_i(Rm_t)+\gamma_{i,v}(DT_t)(s_t) + \sigma_v(s_t) + e_{i,t}, \tag{5.3}$$

where $e_t \overset{iid}{\sim} N(0,1)$, and $v = 1,2$ represent high and low market volatility; α_i comprises a common intercept to both regimes[3] 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*[4]; 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.

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

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

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

$$P(\zeta_{t-1}) = P(s_{t-1} = j) = p_{jk}(t), \tag{5.4}$$

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

$$\begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}, \tag{5.5}$$

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

$$\sum_{t=1}^{n} ln \sum_{v=1}^{2} \frac{1}{\sigma_v} \varphi \;(\left(\frac{y_t - x_t \beta_v}{\sigma_v} \right) \; P \; (s_t = v | \zeta_{t-1}) \tag{5.6}$$

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).

5.5 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 5.6, the weight of the composites of the IBEX35 BANCA are represented from 2015 until 2020.

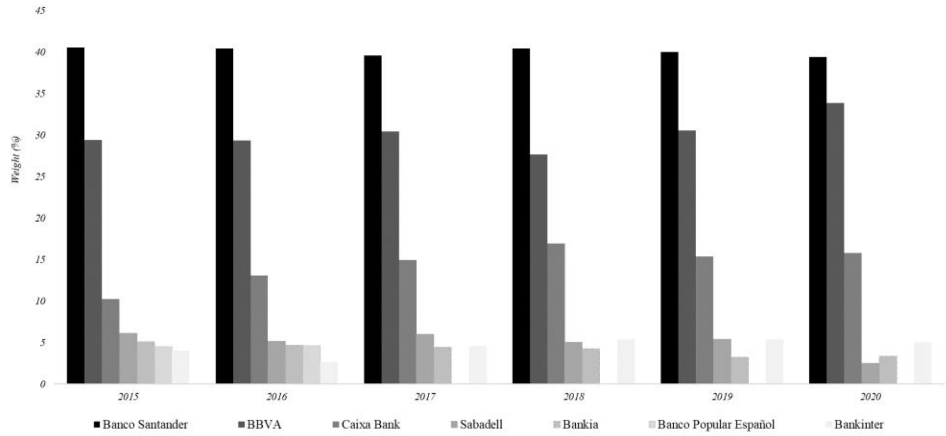

Figure 5.6.: Percentage weight composites of the IBEX35 BANCA End of Year Index (December 31st, 2015, to December 31st, 2020). Data from Bloomberg.

The MSCI ACWI IMI Disruptive Technology ESG Filtered index (MSCI, 2022a) is used as a proxy for disruptive technology, based on the index design appropriate for the purpose 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, 2022b) was retrieved from Investing (2022) to construct the market portfolio, and since its values were expressed in USD, we converted them using the USDEUR exchange rate published by OFX (2022, August 15), while the TBILL 3-month rate retrieved from the Federal Reserve Bank of St. Louis (2021) 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 pandemics. To formalize, the following expression was used to obtain the form of log returns for the used times series:

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right). \tag{5.7}$$

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 5.1, 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 ~~reject~~ 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, Startz, & Nelson (1989). However, our analysis is robust, as are models applying Huber-White robust standard errors in non-normal cases.

Table 5.1.: 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

Figures 5.7 to 5.12 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.

Figure 5.7.: Daily closing price, Spanish banking (November 25th, 2015 to January 30th, 2020).

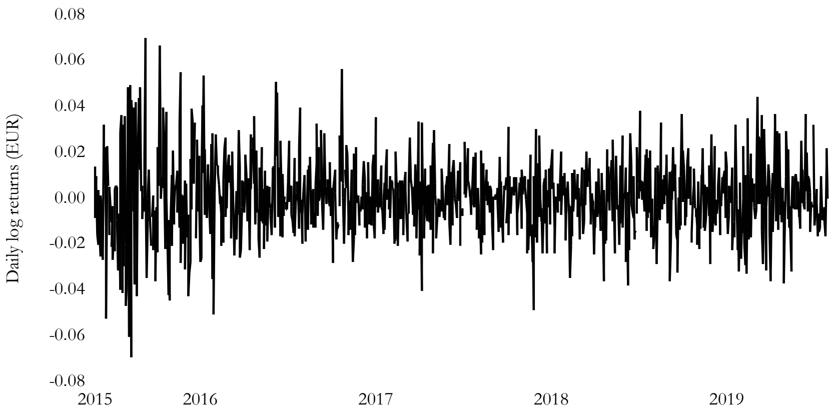

Figure 5.8.: Daily log returns, Spanish banking (November 26th, 2015, to January 30th, 2020).

Figure 5.9.: Daily closing price, Market portfolio (November 25th, 2015, to January 30th, 2020).

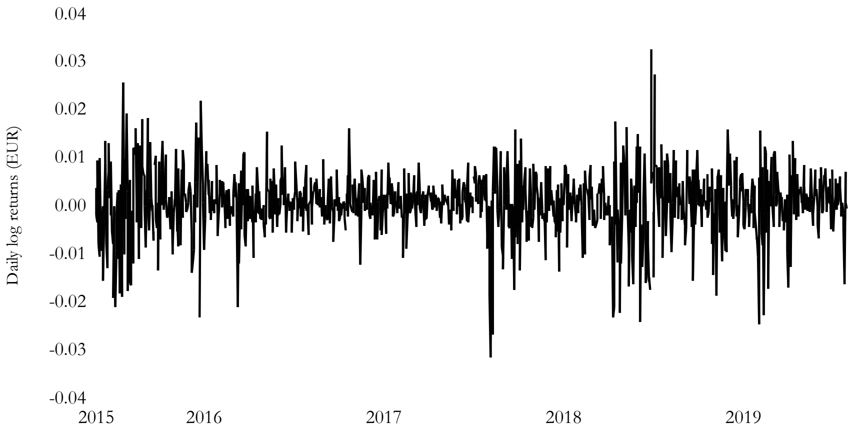

Figure 5.10.: Daily log returns, Market portfolio (November 26th, 2015 to January 30th, 2020).

Figure 5.11.: Daily closing price, Disruptive technology (November 25th, 2015, to January 30th, 2020).

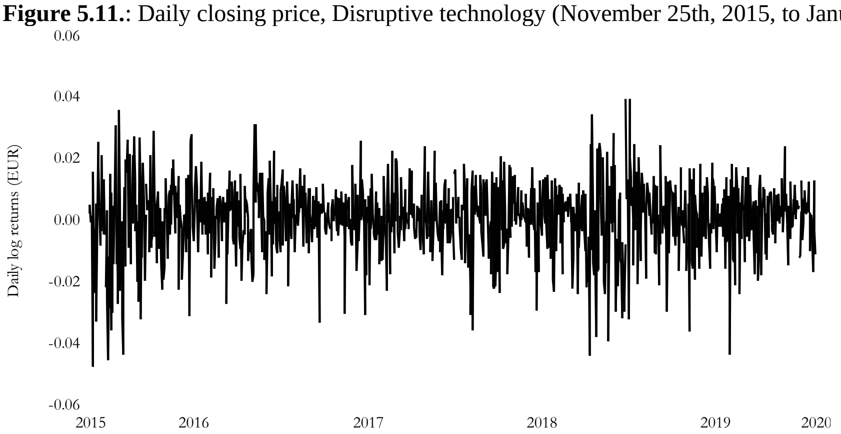

Figure 5.12.: Daily log returns, Disruptive technology (November 26th, 2015, to January 30th, 2020).

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 Brock and Dechert (1988) and Brock, et al. (1996) was run to confirm the nonlinearity of the series. The results for the BDS test, as shown in Table 5.2, 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 5.3.

Table 5.2.: 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 5.3.: 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, Durbin, and Evans (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 5.13 below). The movement outside the critical line indicates parameter or variance instability.

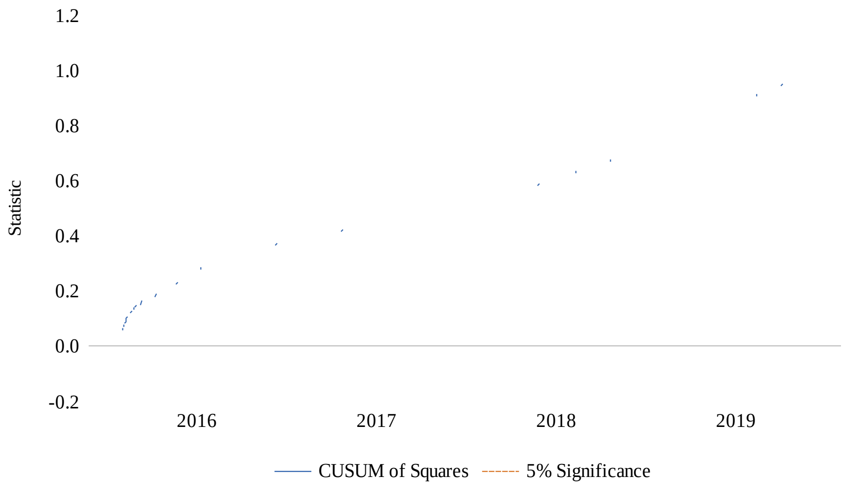

Figure 5.13.: CUSUM of Square Test for Spanish banking.

The Multiple breakpoint Bai–Perron test determined the existence of one break for the Spanish banking index log returns (see Table 5.4 below).

Table 5.4.: 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%.

5.6 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 5.5. 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 5.6.

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 unfavorable market conditions and less influence under stable ones.

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 5.14 illustrates the probability transitions for the high volatility and low volatility regime MRS estimation.

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.

Table 5.5.: 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: $\text{Log(sigma)}_h = \text{Log(sigma)}_l$.

Table 5.6.: 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%.

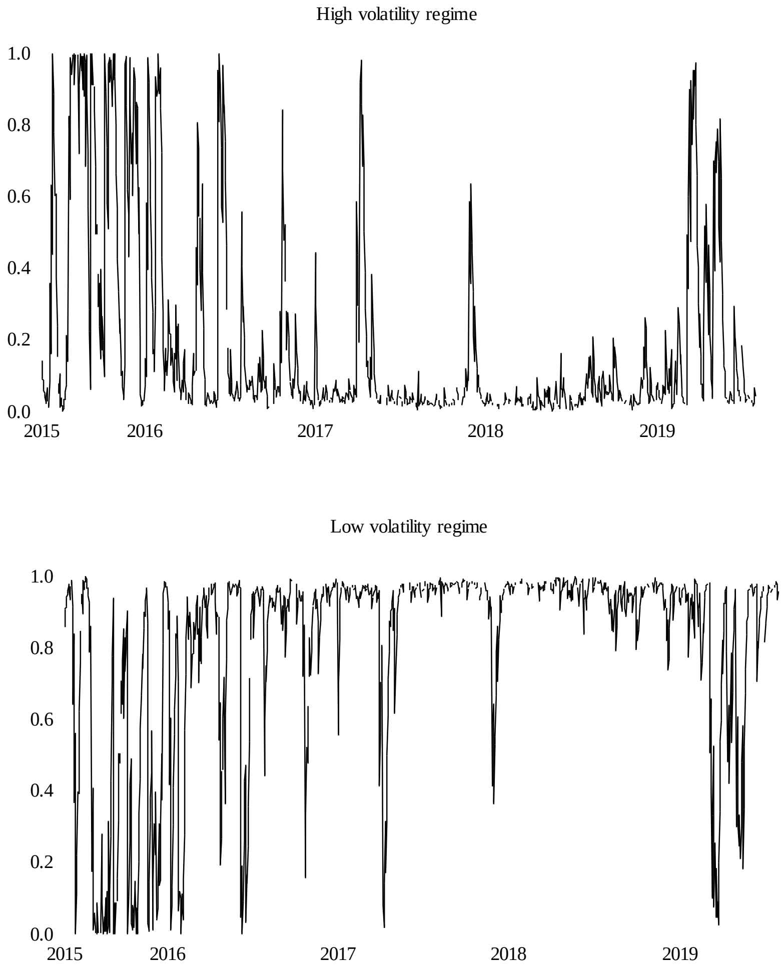

Figure 5.14.: Markov Switching Filtered Regime Probabilities for Spanish banking.

5.7 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.

6 Banking FinTech and stock market volatility? The BIZUM case

Abstract. 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.

Keywords: Stock market volatility; GARCH- M; BIZUM, FinTech, Digital payment, Banking.

6.1 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 & 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 & 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 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 & Zhang 2020; Lee & Shin 2018; Moro-Visconti, Cruz-Rambaud, & López-Pascual, 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. 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 & 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 2021 (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 to 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.

6.2 Literature review

6.2.1 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 & Morris Lampert, 2001), (Schoenmakers & 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 (1981a) 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 & 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 & Satchell 2000). Investors induce the variability of prices in the stock market by interpreting the flows of information.

6.2.2 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, Brynjolsson et al. (2019) and Wu, Lou, & Hitt (2019) found that it is promoted by digital technology adoption, but Babina, Fedyk, He, & Hodson (2024) found that AI adoption has no impact on productivity. On the other hand, evidence suggests that digital transformation promotes firms' innovation abilities (Trocin, Hovland, Mikalef, & Dremel, 2021; Usai, Fiano, Petruzzelli, Paoloni, Briamonte, & Orlando, 2021).

Existing literature has found that the adoption of disruptive technology improves performance (Chen & Srinivasan 2023; Ferreira, Fernandes, & Ferreira, 2019; Mikalef, Krogstie, Pappas, & Pavlou, 2020; Rialti, Zollo, Ferraris, & Alon, 2019; Babina et al., 2024). Meanwhile, Chen and Srinivasan (2023) 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. Dranev, Frolova, and Ochirova, (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, Lee, Yeh, and Yuen (2020) reported that FinTech enhances stability in emerging (developed) financial markets and impacts it through profitability. Daud, Khalid, and Azman-Saini (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, Xiuping, and Zhang (2021) testify the relationship between

FinTech and different types of commercial banks and find that FinTech can boost the latter's productivity in China. Le, Ho, Nguyen, and Ngo (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, Liu, and Luo (2021) 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, Du, and Chen (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.

6.2.3 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 & 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, Stupariu, & Vilariño, 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 & 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.

The year of 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.

6.3 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, De Jonghe, & Vander Vennet, 2007; Sawada 2013; Anginer et al. 2014; Bennett et al. 2015; Laeven, Ratnovski, & Tong, 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 & Worthington, 2004; Lael Joseph, & Vezos, 2006; Khan & Zia 2019; Hu, Tao, Xing, Pan, Zhao, & Chen, 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 & 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 & Mansur 1998). The numerical specifications are detailed below.

6.3.1 GARCH Fundamentals

GARCH is a predominant approach in the literature to the modeling and forecasting of volatility (Kalev et al. 2004; Ho et al. 2013; Ho et al. 2020). It was developed by Bollerslev (Bollerslev, 1986) to generalize the ARCH model proposed by Engle (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,

$$y_t = \delta + \sum_{i=0}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t, \tag{6.1}$$

where δ is a constant term, $\emptyset_i$ 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 modeled as,

$$\varepsilon_t = \sqrt{v_t} z_t, \tag{6.2}$$

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,

$$v_t = \vartheta_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \cdots + \alpha_l \varepsilon_{t-l}^2, \tag{6.3}$$

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,

$$v_t = \vartheta_0 + \sum_{i=1}^{l} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{k} \beta_i v_{t-i}, \tag{6.4}$$

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 & Bollerslev, 1986).

6.3.2 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 Lovreta and Pascual (2020), and Sreenu and Naik (2021).

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,

$$y_t = \delta + \sum_{i=0}^{p} \emptyset_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \gamma_0 v_t + \varepsilon_t, \tag{6.5}$$

$$v_t = \vartheta_0 + \sum_{i=1}^{l} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{k} \beta_i v_{t-i}, \tag{6.6}$$

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.

6.3.3 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:

$$v_t = \vartheta_0 + \sum_{i=1}^{l} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{k} \beta_i v_{t-i} + \xi d_t, \tag{6.7}$$

where ξd_t is defined as the dummy variable for a particular event window $\{s_1, s_2\}$ $d_t = 1$ if $s_1 \leq$ t $\leq s_2$; 0 otherwise. The Likelihood function can be expressed as follows,

$$l(\varphi) = \frac{-1}{2} \sum_{t=1}^{\tau} \square \tag{6.8}$$

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:

$$H_0: \xi \geq 0$$
$$H_1: \xi < 0$$

6.3.4 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, Gonpot, and Sookia (2011), Gao Zhang, and Zhang (2012), Wiśniewska and Wyłomańska (2017). The standardized GED proposed by Nelson can be simplified as follows:

$$f(z_t, v) = 2^{-1} v \Gamma \left(\frac{3}{v}\right)^{1/2} \left[\Gamma \left(\frac{1}{v}\right)^{3/2}\right]^{-1} exp \tag{6.9}$$

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.

6.4 Data description

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

Table 6.1.: 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

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.

Table 6.2.: 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.

The incumbent banks were selected based on data availability 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 4,800 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, 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 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, 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 1,815,000 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, 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 (Banc Sabadell, 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 (El Pais, 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, 2022).

The selected sample period is from 01/07/2013 to 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 6.3 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 (2022, April 6).

Table 6.3.: Summary statistics for daily returns from 01/07/2013 to 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

[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.

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.

Figure 6.1 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, Faff, McKenzie, & Mitchell, 2000). However, our analysis is robust. Indeed, the GARCH-M GED specification is robust in non-normal cases.

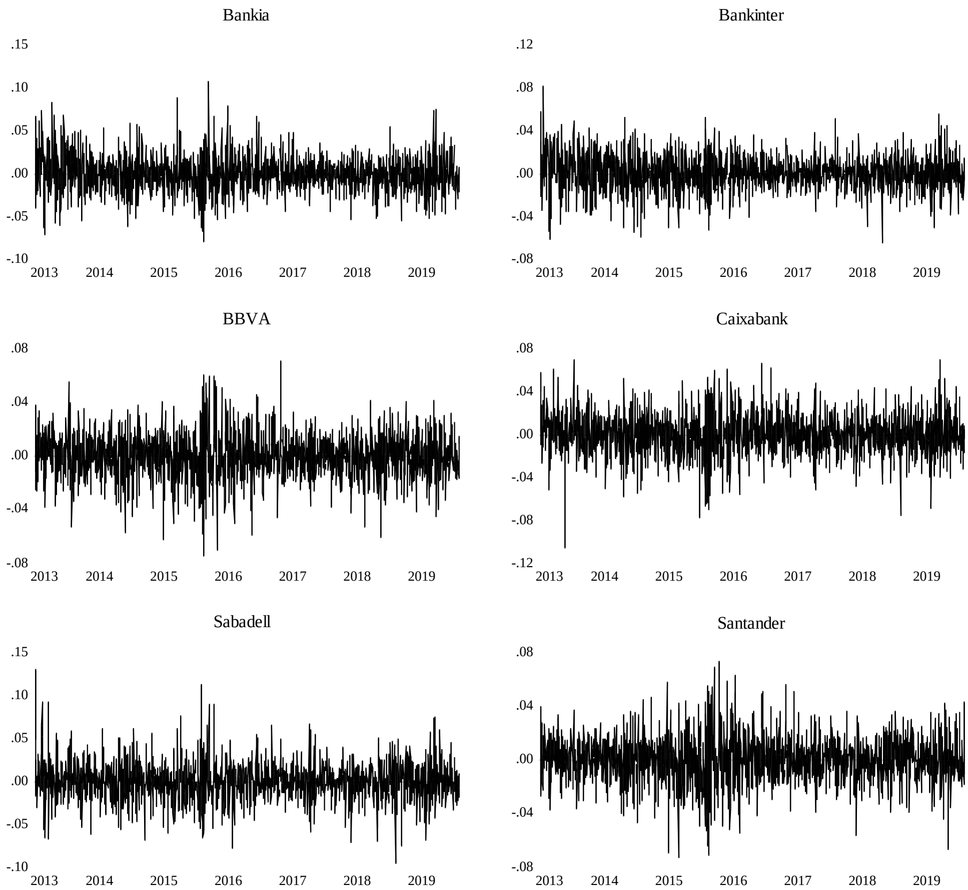

Figure 6.1.: Daily returns of Spanish bank stocks from 01/07/2013 to 30/01/2020.

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 and Perron (1988). A stationary time series is mean-reverting and has a finite variance that guarantees that the process will never drift too far away from the mean.

Table 6.4 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 6.4.: ADF Test, daily returns of Spanish bank stocks from 01/07/2013 to 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***

Source: Eviews 10 University Version.

Notes: *significant at level of 10%, **significant at level of 5%, *** significant at level of 1%

The BDS test by Brock, Scheinkman and Dechert was run to confirm the nonlinearity of the series as described in Brock and Dechert (1988) and Brock et al. (1996). The results (see Table 6.5) 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.

Table 6.5.: BDS Test, daily returns of Spanish incumbent bank stocks from 01/07/2013 to 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***

Source: Eviews 10 University Version.

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

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.

6.5 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 to 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:

Table 6.6.: GARCH-M GED for Spanish bank stocks from 01/07/2013 to 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%***

Source: Eviews 10 University Version.

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

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 6.6) 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 6.6). 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)) 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 & 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 6.6). 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 6.6). 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.

6.6 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 to 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. However, this paper is part of a research line and is merely a preliminary attempt to shed some light on the context and present the opportunity for future research directions.

7 Conclusions

This thesis delves into the intersection of technology and finance, focusing on how emerging technologies shape the landscape of financial assets risks and returns dynamics.

This thesis provides a number of contributions to the fields of financial economics and innovation. First, it investigates and demonstrate a significant relationship between emerging technologies and stock market dynamics. Second, it provides evidence that the impact of emerging technologies on the stock market varies depending on the stock market conditions. Third, it shows that the intensity of the impact also depends on the market circumstances reflected through volatility regimes. Previous three findings are shedding light on how emerging technological advancements impact stock market dynamics and investor behavior. Our analysis extends beyond traditional volatility patterns. We identify novel volatility regimes associated with emerging technologies. Moreover, we found that emerging technologies are providing new market opportunities, which entail novel volatility patterns that can be explored by investors and analysts.

The general objective of this thesis is to showcase and encourage investors and risk analysts to use emerging technologies tactically but also underscore the strategically importance to engage with market return and volatility.

Chapter 1 is the introduction to the thesis.

Chapter 2 presents a systematic review of the literature on the constellation of emerging technologies and asset return volatility, documenting several potential explanations for how emerging technologies drive stock volatility. Several specific features of emerging technologies are identified across the literature review, which are described as diffusive, persistent, heterogeneous, and momentum-oriented. The main conclusion of this chapter is that emerging technologies systemically increase stock return and stock return volatility driven by their inherent uncertain nature, the greater complexity to calculate fundamental values, over-enthusiastic and novice investors, and their idiosyncratic properties. The review of recent empirical evidence contributes to the technological innovation, economic and finance literature by providing a state of the art of the relationship between emerging technologies and asset returns and asset return volatility.

Chapter 3 shows how investors' expectations regarding emerging technologies are reflected across Exchange Traded Funds (ETFs), as a particular type of financial security. We investigate the relationship between idiosyncratic volatility and excess return among nine high-tech ETFs using daily data. Markov regime-switching (MRS) modeling involving time series analysis was deemed suitable for this study since idiosyncratic volatility and excess return series are not constant in time. The main finding is the negative relationship between idiosyncratic risk and return for the high-tech ETFs during the high volatility regime. However, this shifts to a positive relationship during the low volatility regime. These results suggest that idiosyncratic volatility matters in high-tech ETF pricing and can lead to under-diversification of portfolios. This chapter contributes to the idiosyncratic risk literature by showcasing a significant relationship between idiosyncratic risk and return, and it provides evidence that idiosyncratic risk is priced negatively or positively depending on volatility regimes in the context of an IT related environment. To diversify investment in the high-tech sector, idiosyncratic risk can play an important role in terms of managing idiosyncratic volatility and return, since the effects are not constant but driven by regimes, leading to changes across the two volatility regimes.

Chapter 4 delve into the time series properties of correlations, volatility clustering, spillover effects, and persistence concerning asset returns and emerging technology-related assets. Our investigation spans across the Spanish Banking sector, the broader Spanish Market, and the finance industry at the European Union (EU) level. The main findings show that developments in emerging technology are a relevant factor for capturing the level of risk in these markets, that emerging technology-related assets are highly integrated, and that volatility spillovers rise during periods of high volatility. The results also provide evidence that an overall market standpoint is more advisable for risk reduction purposes due to the diversified nature of its portfolio across industries. The findings shed light on the importance of considering sector, industry, and market specific features that need to be contemplated and can result in heterogeneous insights into the relationship between emerging technology phenomena and performance variables. The contribution of this study is a more in-depth analysis of opportunities and challenges related to FinTech and the banking industry in the past, present, and future.

Chapter 5 explores whether and how disruptive technology impacts banking stock returns under high volatility and low volatility regimes. The Spanish banking sector was used for this purpose and a classical CAPM was adapted into a two-factor model with heteroscedastic Markov switching regimes. The results indicate that disruptive technologies have an impact on Spanish banking stock returns and that the effects are volatility regime dependent. The impact of disruptive technology varies across volatility regimes, being positive in the high volatility regime and negative in the low volatility one. Additionally, we found that intensity depends on the market circumstances through volatility regimes, having a more significant influence under unfavorable market conditions and less influence under stable ones. 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.

Chapter 6 studies how incumbents banks are shocked by disruptive digital players like FinTech, which introduce disruption and value. Using the case of BIZUM, a real-time digital payment solution, its effect is analyzed on the volatility of the stock returns of Spanish incumbent banks. BIZUM was introduced in 2016 as a joint venture of the Spanish banking system to remain competitive in an increasingly disruptive FinTech Start-up environment. A GARCH-M GED approach was used to model the returns and volatility of those Spanish banks, 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 identify change in the stock price volatility of the incumbent banks, indicating that investors are not indifferent to the adoption of a disruptive technology, and that an impact of FinTech adoption by the incumbent banks led to a reduction in the volatility of their stock prices. 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 the next part, we present the extensions and future work derived from our contributions. Throughout our research process, we have encountered valuable suggestions for future investigations. The thesis has primarily focused on the introduction of emerging technologies, using quantitative approaches such as time series analysis and volatility modeling. To enhance the validity of our research phenomenon, we suggest that these quantitative methods should be complemented with further qualitative interviews. Specifically, we recommend conducting in-depth analyses to explore how emerging technologies are utilized in practice within organizations and to what extent. By doing so, we can explore the nuances of emerging technology adoption, revealing insights that quantitative data alone may not capture to thus contribute to a more comprehensive understanding of the dynamics surrounding emerging technologies in the organizational context.

It could also be of interest to apply various other statistical measures to observe the asset return volatility impact due to emerging technologies, such as the Mixed data sampling (MIDAS) regression methodology, which is commonly used to deal with time series data sampled at different frequencies and could provide alternatives to bridge the gap between long-term economic structures and short-term financial market behaviors to uncover the hidden connections regarding the impact of emerging technologies on market volatility. The credibility could be enhanced by using different methodological approaches to the phenomenon.

In order to generalize the results, we need to sample for a longer time period, and perhaps also broaden the scope to a more cross-sectional and cross-country perspective, in order to observe stock volatility in relationship to emerging technology.

Due to the increasing relevance of market contagion and market spillover, further elaboration in the context of market contagion driven by emerging technologies would be valuable, particularly from regulatory perspectives. Governments and regulators are adopting the tendency to mitigate the economic risks associated with emerging technology. The EU’s AI Act was the first comprehensive law on the matter, while the Markets in Crypto-Assets Act (MiCA), a landmark regulatory framework in the EU, is now a reality. An area we are currently onboarding is how the new regulatory requirements on emerging technology will impact market return and volatility and how the patterns identified in this thesis will be shaped by these additional factors. From an ethical and social implication perspective, this affects society in various areas of application. Governments need to promote research, development, and innovation by maximizing their societal benefits, as well as mitigating the potential risks.

Bibliography

Abdul-Baki, R. (2013). *Do information asymmetry proxies measure information asymmetry?* [Doctoral Thesis, Concordia University]. Concordia Spectrum Library. https://spectrum.library.concordia.ca/id/eprint/977533/4/FINAL_COPY_THESIS_pdf_a_1b_RGB.pdf.

Abdymomunov, A., & Morley, J. (2011). Time variation of CAPM betas across market volatility regimes. *Applied Financial Economics*, *21*(19), 1463–1478.

Aboody, D., & Lev, B. (2000). Information asymmetry, R&D, and insider gains. *The Journal of Finance*, 2000, *55*(6), 2747-2766.

Abrahamson, E., & Rosenkopf, L. (1997). Social network effects on the extent of innovation diffusion: A computer simulation. *Organization Science*, *8*(3), 289-309.

Abreu, D., & Brunnermeier, M. (2003). Bubbles and crashes. *Econometrica*, *71*, 173-204.

Abreu, D., & Markus K. B. (2002). Synchronization risk and delayed arbitrage. *Journal of Financial Economics*, *66*, 341-360.

Adner, R., & Kapoor, R. (2016). Innovation ecosystems and the pace of substitution: Re-examining technology S-curves. *Strategic Management Journal*, *37*(4), 625-648.

Agarwal, S., & Zhang, J. (2020). FinTech, lending and payment innovation: A review. *Asia-Pacific Journal of Financial Studies*, *49*(3), 353-367.

Aggarwal, V.A., & Hsu, D. H. (2014). Entrepreneurial exits and innovation. *Management Science*, 60(4), 867-887.

Agrawal, D., Bharath, S. T., & Viswanathan, S. (2004). Technological change and stock return volatility: Evidence from eCommerce adoptions. *Available at SSRN 387543*.

Ahmed, M. S., & Alhadab, M. (2020). Momentum, asymmetric volatility and idiosyncratic risk-momentum relation: Does technology-sector matter?. *The Quarterly Review of Economics and Finance*, *78*, 355-371.

Ahuja, G., & Morris Lampert, C. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic management journal*, *22*(6-7), 521-543.

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In B. N. Petrov & F. Csáki (Eds.), *2nd international symposium on information theory* (267–281). Budapest, Hungary: Akadémia Kiadó.

Akyildirim, E., Corbet, S., Lucey, B., & Sensoy, A. (2020a). The relationship between implied volatility and cryptocurrency returns. *Finance Research Letters, 33,* 101212.

Akyildirim, E., Corbet, S., Sensoy, A., & Yarovaya, L. (2020b). The impact of blockchain related name changes on corporate performance. *Journal of Corporate Finance, 65*, 101759.

Alfranca, O., Rama, R., & von Tunzelmann, N. (2002). A patent analysis of global food and beverage firms: the persistence of innovation. Agribusiness: *An International Journal, 18*(3), 349-368.

Allen, F. (2012). Trends in financial innovation and their welfare impact: an overview. *European Financial Management, 18*(4), 493-514.

Anderson, A. (1787). *An Historical and chronological deduction of the Origin of Commerce* (Vol. 1). Walter.

Anderson, P., & Tushman, M. L. (2018). Technological discontinuities and dominant designs: A cyclical model of technological change. In *Organizational innovation* (pp. 373-402). Routledge.

Andersson, K., & Styf, A. (2020). *Blockchain Technology & Volatility of Stock Returns: A Quantitative Study that Examines Blockchain Technology's Impact on Volatility in Swedish Stocks*. [Master Thesis, Umeå School of Business, Economics & Statistics]. Diva portal Org.https://www.diva-portal.org/smash/get/diva2:1445361/FULLTEXT01.pdf.

Duqi, A., Jaafar, A., & Torluccio, G. (2015). Mispricing and risk of R&D investment in European *firms*. *The European Journal of Finance*, *21*(5), 444-465.

Ang, A., & Bekaert, G. (2004). How regimes affect asset allocation. *Financial Analysts Journal*, *60*(2), 86-99.

Ang, A., & Timmermann, A. (2012). Regime changes and financial markets. *Annual Review of Financial Economics, 4*(1), 313–337.

Ang, A., Hodrick, R., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance, 61*(1), 259-299.

Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2009). High idiosyncratic volatility and low returns: International and further US evidence. *Journal of Financial Economics*, *91*(1), 1-23.

Angelidis, T. (2010). Idiosyncratic risk in emerging markets. *Financial Review*, *45*(4), 1053-1078.

Anginer, D., Demirguc-Kunt, A., & Zhu, M. (2014). How does deposit insurance affect bank risk? Evidence from the recent crisis. *Journal of Banking &Ffinance*, *48*, 312-321.

Apergis, N., & Andreas, L. A. K. E. (2010). Credit default swaps and stock prices: Further evidence of mean and volatility transmission using a GARCH-M model. *China-USA Business Review, 9*(11), 1-22.

Arce, O., Mayordomo, S., & Peña, J. I. (2013). Credit-risk valuation in the sovereign CDS and bonds markets: Evidence from the euro area crisis. *Journal of International Money and Finance, 35*, 124-145.

Arenas, L. (14 de November de 2019). Impact of emerging technologies in banking and finance in Europe. A time series approach for volatility clustering and spillover effects. Barcelona, Spain: *International workshop for the Innovation, Complexity and Uncertainty*.

Arenas, L. (19 de November de 2020). Regime Switching on High-Tech ETFs: Expected Return, Idiosyncratic Volatility, and Momentum. Paper presentation. Barcelona, Spain: *International Congress (AMSE)*.

Arenas, L. (28 de October de 2021). Emerging technologies and stock market volatility: A mini review. Paper presentation. Sidney, Australia: *Innovation and Sustainability (ICONIS)*.

Arenas, L. (27 de March de 2021). How the emerging technologies and stock markets came into play with the COVID-19 pandemic: A Range-Based GARCH approach. Virtual*: Robotics and Artificial Intelligence Virtual Congress*.

Arenas, L. (3 de December de 2021). The impact of disruptive technologies on European banking under different volatility regimes. Paper presentation. Beijing, China. *International Symposium on Automation, Information and Computing*.

Arenas, L. (23 de March de 2023). FinTech impacting stock markets: BIZUM paper presentation at the *2nd Global Summit on Applied Science, Engineering and Technology*. Rome, Italy.

Arenas, L., & Gil Lafuente, A. M. (2021a). Regime Switching in High-Tech ETFs: Idiosyncratic Volatility and Return. *Mathematics, 9*(7), 742.

Arenas, L., & Gil Lafuente, A. M. (2021b). Impact of emerging technologies in banking and finance in Europe: A volatility spillover and contagion approach. *Journal of Intelligent and Fuzzy Systems, 40*(2), 1903-1919.

Arenas, L., & Gil Lafuente, A. M. (2022). *Tecnología disruptive y banca española: Un enfoque de conmutación de regímenes de volatilidad*. En Economía, Empresa, Contabilidad y Sociedad. Barcelona: 006448 - Librería Universitaria S.L., Barcelona.

Arenas, L., & Gil Lafuente, A. M. (2023). *The Rubik's Cube of Emerging Technologies and Stock Volatility*. En Innovation and Sustainability in Governments and Companies: A Perspective to the New Realities (págs. 221-264). River Publishers.

Arenas, L., Alvarez Carrillo, P., Muñoz Palma, M., & León-Castro, E. (2022). A Multicriteria hierarchical approach to ESG Investment Location Choice: Evidence from Latin America. Paper presentation. Barcelona, Spain. *International Congress of Innovation and Sustainability ICONIS.*

Arenas, L., Gil Lafuente, A., & Reverter, J. (2023). The impact of disruptive technology on banking under switching volatility regimes. *Technological and Economic Development of Economy, 29*(4), 1264-1290.

Arenas, L., Muñoz, M., Anselmo, P., & Gil Lafuente, A. M (2023). *Multicriteria Hierarchical Approach to Investment Location Choice*. In In Artificial Intelligence in Control and Decision-making Systems: Dedicated to Professor Janusz Kacprzyk (305-324). Springer Nature Switzerland.

Arghyrou, M. G., & Kontonikas, A. (2012). The EMU sovereign-debt crisis: Fundamentals, expectations and contagion. Journal of International Financial Markets*, Institutions and Money, 22*(4), 658–677. https://doi.org/10.1016/j.intfin.2012.03.003.

Arthur, W. B. (1996). Increasing returns and the new world of business. *Harvard Business Review, 74*(4), 100-109.

Arthur, W. B. (2010). *The nature of technology: What it is and how it evolves*. Penguin UK.

Asmarani, S. C., & Wijaya, C. (2020). Effects of FinTech on stock return: Evidence from retail banks listed in Indonesia stock exchange. *The Journal of Asian Finance, Economics and Business*, *7*(7), 95-104.

Augustin, P., Subrahmanyam, M. G., Tang, D. Y., & Wang, S. Q. (2014). Credit default swaps: A survey. *Foundations and trends® in Finance*, *9*(1–2), 1-196.

Augustin, P., Subrahmanyam, M. G., Tang, D. Y., & Wang, S. Q. (2016). Credit default swaps: Past, present, and future. *Annual Review of Financial Economics, 8*, 175-196.

Aunon-Nerin, D., Cossin, D., Hricko, T., & Huang, Z. (2002). Exploring for the determinants of credit risk in credit default swap transaction data: Is fixed-income markets' information sufficient to evaluate credit risk?. *FAME Research Paper*, (65).

Axtell, R. L. (2001). Zipf distribution of US firm sizes. *science*, *293*(5536), 1818-1820.

Ba, S., Lisic, L. L., Liu, Q., & Stallaert, J. (2013). Stock market reaction to green vehicle innovation. *Production and Operations Management*, *22*(4), 976-990.

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, *151*, 103745.

Badi, M., Dab, S., Drummond, A., Malhotra, S., Muxí, F., Peeters, M., Roongta P., Strauß M. & Sénant, Y. (2018, October 18). *Global Payments 2018: Reimagining the Customer Experience.* BCG. https://www.bcg.com/publications/2018/global-payments-reimagining-customer-experience.

Baek, C., & Elbeck, N. (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters, 22*(1), 30-34.

Baele, L., De Jonghe, O., & Vander Vennet, R. (2007). Does the stock market value bank diversification?. *Journal of Banking & Finance*, *31*(7), 1999-2023.

Bagella, M., Becchetti, L., & Adriani, F. (2005). Observed and "fundamental" price–earning ratios: A comparative analysis of high-tech stock evaluation in the US and in Europe. *Journal of International Money and Finance*, *24*(4), 549-581.

Bajpai, N. (2011). *Business research methods*. Pearson Education India.

Bakker, S. (2010). The car industry and the blow-out of the hydrogen hype. *Energy Policy, 38*(11), 6540-6544.

Bali, T. G., & Cakici, N. (2008). Idiosyncratic volatility and the cross section of expected returns. *Journal of Financial and Quantitative Analysis*, *43*(1), 29-58.

Bali, T. G., Cakici, N., & Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, *99*(2), 427-446.

Banc Sabadell. (2022, November 3). *Datos Financieros 2022 3T*. https://www.grupbancsabadell.com/corp/es/accionistas-e-inversores/informacion-economico-financiera.html.

Bankinter. (2022, November 3). *Bankinter incrementa un 21,2% el beneficio recurrente en el tercer trimestre de 2022*. https://www.bankinter.com/blog/noticias-bankinter/resultados-bankinter-3t2022.

Barber, B. M., & Odean, T. (2000). Trading is hazardous to your wealth: The common stock investment performance of individual investors. *The journal of Finance*, *55*(2), 773-806.

Barberis, N., Shleifer, A., & Vishny, R. (1998). A model of investor sentiment. *Journal of Financial Economics*, *49*(3), 307-343.

Barron, O.E., Byard, D., Kile, C., & Riedl, E. J. (2002). High-technology intangibles and analysts' forecasts. *Journal of Accounting Research, 40*(2), 289-312.

Bartholomew, S. (1997). National systems of biotechnology innovation: complex interdependence in the global system. *Journal of International Business Studies, 28*(2), 241-266.

Basalla, G. (1988). *The evolution of technology*. Cambridge University Press, Cambridge.

Bathia, D., & Bredin, D. (2018). Investor sentiment: does it augment the performance of asset pricing models?. *International Review of Financial Analysis*, *59*, 290-303.

BBVA. (2022, November 3). *Datos Básicos*. https: https://www.bbva.com/es/informacion-corporativa/#datos-basicos.

Begley, T. A., Purnanandam, A., & Zheng, K. (2017). The strategic underreporting of bank risk. The *Review of Financial Studies, 30*(10), 3376–3415.

Benartzi, S., & Thaler, R. H. (2001). Naive diversification strategies in defined contribution saving plans. *American Economic Review*, *91*(1), 79-98.

Ben-David, I., Franzoni, F., & Moussawi, R. (2014). *Do ETFs increase volatility?* (No. w20071). National Bureau of Economic Research.

Ben-David, I., Franzoni, F., & Moussawi, R. (2011). *ETFs, arbitrage, and contagion*. Geneva: University of Geneva.

Benner, M. J., & Ranganathan, R. (2013). Divergent reactions to convergent strategies: Investor beliefs and analyst reactions during technological change. *Organization Science*, *24*(2), 378-394.

Benner, M. J. (2007). The incumbent discount: Stock market categories and response to radical technological change. *Academy of Management Review*, *32*(3), 703-720.

Bennett, R. L., Güntay, L., and Unal, H. (2015). Inside debt, bank default risk, and performance during the crisis. *Journal of Financial Intermediation, 24*(4), 487–513.

Berente, N., Lee, J., Potts, A., & Srinivasan, N. (2020). Do" Digital" Firms Live Longer as Fields Converge? A Survival Analysis of the S&P 500. In *AMCIS*.

Berg, S., Wustmans, M., & Bröring, S. (2019). Identifying first signals of emerging dominance in a technological innovation system: A novel approach based on patents, *Technological Forecasting and Social Change*, 146, 706-722.

Berman, E., Bound, J., & Machin, S. (1998). Implications of skill-biased technological change: international evidence. *The quarterly journal of economics*, *113*(4), 1245-1279.

Bigelow, J. (1829). *Elements of technology: taken chiefly from a course of lectures delivered at Cambridge, on the application of the sciences to the useful arts: now published for the use of seminaries and students*. Hilliard, Gray, Little and Wilkins.

Bitterly, T. B. (2023). Unpredictable volatility and trust: The VISA model of person perception. *Current Opinion in Psychology,* 101718.

Black, F. (1972). Capital market equilibrium with restricted borrowing. *The Journal of business*, *45*(3), 444-455.

Black, F., & Scholes, M. (1972). The valuation of option contracts and a test of market efficiency. *The Journal of Finance, 27*(2), 399-417.

Blanco, R., Brennan, S., and Marsh, I. W. (2004). An empirical analysis of the dynamic relationship between investment grade bonds and credit default swaps.

Blanco-Oliver, A. (2021). Banking reforms and bank efficiency: Evidence for the collapse of Spanish savings banks. International Review of Economics & Finance, 74, 334–347. https://doi.org/10.1016/j.iref.2021.03.015

Blaze Trends. (2022, January 17). *Bizum exceeds 19 million users in 2021*. retrieved form: https://blazetrends.com/bizum-exceeds-19-million-users-in-2021/.

Blazenko, G.W. (1987). Managerial preference, asymmetric information, and financial structure. *The Journal of Finance, 42*(4), 839-862.

Bloomberg. (2021, December 30). Bloomberg Professional.

BME. (2021, January 27). Market Data.

Bocquet, R.B. (2007). Complementarities in organizational design and the diffusion of information technologies: An empirical analysis. *Research Policy, 36*(3), 367-386.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327.

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. *The review of economics and statistics*, 542-547.

Boon, W., and Moors, E. (2008). Exploring emerging technologies using metaphors–a study of orphan drugs and pharmacogenomics. Social science & medicine, 66(9), 1915-1927.

Borah, N., Pan, L., Chul Park, J., & Shao, N. (2018). Does corporate diversification reduce value in high technology firms? *Review of Quantitative Finance and Accounting, 51*(3), 683-718.

Bovi, M. (2009). Economic versus psychological forecasting. Evidence from consumer confidence surveys. *Journal of Economic Psychology, 30*(4), 563-574.

Bower, J. L., & Christensen, C. M. (1995). Disruptive technologies: catching the wave. *Harward Business Review, 73*(1), 43-53.

Boyer, B., Mitton, T., & Vorkink, K. (2010). Expected idiosyncratic skewness. *The Review of Financial Studies*, *23*(1), 169-202.

Bresnahan, T.F., Brynolfsson, E., Hitt, L.M. (2002). Information Technology, Workplace Organisation and the Demand for Skilled Labour; Firm-Level evidence. *Quarterly Journal of Economics, 117*, 339-376.

Brey, P. (2009). *Philosophy of technology meets social constructivism: A Shopper's guide*. In David M. Kaplan 8Ed), Readings in the Philosophy of Technology, Lanham: Rowman & Littlefield Publishers.

Brock, W., & Dechert, W. (1988). A General Class of Specification Tests: The Scalar Case. *Business and Economics Statistics Section of the Proceedings of the American Statistical Society*, 70-79.

Brock, W., Scheinkman, J., Dechert, W., & LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric reviews*, *15*(3), 197-235.

Brockman, P.; Yan, X. S. (2008). The Time-Series Behavior and Pricing of Idiosyncratic Volatility: Evidence from 1926–1962. *Available at SSRN 1117284*.

Brooks, C., & Katsaris, A. (2003). Rational speculative bubbles: an empirical investigation of the London Stock Exchange. *Bulletin of Economic Research, 55*(4), 319-346.

Brooks, R. D., Faff, R. W., McKenzie, M. D., & Mitchell, H. (2000). A multi-country study of power ARCH models and national stock market returns. *Journal of International money and Finance*, *19*(3), 377-397.

Brown, D. P., & Ferreira, M. A. (2004). Information in the idiosyncratic volatility of small firms. *Available at SSRN 475401*.

Brown, J.R., Martinsson, G., & Petersen, B.C. (2017). Stock markets, credit markets, and technology-led growth. *Journal of Financial Intermediation, 32*, 45-59.

Brown, R. L., Durbin, J., and Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society: Series B (Methodological), 37*(2), 149–163.

Brunnermeier, M., and Nagel, S. (2004). Hedge funds and the technology bubble. *The journal of Finance, 59*(5), 2013-2040.

Bryman, A. (2016). *Social research methods*. Oxford university press.

Brynjolfsson, E., & Hitt, L.M. (2000). Beyond Computation: Information Technology, Organizational Transformation and Business Performance. *Journal of Economics Perspective, 14*(4), 23-48.

Brynjolfsson, E., & Hitt, L.M. (2003). Computing Productivity: Firm-level Evidence. Review of *Economics and Statistics, 85*(4), 793-808.

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox. *The economics of artificial intelligence: An agenda*, *23*, 23-57.

Buchak, G., Matvos, G., Piskorski, T., & Seru, A. (2018). FinTech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics, 130*(3), 453-483.

Caixabank. (2022, November 3). *Principales datos*. https: https://www.caixabank.com/es/sobre-nosotros/nuestro-negocio/principales-datos.html.

Cambridge Dictionary. (2023, January 1). https://dictionary.cambridge.org/dictionary/english/tactic.

Campanella, F., Della Peruta, M. R., & Del Giudice, M. (2017). The effects of technological innovation on the banking sector. *Journal of the Knowledge Economy, 8*(1), 356-368.

Campbell, J. Y., & Shiller, R. J. (1988). Stock prices, earnings, and expected dividends. *The Journal of Finance, 43*(3), 661-676.

Campbell, J.Y., Lettau, M., Malkiel, B. G., & Xu, Y. (2001). Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *The Journal of Finance, 56*(1), 1-43.

Cao, C., Timothy, S., & Zhao, J. (2008). Can growth options explain the trend in idiosyncratic risk?. *The Review of Financial Studies, 21*(6), 2599-2633.

Capelle-Blancard, G., & Raymond, H. (2004). Empirical evidence on periodically collapsing stock price bubbles. *Applied Economics Letters, 11*(1), 61-69.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance, 52*(1), 57–82.

Castellacci, F. (2008). Innovation and the competitiveness of industries: Comparing the mainstream and the evolutionary approaches. *Technological Forecasting and Social Change, 75*(7), 984-1006.

CBOE. (28 de May de 2023). Cboe VIX FAQ," Select "How is the VIX Index calculated?". https://www.cboe.com/tradable_products/vix/faqs/.

Cefis, E. (2003). Is there persistence in innovative activities*? International Journal of Industrial Organization, 21*(4), 489-515.

Chan, L.K., Lakonishok, J., & Sougiannis, T. (2001). The stock market valuation of research and development expenditures. *The Journal of Finance, 56*(6), 2431-2456.

Chang, C. L., & McAleer, M. (2019). The fiction of full BEKK: Pricing fossil fuels and carbon emissions. *Available at SSRN 3135899.*

Chang, C. L., Li, Y., & McAleer, M. (2018). Volatility spillovers between energy and agricultural markets: A critical appraisal of theory and practice. *Energies*, *11*(6), 1595.

Chang, C. L., McAleer, M., and Zuo, G. (2017). Volatility spillovers and causality of carbon emissions, oil and coal spot and futures for the EU and USA. *Sustainability, 9*(10), 1789.

Chen, B., Yang, X., & Ma, Z. (2022). FinTech and financial risks of systemically important commercial banks in China: An inverted u-shaped relationship. *Sustainability, 14*(10), 5912.

Chen, J., & Kawaguchi, Y. (2018). Multi-factor asset-pricing models under markov regime switches: Evidence from the Chinese stock market. *International Journal of Financial Studies, 6*(2), 54.

Chen, W., & Srinivasan, S. (2023). Going digital: Implications for firm value and performance. *Review of Accounting Studies*, 1-47.

Cheng, M., & Qu, Y. (2020). Does bank FinTech reduce credit risk? Evidence from China. *Pacific-Basin Finance Journal*, *63*, 101398.

Christensen, C. M. (1992). Exploring the limits of the technology S-curve. Part I: component technologies. *Production and Operations Management, 1*(4), 334-357.

Christensen, C. M. (1997). The innovator’s dilemma. Harvard Business School Press. *Boston, MA*.

Christensen, C. M. (2003). The innovator's solution: creating and sustaining successful growth. Harvard Business Press.

Christensen, C. M. (2015). What is disruptive innovation? *Harvard Business Review, 93*(12), 44-53.

Christensen, C. M., & Overdorf, M. (2000). Meeting the challenge of disruptive change. *Harvard business review, 78*(2), 66-77.

Christensen, C. M., Verlinden, M., & Westerman, G. (2002). Disruption, disintegration and the dissipation of differentiability. *Industrial and Corporate Change, 11*(5), 955-993.

Chua, C. T., Goh, J., & Zhang, Z. (2006). Idiosyncratic volatility matters for the cross-section of returns-in more ways than one. *Unpublished working paper, Singapore Management University*.

Ciarli, T., Kenney, M., Massini, S., & Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, *50*(7), 104289.

Coccia, M. (2019). What is technology and technology change? A new conception with systemic-purposeful perspective for technology analysis. *Journal of Social and Administrative Sciences*, *6*(3), 145-169.

Coakley, J., & Fuertes, A.-M. (2006). Valuation ratios and price deviations from fundamentals. *Journal of Banking & Finance, 30*(8), 2325-2346.

Cochrane, J. H. (2011). Presidential address: Discount rates. *The Journal of Finance, 66*(4), 1047-1108.

Coeckelbergh, M. (2016). *Money machines: Electronic financial technologies, distancing, and responsibility in global finance*. Routledge.

Cohen, W. M., & Levinthal, D. A. (1989). Innovation and learning: the two faces of R & D. *The Economic Journal, 99*(397), 569-596.

Collin-Dufresn, P., Goldstein, R. S., and Martin, J. S. (2001). The determinants of credit spread changes. *The Journal of Finance, 56*(6), 2177-2207.

Collis, J., and Hussey, R. (2014). Writing up the Research. In Business Research, 197-330.

Comin, D. (2009). On the integration of growth and business cycles. *Empirica, 36*(2), 165/176.

Cooper, A., and Smith, C. (1992). How established firms respond to threatening technologies. *Academy of Management Perspectives, 6*(2), 55-70.

Cooper, M., Dimitrov, O., and Rau, P. (2001). A rose. com by any other name. *The Journal of Finance, 56*(6), 2371-2388.

Corbet, S. (2021). Understanding elevated operational and reputational risks through the corporate usage of cryptocurrency. *Understanding cryptocurrency fraud: The challenges and headwinds to regulate digital currencies*, *2,* 159.

Cozzens, S., Gatchair, S., Kang, J., Kim, K. S., Lee, H. J., Ordóñez, G., & Porter, A. (2010). Emerging technologies: quantitative identification and measurement. *Technology Analysis & Strategic Management, 22*(3), 361-376.

Crombez, J. (2001). Momentum, rational agents and efficient markets. *The Journal of Psychology and Financial Markets, 2*(4), 190-200.

Crotty, M. J. (1998). The foundations of social research: Meaning and perspective in the research process. *The foundations of social research*, 1-256.

Daniel, K. D., Hirshleifer, D.A., & Subrahmanyam, A. (1997). A theory of overconfidence, self-attribution, and security market under-and over-reactions. Self-Attribution, and Security Market Under-and Over-Reactions.

Danneels, E. (2004). Disruptive technology reconsidered: a critique and research agenda. *Journal of Product Innovation Management, 21*(4), 246-258.

Darby, M. R., Liu, Q., & Zucker, L. G. (2004). High stakes in high technology: High-tech market values as options. *Economic Inquiry*, *42*(3), 351-369.

Daud, S. N. M., Khalid, A., & Azman-Saini, W. N. W. (2022). FinTech and financial stability: Threat or opportunity?. *Finance Research Letters*, *47*, 102667.

Davies, S. (1979). *The diffusion of process innovations*. CUP Archive.

Day, G., & Schoemaker, P. (2000). Avoiding the pitfalls of emerging technologies. *California Management Review, 42*(2), 8-33.

Dell'Acqua, A., Perrini, F., and Caselli, S. (2010). Conference calls and stock price volatility in the post-reg FD era. *European Financial Management, 16*(2), 256-270.

Demirel, P., & Mazzucato, M. (2013). Innovation and economic performance (industrial and financial): Recent results and questions for future research. In *Innovation and finance* (pp. 46-68). Routledge.

Demirer, M., Diebold, F. X., Liu, L., and Yilmaz, K. (2018). Estimating global bank network connectedness. *Journal of Applied Econometrics, 33*(1), 1-15.

Di Iorio, A., & Liu, B. Idiosyncratic Volatility and Momentum: The Performance of Australian Equity Pension Funds. 2015. Annual Meetings, 1-30. Amsterdam, Netherlands: European Financial Management Association.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica: Journal of the Econometric Society*, 1057-1072.

Domanski, D. (2003). *Idiosyncratic Risk in the 1990s: Is it an IT Story?* (No. 2003/07). WIDER Discussion Paper.

Dosi, G. (1982). Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. Research policy, 11(3), 147-162.

Dosi, G. (1988). Sources procedures and microeconomic effects of innovation. *Journal of Economic Literature*, 26(3), 1120-1171.

Dosi, G. (1995). Learning, market selection and the evolution of industrial structures. *Small Business Economics, 7*(6), 411-436.

Dosi, G. (2005). *Statistical regularities in the evolution of industries: a guide through some evidence and challenges for the theory* (No. 2005/17). LEM working paper series.

Dou, P. Y., Gallagher, D. R., Schneider, D., and Walter, T. S. (2014). Cross-region and cross-sector asset allocation with regimes. *Accounting & Finance, 54*(3), 809-846.

Dranev, Y., Frolova, K., & Ochirova, E. (2019). The impact of fintech M&A on stock returns. *Research in International Business and Finance*, *48,* 353-364.

Duqi, A., Jaafar, A., & Torluccio, G. (2015). Mispricing and risk of R&D investment in European firms. *The European Journal of Finance*, *21*(5), 444-465.

El Confidencial. (2022, October 30). *A la desesperada: 27 bancos españoles lanzan una 'FinTech' para luchar con internet*. https:// https://www.elconfidencial.com/tecnologia/2016-08-04/banca-FinTech-pago-movil-bizum_1241535.

El Pais. (2022, November 3). *Arranca la nueva CaixaBank, el mayor banco de España*. https://cincodias.elpais.com/cincodias/2021/03/25/companias/1616697188_648039.html.

Ellul, J. (1964). The technological society (J. Wilkinson, Trans., pp. 133-143).

Elyasiana, E., & Mansur, I., (1998). Sensitivity of the bank stock returns distribution to changes in the level and volatility of interest rate: A GARCH-M model. *Journal of Banking and Finanance, 22*(5); 535-563.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.

Engle, R. (2004). Risk and volatility: Econometric models and financial practice. *American Economic Review, 94*(3), 405-420.

Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. *Econometric theory*, *11*(1), 122-150.

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. *Econometric reviews*, *5*(1), 1-50.

Engle, R. F., Lilien, D. M., & Robins, R. P. (1987). Estimating time varying risk premia in the term structure: The ARCH-M model. *Econometrica: journal of the Econometric Society*, 391-407.

European Central Bank. (2019, December). *Innovation and its impact on the European retail payment landscape*. Note by the ECB for the Economic and Financial Affairs Council. https://www.ecb.europa.eu/pub/pdf/other/ecb.other191204~f6a84c14a7.en.pdf.

European Central Bank. (2021, December 30). Statistical Data Warehouse. https://sdw.ecb.europa.eu/

European Commission. (2021, January 7). *Future & Emerging Technologies*. Futurium. https://ec.europa.eu/futurium/en/content/fet-flagships.html.

Falkenstein, E. G. (1996). Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *The Journal of Finance, 51*(1), 111-135.

Fama, E. F. (1965). The behavior of stock-market prices. *The Journal of Business, 38*(1), 34-105.

Fama, E. F., and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010.

Fama, E., and French, K. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*, 427–465.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics, 33*, 3-56.

Fama, E., & French, K. (1996). Multifactor explanations of asset pricing anomalies. *The Journal of Finance, 51*, 55-84.

Fan, S., Lau, R. Y., & Leon, Z.J. (2015). Demystifying big data analytics for business intelligence through the lens of marketing mix. *Big Data Research, 2*(1), 28-32.

Federal Reserve Bank of St. Louis. (2021, August 15). 3-Month Treasury Bill Secondary Market Rate, Discount Basis. https://fred.stlouisfed.org/series/TB3MS.

Feldstein, M. (2015). The US underestimates growth. *Wall Street Journal*, *18*(2015), 105-128.

Ferrari, R. (2016). FinTech impact on retail banking–from a universal banking model to banking verticalization. *The FinTech book: The financial technology handbook for investors, entrepreneurs and visionaries*, 248-252.

Ferreira, J. J., Fernandes, C. I., & Ferreira, F. A. (2019). To be or not to be digital, that is the question: Firm innovation and performance. *Journal of Business research*, *101*, 583-590.

Fichman, R. G. (2000). The diffusion and assimilation of information technology innovations. *Framing the domains of IT management: Projecting the future through the past*, *105127*, 105-128.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management science*, *47*(1), 117-132.

Fornari, F.; and Pericoli, (2001). M. Characteristics of Stock Prices in TMT and Traditional Sectors. Banca d'Italia Temi Discuss (unpublished).

Foster, R. (1986). Innovation: The Attacker's Advantage. Summit Books New York.

Freeman, C. (1995). The 'National System of Innovation'in historical perspective. *Cambridge Journal of Economics, 19*(1), 5-24.

Freeman C., & Soete L. (1987). *Technical Change and Full Employment*, Basil Blackwell, Oxford, UK.

Freeman, C. (2013). Economics of industrial innovation. Routledge.

Frehen, R. G., Goetzmann, W. N., & Rouwenhorst, K. G. (2013). New evidence on the first financial bubble. *Journal of Financial Economics*, *108*(3), 585-607.

Friedman, M. (1953). The case for flexible exchange rates. *Essays in positive economics*, *157*(203), 33.

Frizzo-Barker, J., Chow-White, P. A., Adams, P. R., Mentanko, J., Ha, D., & Green, S. (2020). Blockchain as a disruptive technology for business: A systematic review. *International Journal of Information Management*, *51*, 102029.

Froot, K., & Obstfeld, M. (1991). Intrinsec bubble: the case of stock prices. *American Economic Review, 81*, 1189-1217.

Fu, F. (2009). Idiosyncratic risk and the cross-section of expected stock returns. *Journal of financial Economics*, *91*(1), 24-37.

Fudenberg, D., Tirole, J. (1985). Preemption and rent equalization in the adoption of new technology. *The Review of Economic Studies, 52*(3), 383-401.

Fung, D. W., Lee, W. Y., Yeh, J. J., & Yuen, F. L. (2020). Friend or foe: The divergent effects of FinTech on financial stability. *Emerging Markets Review*, *45*, 100727.

Gallagher, L. A., and Taylor, M. P. (2001). Risky arbitrage, limits of arbitrage, and nonlinear adjustment in the dividend-price ratio. *Economic Inquiry, 39*(4), 524-536.

Gao, Y., Zhang, C., & Zhang, L. (2012). Comparison of GARCH Models based on Different Distributions. *J. Comput.*, *7*(8), 1967-1973.

Garud, R.R., & Gehman, J. (2012). Metatheoretical perspectives on sustainability journeys: Evolutionary, relational and durational. *Research Policy, 41*(6), 980-995.

Geels, F., & Raven, R. (2006). Non-linearity and expectations in niche-development trajectories: ups and downs in Dutch biogas development (1973–2003). *Technology Analysis & Strategic Management*, *18*(3-4), 375-392.

Gharbi, S., Sahut, J.-M., & Teulon, F. (2014). R&D investments and high-tech firms' stock return volatility. *Technological Forecasting and Social Change*, 88, 306-312.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). Bitcoin-asset or currency? revealing users' hidden intentions. *Revealing Users' Hidden Intentions (April 15, 2014). ECIS*.

Glosten, L., Jagannathan, R., & Runkle, D. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779-1801.

Goffman, W., & Newill, V. (1964). Generalization of epidemic theory. *Nature, 204*(4955), 225-228.

Gold, B., Peirce, W.S., & Rosegger, G. (1970). Diffusion of major technological innovations in US iron and steel manufacturing. *The Journal of Industrial Economics*, 218-241.

Goldfarb, B., & Kirsch, D.A. (2019). *Bubbles and crashes: The boom and bust of technological innovation*. Stanford University Press.

Goldfeld, S. M., & Quandt, R. E. (1973). A Markov model for switching regressions. *Journal of Econometrics, 1*(1), 3-15.

Gompers, P., & Lerner, J. (2003). Short-term America revisited? Boom and bust in the venture capital industry and the impact on innovation. *Innovation policy and the economy*, *3*, 1-27.

Goyal, A., & Santa-Clara, P. (2003). Idiosyncratic risk matters!. *The journal of finance*, *58*(3), 975-1007.

Gray, S. F. (1996). Modeling the conditional distribution of interest rates as a regime-switching process. *Journal of financial economics*, *42*(1), 27-62.

Greenan, N., & Guellec, D. (1998). Firm organization, technology and performance: an empirical study. *Economics of Innovation and New Technology*, *6*(4), 313-347.

Greenwood, J., and Jovanovic, B. (1999). The information-technology revolution and the stock market. *American Economic Review, 89*(2), 116-122.

Greenwood, R., and Nagel, S. (2009). Inexperienced investors and bubbles. *Journal of Financial Economics, 93*(2), 239-258.

Griffin, J. M., Harris, J. H., Shu, T., & Topaloglu, S. (2011). Who drove and burst the tech bubble?. *The Journal of Finance*, *66*(4), 1251-1290.

Griliches, Z. (1975). Hybrid corn: an exploration in the economics of technological change. *Econometrica, 48*, 501-522.

Grübler, A. (1991). Diffusion: long-term patterns and discontinuities. In Diffusion of technologies and social behavior. Berlin, Heidelberg.: Springer.

Gu, F., & Li, J. Q. (2007). The credibility of voluntary disclosure and insider stock transactions. *Journal of Accounting Research, 45*(4), 771-810.

Gu, F., & Wang, W. (2005). Intangible assets, information complexity, and analysts' earnings forecasts. *Journal of Business Finance & Accounting, 32*(9-10), 1673-1702.

Guidolin, M., & Timmermann, A. (2008). International asset allocation under regime switching, skew, and kurtosis preferences. *The Review of Financial Studies*, *21*(2), 889-935.

Guo, Y., and Liang, C. (2016). Blockchain application and outlook in the banking industry. *Financial Innovation, 2*(1), 24.

Halaweh, M. (2013). Emerging technology: What is it. *Journal of technology management & innovation*, *8*(3), 108-115.

Hall, B. H. (2002). The financing of research and development. *Oxford review of economic policy*, *18*(1), 35-51.

Hall, B. H., & Rosenberg, N. (Eds.). (2010). *Handbook of the Economics of Innovation*. Elsevier.

Hamao, Y., Mei, J., & Xu, Y. (2003). Idiosyncratic risk and the creative destruction in Japan.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the econometric society*, 357-384.

Han, Y., & Lesmond, D. (2011). Liquidity biases and the pricing of cross-sectional idiosyncratic volatility. *The Review of Financial Studies*, *24*(5), 1590-1629.

Hannan, E. J. (1980). The estimation of the order of an ARMA process. *The Annals of Statistics, 8*(5), 1071-1081.

Hannan, E. J., & Quinn, B. G. (1979). The determination of the order of an autoregression. *Journal of the Royal Statistical Society: Series B (Methodological), 41*(2), 190-195.

Harrison, H., Scheinkman, J., & Xiong, W. (2008). Advisors and Asset Prices: A Model of the Origins of Bubbles. *Journal of Financial Economics, 89*(2), 268-287.

Hassani, H., Huang, X., & Silva, E. (2018). Banking with blockchain-ed big data. *Journal of Management Analytics, 5*(4), 256-275.

Henderson, R. (1995). Of life cycles real and imaginary: the unexpectedly long old age of optical lithography. *Research Policy, 24*(4), 631–643.

Henderson, R. M., & Clark, K. B. (1990). Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly*, 9-30.

Hickman, L. (2001). *Philosophical Tools for Technological Culture: Putting Pragmatism to Work*. Bloomington: Indiana University Press.

Higgins, M. L., & Bera, A. K. (1992). A class of nonlinear ARCH models. *International Economic Review*, 137-158.

Ho, K. Y., Shi, Y., & Zhang, Z. (2013). How does news sentiment impact asset volatility? Evidence from long memory and regime-switching approaches. *The North American Journal of Economics and Finance*, *26*, 436-456.

Ho, K. Y., Shi, Y., & Zhang, Z. (2020). News and return volatility of Chinese bank stocks. *International Review of Economics & Finance, 69*, 1095-1105.

Hobjin, B., & Jovanovic, B. (2001). The information-technology revolution and the stock market: Evidence. *American Economic Review, 91*(5), 1203–1220.

Hopkins, M.M., Crane, P.A., Nightingale, P., & Baden-Fuller, C. (2013). Buying big into biotech: scale, financing, and the industrial dynamics of UK biotech, 1980–2009. *Industrial and Corporate Change, 22*(4), 903-952.

Hosler, D. (1994). *The Sounds and Colors of Power: The Sacred Metallurgical Technology of Ancient West Mexico*. MIT Press, Cambridge.

Hu, Y., Tao, Z., Xing, D., Pan, Z., Zhao, J., & Chen, X. (2020). Research on stock returns forecast of the four major banks based on ARMA and GARCH model. In *Journal of Physics: Conference Series* (Vol. 1616, No. 1, p. 012075). IOP Publishing.

Huang, H. C. (2000). Tests of regimes-switching CAPM. *Applied Financial Economics, 10*(5), 573-578.

Huang, W., Liu, Q., Rhee, S. G., & Zhang, L. (2010). Return reversals, idiosyncratic risk, and expected returns. *The Review of Financial Studies*, *23*(1), 147-168.

Hung, S.-C., & Yee-Yeen, C. (2006). Stimulating new industries from emerging technologies: challenges for the public sector. *Technovation, 26*(1), 104-110.

Hwang, S., & Satchell, S. E. (2000). Market risk and the concept of fundamental volatility: measuring volatility across asset and derivative markets and testing for the impact of derivatives markets on financial markets. *Journal of Banking & Finance*, *24*(5), 759-785.

Inbert, F. (2017, Octobrer 6). *Investors are losing out on billions because tech stocks don't pay dividends*. Investing. https://www.cnbc.com/2017/10/06/investors-are-losing-out-on-billions-because-tech-dont-pay-dividends.html.

Investing. (2022, Seprember 16). MSCI World Historical Data. https://es.investing.com/indices/msci-world-historical-data.

Iraola, M. A., & Santos, M. (2007). Technological waves in the stock market.

Isaic-Maniu, I. (2006). Caracterizarea statistica a riscului- Concepte, technici, aplicatii. Bucuresti: ASE, Bucutesti, XI.

Jacobides, M. G. (2019). In the ecosystem economy, what's your strategy?. *Harvard Business Review*, *97*(5), 128-137.

Jaggia, S., & Thosar, S. (2004). The medium-term aftermarket in high-tech IPOs: Patterns and *implications*. *Journal of banking & Finance*, *28*(5), 931-950.

Jensen, M. C. (1993). The modern industrial revolution, exit, and the failure of internal control systems. *The Journal of Finance, 43*(8), 831-880.

Jiang, K., Du, X., & Chen, Z. (2022). Firms' digitalization and stock price crash risk. *International review of financial analysis*, *82*, 102196.

Jiang, P., Liu, Q., & Tse, Y. (2015). International Asset Allocation with Regime Switching: Evidence from the ETF s. *Asia-Pacific Journal of Financial Studies*, *44*(5), 661-687.

Jiang, X., & Lee, B. S. (2006). The dynamic relation between returns and idiosyncratic volatility. *Financial Management*, *35*(2), 43-65.

Johnson, K. N. (2015). Cyber risks: Emerging risk management concerns for financial institutions. *Ga. L. Rev.*, *50*, 131.

Johnstone, D. J. (2021). Accounting information, disclosure, and expected utility: Do investors really abhor uncertainty?. *Journal of Business Finance & Accounting*, *48*(1-2), 3-35.

Jones, C. M., & Rhodes-Kropf, M. (2003). *The price of diversifiable risk in venture capital and private equity*. working paper, Columbia University.

Lael Joseph, N., & Vezos, P. (2006). The sensitivity of US banks' stock returns to interest rate and exchange rate changes. *Managerial Finance*, *32*(2), 182-199.

Jovanovic, B., & Rousseau, P. L. (2002). *Stock markets in the new economy*. Cambridge, MA: The MIT Press.

Jun, J., & Yeo, E. (2016). Entry of FinTech firms and competition in the retail payments market. *Asia-Pacific Journal of Financial Studies*, *45*(2), 159-184.

Junttila, J., Kallunki, J.-P., Kärja, A., & Martikainen, M. (2005). Stock market response to analysts' perceptions and earnings in a technology-intensive environment. *International Review of Financial Analysis, 14*(1), 77-92.

Kahneman, D., Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica: The Econometric Society, 47*(2), 263-291.

Kalev, P. S., Liu, W. M., Pham, P. K., & Jarnecic, E. (2004). Public information arrival and volatility of intraday stock returns. *Journal of Banking & Finance*, *28*(6), 1441-1467.

Kapoor, R., and Klueter, T. (2020). Progress and setbacks: The two faces of technology emergence. *Research Policy, 49*(1), 103874.

Karshenas, M., & Stoneman, P. (1993). Rank, stock, order, and epidemic effects in the diffusion of new process technologies: An empirical model. *RAND Journal of Economics, 24*(4), 503-528.

Kearney, C., & Potì, V. (2008). Have European stocks become more volatile? An empirical investigation of idiosyncratic and market risk in the Euro area. *European Financial Management, 14*(3), 419-444.

Keynes, J. M., & Hutchison, T. W. (1973). The Collected Writings of John Maynard Keynes, Volumes I-VI and XV-XVI. *The Economic History Review*, *26*(1), 141-152.

Khan, A., & Zia, A. (2019). Market volatility of banking stock return vis-à-vis banks merger: An application of GARCH model. *Management Science Letters*, *9*(5), 629-638.

Killam, L. (2013). *Research terminology simplified: Paradigms, axiology, ontology, epistemology and methodology*. Laura Killam.

Kim, C. J., & Nelson, C. R. (2017). *State-space models with REGIME Switching: Classical and gibbs-sampling approaches with applications*. MIT press.

Kleinknecht, A. (1987). *Innovation patterns in crisis and prosperity: Schumpeter's long cycle reconsidered*. Springer.

Kline, J., & Rosenberg, N. (1986). «An overview of innovation», in Landau R., Rosenberg N.(eds) The positive sum strategy: harnessing technology of economic growth. Washington: National Academic Press.

Klöckner, M., Schmidt, C. G., & Wagner, S. M. (2022). When blockchain creates shareholder value: empirical evidence from international firm announcements. *Production and Operations Management, 31*(1), 46-64.

Knight, F. H. (1921). *Risk, uncertainty and profit* (Vol. 31). Houghton Mifflin.

Kothari, S. P., Laguerre, T. E., & Leone, A. J. (2002). Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of accounting Studies*, *7*(4), 355-382.

KPMG. (2021, December 30). *Transición digital y transformación del negocio bancario en España impulsado por la COVID-19*. https://home.kpmg/es.

Kritzman, M., Page, S., & Turkington, D. (2012). Regime shifts: Implications for dynamic strategies (corrected). *Financial Analysts Journal, 68*(3), 22-39.

Kucharavy, D., & De Guio, R. (2008). Technological forecasting and assessment of barriers for emerging technologies. In 17th International Conference on Management of Technology (IAMOT 2008), (pp. 14-2). Dubai. https://hal.archives-ouvertes.fr/hal-00282751.

Kwon, S.S., & Yin, J. (2006). Executive compensation, investment opportunities, and earnings management: High-tech firms versus low-tech firms. *Journal of Accounting, Auditing & Finance, 21*(2), 119-148.

Kwon, S.S., & Yin, J. (2015). A comparison of earnings persistence in high-tech and non-high-tech firms. *Review of Quantitative Finance and Accounting, 44*(4), 645-668.

Kydland, F. E., & Prescott, E. C. (1982). Time to build and aggregate fluctuations. *Econometrica: Journal of the Econometric Society, 50*(6), 1345–1370.

Laeven, L., Ratnovski, L., & Tong, H. (2016). Bank size, capital, and systemic risk: Some international evidence. *Journal of Banking & Finance*, *69*, S25-S34.

Laitner, J., and Stolyarov, D. (2003). Technological change and the stock market. *American Economic Review, 93*(4), 1240-1267.

Laitner, J., & Stolyarov, D. (2019). Asset Pricing Implications of Disruptive Technological Change. *On-line publication at semanticscholar https://www. semanticscholar. org/paper/Asset-Pricing-Implications-of-Disruptive-Change-Laitner-Stolyarov/cd56654a1dba110e29592dc33107012aeea21151*.

Lamoureux, C. G., and Lastrapes, W. D. (1990). Heteroskedasticity in stock return data: Volume versus GARCH effects. *The Journal of Finance, 45*(1), 221-229.

Lander, R. (2019, November 5). *Carlos Trascasa: "El daño que están haciendo las 'FinTech' a la banca es cero"*. Expansión. https://www.expansion.com/empresas/banca/2019/11/05/5dc07817e5fdea39208b4677.html.

Lane, P. R. (2012). The European sovereign debt crisis. *Journal of Economic Perspectives, 26*(3), 49–68.

Lantz, J. S., & Sahut, J. M. (2005). R&D investment and the financial performance of technological firms. *International Journal of Business, 10*(3), 251.

Le, T. D., Ho, T. H., Nguyen, D. T., & Ngo, T. (2021). FinTech credit and bank efficiency: International evidence. *International Journal of Financial Studies*, *9*(3), 44.

Lee, I., & Shin, Y. J. (2018). FinTech: Ecosystem, business models, investment decisions, and challenges. *Business horizons*, *61*(1), 35-46.

Lee, P. M. (2001). What's in a name. com?: The effects of '. com'name changes on stock prices and trading activity. *Strategic Management Journal, 22*(8), 793-804.

Lehmann, B. N. (1990). Residual risk revisited. *Journal of Econometrics*, *45*(1-2), 71-97.

Leifer, R., O'Connor, G.C., & Rice, M. (2001). Implementing radical innovation in mature firms: The role of hubs. *Academy of Management Perspectives, 15*(3), 102-113.

Leroy, S., & Porter, R. (1981). The Present-Value Relation: Tests Based on Variance Bounds. Econometrica, 49, 555-574. doi:https://doi.org/10.2307/1911512

Leskovec, J., Adamic, L. A., & Huberman, B. A. (2007). The dynamics of viral marketing. *ACM Transactions on the Web (TWEB)*, *1*(1), 5-es.

Levy, H. (1978). Equilibrium in an Imperfect Market: A Constraint on the Number of Securities in the Portfolio. *The American Economic Review*, *68*(4), 643-658.

Lewellen, J. (2003). Discussion of "The Internet Downturn: Finding Valuation Factors in Spring 2000". *Journal of Accounting and Economics, 34*, 237-247.

Leydesdorff, L., & Rafols, I. (2011). How do emerging technologies conquer the world? An exploration of patterns of diffusion and network formation. *Journal of the American Society for Information Science and Technology*, *62*(5), 846-860.

Li, F. W., Teo, M., & Yang, C. C. (2019). ETF Momentum. Res. Collect. Lee Kong Chian Sch. Bus., 1-51, https://ink.library.smu.edu.sg/lkcsb_research/6446

Li, M., Porter, A.L., & Suominen, A. (2018). Insights into relationships between disruptive technology/innovation and emerging technology: A bibliometric perspective. *Technological Forecasting and Social Change, 129*, 285-296.

Li, X. (2005). Cheap talk and bogus network externalities in the emerging technology market. *Marketing Science, 24*(4), 531-543.

Li, Y., Spigt, R., and Swinkels, L. (2017). The impact of FinTech start-ups on incumbent retail banks' share prices. *Financial Innovation, 3*(1), 1–16. https://doi.org/10.1186/s40854-017-0076-7.

Li-Hua, R. (2009). Definitions of technology. *A companion to the philosophy of technology*, 18-22.

Lim, E. N. (2015). The role of reference point in CEO restricted stock and its impact on R&D intensity in high-technology firms. *Strategic Management Journal, 36*(6), 872-889.

Lin, X., Palazzo, D., & Yang, F. (2017). *The risks of old age: Asset pricing implication of technology adoption*. Working Paper, Ohio State University.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The Journal of Finance, 20*(4), 587-615.

Linton, J. D., & Walsh, S. T. (2008). Acceleration and extension of opportunity recognition for nanotechnologies and other emerging technologies. *International Small Business Journal, 26*(1), 83-99.

Lo, A.W., and Mackinlay, A.C. (1990). Data-snooping biases in tests of financial asset pricing models. *The Review of Financial Studies, 3*(3), 431-467.

Lovreta, L., & López Pascual, J. (2020). Structural breaks in the interaction between bank and sovereign default risk. *SERIEs*, *11*(4), 531-559.

Low, C., & Wong, M. (2021, May). The effect of FinTech on the financial institution in Six ASEAN countries: Fama-French five-factor asset pricing model approach. In *Ninth International Conference on Entrepreneurship and Business Management (ICEBM 2020)* (pp. 224-232). Atlantis Press.

Lucas Jr, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics, 22(*1), 3-42.

Lui, A., Lee, M., and Ngai, E. (2022). Impact of artificial intelligence investment on firm value. *Annals of Operations Research, 308*(1), 373-388.

Mahmood, M., Arslan, F., Dandu, J., & Udo, G. (2014). Impact of cloud computing adoption on firm stock price–an empirical research. Twentieth Americas Conference on Information Systems. Savannah.

Majid, S., Sultana, N., Abid, G., & Elahi, A. (2021). The Impact of Corporate Innovation on Abnormal Stock Returns: The Moderating Role of Investor Sentiment. *Academy of Strategic Management Journal, 20*, 1-16.

Malerba, F., Orsenigo, L., & Peretto, P. (1997). Persistence of innovative activities, sectoral patterns of innovation and international technological specialization. *International Journal of Industrial Organization, 15*(6), 801-826.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance, 25*(2), 383-417.

Malkiel, B. G., & Xu, Y. (2002). Idiosyncratic risk and security returns. *University of Texas at Dallas (November 2002).*

Mankiw, N., Romer, D., & Shapiro, M. (1985). An Unbiased Reexamination of Stock Price Volatility. *Journal of Finance, 40*, 677-687.

Mann, D. M., Chen, J., Chunara, R., Testa, P. A., & Nov, O. (2020). COVID-19 transforms health care through telemedicine: evidence from the field. *Journal of the American Medical Informatics Association*, *27*(7), 1132-1135.

Mansfield, E. (1961). Technological change and the rate of imitation. *Econometrica, 29*, 741-766.

Mansfield, E. (1968). Industrial Research and Technological Innovation. New York: Norton.

Mansfield, E. (1989). The diffusion of industrial robots in Japan and United States. *Research Policy, 18*, 183-192.

Manso, G. (2011). Motivating innovation. *The Journal of Finance, 66*(5), 823-1860.

Manuelli, R.E. (2000). Technological Change, the Labor Market and the Stock Market. Working Paper 8022. National Bureau of Economic Research.

Manzan, S. (2007). Nonlinear mean reversion in stock prices. *Quantitative and Qualitative Analysis in Social Sciences, 1*(3), 1-20.

Marczyk, G. R., DeMatteo, D., & Festinger, D. (2010). *Essentials of research design and methodology* (Vol. 2). John Wiley & Sons.

Martin, B. (1995). Foresight in science and technology. *Technology analysis & strategic management, 7*(2), 139-168.

Martin, S., & Scott, J.T. (2000). The nature of innovation market failure and the design of public support for private innovation. *Research policy, 29*(4-5), 437-447.

Markowitz, H. (1952). Portfolio Selection. *Journal of Finance, 7*(1), 77-91.

Martinelli, A., Mina, A., & Moggi, M. (2021). The enabling technologies of industry 4.0: Examining the seeds of the fourth industrial revolution. *Industrial and Corporate Change, 30*(1), 161-188.

Mascitelli, R. (2000). From experience: harnessing tacit knowledge to achieve breakthrough innovation. *Journal of Product Innovation Management: an International Publication of the Product Development & Management Association*, *17*(3), 179-193.

Mazzucato, M. (2002). The PC industry: New economy or early life-cycle?. *Review of Economic Dynamics*, *5*(2), 318-345.

Mazzucato, M. (2006). Innovation and stock prices: a review of some recent work. *Revue de l'OFCE, (5)*, 159–179.

Mazzucato, M., & Tancioni, M. (2008a). Innovation and idiosyncratic risk: An industry-and firm-level analysis. *Industrial and Corporate Change, 17*(4), 779–811.

Mazzucato, M., & Tancioni, M. (2008b). Stock Price Volatility and Patent Citation Dynamics: the case of the pharmaceutical industry.

Mazzucato, M., & Tancioni, M. (2012). R&D, patents and stock return volatility. *Journal of Evolutionary Economics, 22*(4), 811-832.

McAleer, M., Chan, F., Hoti, S., & Lieberman, O. (2008). Generalized autoregressive conditional correlation. *Econometric Theory, 24*(6), 1554-1583.

Mensch, G. (1975). Das technologische Putt: Innovationen iiberwinden die Depression. Frankfurt: Umschau Verlag.

Merigó, J. M., Gil Lafuente, A. M., & Gil Lafuente, J. (2016). Business, industrial marketing and uncertainty. *Journal of Business & Industrial Marketing, 31*(3), 325-327.

Merton, R. K. (1948). The self-fulfilling prophecy. *The antioch review*, *8*(2), 193-210.

Merton, R. C. (1973). Theory of rational option pricing. *The Bell Journal of economics and management science*, 141-183.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information.

Mikalef, P., Krogstie, J., Pappas, I.O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Inf. & Manag. 57*(2); 103169.

Miller, D., & Liu, K. (2014). Creative Destruction: Evidence From Initial Public Offerings. In *Academy of Management Proceedings* (Vol. 2014, No. 1, p. 17308). Briarcliff Manor, NY 10510: Academy of Management.

Mishkin, F.S. (2016). *The Economics of Money, Banking, and Financial Markets.* Eleventh Edition (Global Edition). Harlow: Pearson.

Mizrach, B. (1996). Learning and conditional heteroscedasticity in asset returns (Departmental Working Papers 199526). Department of Economics, Rutgers University, New Brunswick, NJ, USA.

Moehrle, M.G., & Caferoglu, H. (2019). Technological speciation as a source for emerging technologies. Using semantic patent analysis for the case of camera technology. *Technological Forecasting and Social Change*, 146, 776-784.

Mokyr, J. (2014). Secular stagnation? Not in your life. *Secular stagnation: facts, causes and cures*, *83*.

Montobbio, F., Staccioli, J., Virgillito, M. E., & Vivarelli, M. (2022). Robots and the origin of their labour-saving impact. *Technological Forecasting and Social Change*, *174*, 121122.

Moro-Visconti, R., Cruz-Rambaud, S., & López-Pascual, J. (2020). Sustainability in FinTechs: An Explanation through Business Model Scalability and Market Valuation. *Sustainability 12*(24); 10316.

MSCI. (2022a, Septermber 16). MSCI ACWI IMI Disruptive Technology ESG Filtered Index (EUR). https://www.msci.com/documents/10199/f1e29c8e-8600-508d-6e8f-155c7c429a88.

MSCI. (2022b, September 16). MSCI World Index (USD). https://www.msci.com/documents/10199/178e6643-6ae6-47b9-82be-e1fc565ededb.

Nartea, G.V.; Ward, B.D. (2017). Does Idiosyncratic Risk Matter? Evidence from the Philippine Stock Market. *AJBA, 2*, 47–67.

Navaretti, G., Calzolari, G., Mansilla-Fernande, J., & Pozzolo, A. (2018). FinTech and banking. Friends or foes?. Friends or Foes. Friends or Foes. (January 10, 2018) *Available at SSRN*.

Nelson, D. B. (1991). Conditional heteroscedasticity in asset returns: A new approach. Econometrical, 59 (2), 347-370. *Journal of Financial and Quantitative Analysis*, *40*, 1129-1148.

Nelson, R. R., & Winter, S. G. (1975). *Dynamic competition and technical progress*. Institute of Public Policy Studies, University of Michigan.

Neuberger, J. A. (1991). Risk and return in banking: Evidence from bank stock returns. *Economic Review-Federal Reserve Bank of San Francisco*, (4), 18.

Neuman, W. (2003). *Social Research Methods: Qualitative and Quantitative Approaches* (Vol. 5th ed.). Boston: Allyn and Bacon.

Nicholas-Donald, A., Mahmood, M., & Trevino, L. (2018). Does adoption of cloud computing matter? The economic worth of cloud computing implementation. *International Journal of Information Systems and Management, 1*(4), 328-342.

Noda, T., and Bower, J.L. (1996). Strategy making as iterated processes of resource allocation. *Strategic Management Journal, 17*(S1), 159-192.

OFX. (2022, August 15). USD to EUR historical exchange rates. https://www.ofx.com/en-au/forex-news/historical-exchange-rates/usd/eur/.

O'Reilly III, C.A., and Tushman, M.L. (2011). Organizational ambidexterity in action: How managers explore and exploit. *California Management Review, 53*(4), 5-22.

Parameswaran, S., Venkatesan, S., & Gupta, M. (2013). Cloud computing security announcements: assessment of investors' reaction. *Journal of Information Privacy and Security, 9*(1), 17-46.

Parameswaran, S., Venkatesan, S., Gupta, M., Sharman, R., & Rao, H. R. (2011). Impact of cloud computing announcements on firm valuation.

Pástor, Ľ., & Veronesi, P. (2003). Stock Valuation and Learning about Profitability. *Journal of Finance, 58*(5), 749-1789.

Pástor, Ľ., and Veronesi, P. (2005) Technological revolutions and stock returns. *National Bureau of Economic Research* w11876

Pástor, Ľ., & Veronesi, P. (2006). Was there a Nasdaq bubble in the late 1990s? *Journal of Financial Economics, 81*(1), 61–100.

Pástor, Ľ., & Veronesi, P. (2009). Technological revolutions and stock prices. *American Economic Review, 99*(4), 1451-83.

Peralta-Alva, A. (2007). The information technology revolution and the puzzling trends in Tobin's average q. *International Economic Review, 48*(3), 929-951.

Pérez, C. (1983). Structural change and assimilation of new technologies in the economic and social systems. *Futures, 15*(5), 357-375.

Pérez, C. (1985). Microelectronics, long waves and world structural change: New perspectives for developing countries. *World Development, 14*, 441-463.

Pérez, C. (2003). *Technological revolutions and financial capital*. Cheltenham, UK: Edward Elgar Publishing.

Pérez, C. (2012). *Financial bubbles, crises and the role of government in unleashing golden ages*. FINNOV Milton Keynes, UK: Open University.

Perron, P. (1997). Further evidence on breaking trend functions in macroeconomic variables. *Journal of Econometrics, 80*(2), 355-385.

Pezzoni, M., Veugelers, R., & Visentini, F. (2019). Technology diffusion trajectories: New evidence.

PGIM. (2018, July 17). *The End of Sovereignty*. Megatrend. https://www.pgim.com/insights/megatrends/sovereignty.

Phan, D. H. B., Narayan, P. K., Rahman, R. E., & Hutabarat, A. R. (2020). Do financial technology firms influence bank performance?. *Pacific-Basin Finance Journal, 62*, 101210.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika, 75*(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

Porter, L., Roessner, J., Jin, X.-Y., & Newman, N. (2002). Measuring national 'emerging technology'capabilities. *Science and Public Policy, 29*(3), 189-200.

Powell, W. W., Koput, K. W., & Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative science quarterly*, 116-145.

Prendergast, C., & Stole, l. (1996). Impetuous youngsters and jaded old-timers: Acquiring a reputation for learning. *Journal of Political Economy, 104*(6), 1105-1134.

Pyka, A., & Burghof, H.-P. (2013). *Innovation and Finance*. Routledge.

Quandt, R. E. (1960). Tests of the hypothesis that a linear regression system obeys two separate regimes. *Journal of the American statistical Association, 55*(290), 324–330.

Quandt, R. E. (1958). The estimation of the parameters of a linear regression system obeying two separate regimes. *Journal of the american statistical association*, *53*(284), 873-880.

Rachwalski, M., & Wen, Q. (2016). Idiosyncratic risk innovations and the idiosyncratic risk-return relation. *The Review of Asset Pricing Studies*, *6*(2), 303-328.

Ranciere, R., Tornell, A., & Westermann, F. (2008). Systemic crises and growth. *The Quarterly Journal of Economics, 123*(1), 359-406.

Ratten, V. (2008). Technological innovations in the m-commerce industry: A conceptual model of WAP banking intentions. *The Journal of High Technology Management Research, 18*(2), 111-117.

Reinganum, M. R. (1981a). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values. *Journal of financial Economics*, *9*(1), 19-46.

Reinganum, M. (1981b). The arbitrage pricing theory: Some empirical results. *The Journal of Finance, 36*(2), 313-321.

Rialti, R., Zollo, L., Ferraris, A., & Alon, I. (2019). Big data analytics capabilities and performance: Evidence from a moderated multi-mediation model. *Tech. Forecasting and Social Change, 149*, 119781.

Riccardi, V., Simon, H. (2000). What is behavioral finance? *Business, Education & Technology Journal, 2*(2), 1-9.

Richards, M. A. J. (1999). *Idiosyncratic risk: An empirical analysis, with implications for the risk of relative-value trading strategies*. International Monetary Fund.

Riordan, M. H., & Salant, D. J. (1994). Preemptive adoptions of an emerging technology. *The journal of industrial economics*, 247-261.

Rishi, M., & Saxena, S. C. (2004). Technological innovations in the Indian banking industry: the late bloomer. *Accounting, Business & Financial History, 14*(3), 339-353.

Rock, D. (2019). Engineering value: The returns to technological talent and investments in artificial intelligence. *Available at SSRN 3427412*.

Rodríguez-Ruiz, Ó., Rodríguez-Duarte, A., & Gómez-Martínez, L. (2016). Does a balanced gender ratio improve performance? The case of Spanish banks (1999–2010). *Personnel Review, 45*(1), 103–120.

Rogers, E.M. (1995). Diffusion of Innovations. [Google Scholar]. New York: The Free Press.

Romer, P. M. (1990). Endogenous technological change. *Journal of political Economy*, *98*(5, Part 2), S71-S102.

Rooney, D. (1997). A contextualizing, socio-technical definition of technology: Learning from Ancient Greece and Foucault. *Prometheus, 15*(3), 399-407.

Rosenberg, N. (1976). *Perspectives on technology*. Cambridge University Press.

Rosenberg, N., & Nelson, R.R. (1994). American universities and technical advance in industry. *Research policy*, 23(3), 323-348.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory, 13*, 341–360.

Ross, S. Westerfield, R. & Jaffe, J. (2002). *Capital market theory: An overview. Corporate finance* (6th ed.) (226-247). New York, NY: McGraw-Hill.

Rotolo, D., Hicks, D., and Martin B. R. (2015). What is an emerging technology? *Research Policy, 44*(10), 1827-1843.

Rubera, G., and Kirca, A.H. (2012). Firm innovativeness and its performance outcomes: A meta-analytic review and theoretical integration. *Journal of Marketing, 76*(3), 130-147.

Ruiz, J. R., Stupariu, P., & Vilariño, Á. (2016). The crisis of Spanish savings banks. *Cambridge journal of economics*, *40*(6), 1455-1477.

Ryan, S., & Worthington, A. (2004). Market, interest rate & foreign exchange rate risk in Australian banking: a GARCH-M approach. *International Journal of Applied Business and Economic Research*, *2*(2), 81-103.

Sabi-bvdinfo. (2022, November 3). https://sabi-bvdinfo-com.sire.ub.edu/version-20221115/Report.serv?_CID=49&product=sabineo.

Sahal, D. (1985). Technological guideposts and innovation avenues. *Research Policy, 14*(2), 61-82.

Sahi, H. (2017). S*tudying market reactions to FinTech companies-Acquisitions and initial public offerings in OECD Countries*, [Master Thesis, Lappeenranta University of Technology, School of Business and Management]. https://urn.fi/URN:NBN:fi-fe201705226703.

Sahni, D. (2012). Behavioral finance: Testing applicability on Indian investors. *International Journal of in Multidisciplinary and Academic Research, 1*(2), 1-12.

Salazar Cantú, J., Arenas, L., & Gil Lafuente, A. M. (2021). Determinantes de la satisfacción con la vida en adultos mayores en México. *Cuadernos del CIMBAGE*, *23*(2).

Salter, A.J., and Martin, B.R. (2001). The economic benefits of publicly funded basic research: a critical review. *Research Policy, 30*(3), 509-532.

Santander. (2022, November 3). *Informe Financiero. Enero – Septiembre 2022*. https://www.santander.com/content/dam/santander-com/es/documentos/resultados-trimestrales/2022/3t/rt-3t-2022-informe-financiero-banco-santander-es.pdf.

Saunders, M., Lewis, P., & Thornhill, A. (2016). *Research Methods for Business Students* (Vol. 7th). Pearson.

Sawada, M. (2013). How does the stock market value bank diversification? Empirical evidence from Japanese banks. *Pacific-Basin Finance Journal, 25*, 40–61.

Schmidt, W. C., & González, A. (2020). FinTech and Tokenization: A legislative study in Argentina and Spain about the application of Blockchain in the field of properties. *ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal*, *9*(1), 51.

Schmitt-Beck, R. (2015). Bandwagon effect. *The International Encyclopedia of Political Communication*, 1-5.

Schmookler, J. (2013). *Invention and economic growth. In Invention and Economic Growth*. Harvard University Press.

Schulze, S. (2003). Views on the combination of quantitative and qualitative research approaches. *Progressio, 25*(2), 8-20.

Schoenmakers, W., & Duysters, G. (2010). The technological origins of radical inventions. Research Policy, 39(8), 1051-1059.

Schumpeter, J. A. (1912). *Theorie der wirschaftlichen Entwicklung*. Duncker & Humblot.

Schumpeter, J. (1942). *Creative destruction. Capitalism, socialism and democracy*. Routledge.

Schwab, K. (2017). *The fourth industrial revolution*. Crown Currency.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6*(2), 461–464.

Schwert, G. (1989). Why does stock market volatility change over time? *The Journal of Finance, 44*(5), 1115-1153.

Schwert, G. W. (2002). Stock volatility in the new millennium: how wacky is Nasdaq? *Journal of Monetary Economics, 49*(1), 3-26.

Sentana, E. (1995). Quadratic ARCH models. *The Review of Economic Studies, 64*(2), 639-661.

Setiawan, R., Cavaliere, L., Koti, K., Ogunmola, G., Jalil, N. A., Chakravarthi, M. K., Rajest, S. S., Regin, R., & Singh, S. (2021). The artificial intelligence and inventory effect on banking industrial performance. *Turkish Online Journal of Qualitative Inquiry (TOJQI),* 12(6), 8100-8125.

Shapiro, C., and Varian, H.R. (1998*). Networks and Positive Feedback. In Information rules: A strategic guide to the network economy*. Harvard Business Press.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance, 19*(3), 425-442.

Shiller, R. (1981a). Do Stock Prices Move Too Much to Be Justified by Subsequent Changes in Dividends? *American Econ. Rev. 71*(3); 421-436.

Shiller, R.J. (1981b). Aternative Tests of Rational Expectation Models: The Case of the Term Structure. *Journal of Econometrics, 16*, 71-78.

Shiller, R. C. (2000). Irrational exuberance. *Philosophy and Public Policy Quarterly, 20*(1), 18-23.

Siegel, J. J. (2021). *Stocks for the long run: The definitive guide to financial market returns & long-term investment strategies*. (5th, Ed.) McGraw-Hill Education, 2021.

Small, H. (1973). Co-citation in the scientific literature: A new measure of the relationship between two documents. *Journal of the Association for Information Science and Tehcnology, 24*(4), 265-269.

Small, H., Boyack, K., and Klavans, R. (2014). Identifying emerging topics in science and technology. Research policy, 43(8), 1450-1467. doi:https://doi.org/10.1016/j.respol.2014.02.005.

Son, I., Lee, D., Lee, J.-N., & Bong, Y. (2014). Market perception on cloud computing initiatives in organizations: An extended resource-based view. *Information & Management, 51*(6), 653-669.

Sood, A., & Tellis, G. J. (2009). Do innovations really pay off? Total stock market returns to innovation. *Marketing Science*, *28*(3), 442-456.

Spiegel, M. I., & Wang, X. (2005). Cross-sectional variation in stock returns: Liquidity and idiosyncratic risk.

Spinaci, S. (2019). Cross-border euro transfers and currency conversions: A step forward in favour of the single market. https://www.europarl.europa.eu/thinktank/en/document/EPRS_BRI(2018)628291.

Sreenu, N., & Naik, S. (2021). Investor sentiment and stock return volatility: evidence from the Indian Stock Exchange. *Asia-Pacific Journal of Business Administration*, *14*(4), 467-478.

Srinivasan, R. (2008). Sources, characteristics, and effects of emerging technologies: Research opportunities in innovation. *Industrial Marketing Management, 37*(6), 633-640.

Statista. (2021, December 30). *Non-performing loans (NPL) and advances as a share of total lending of selected banks in Spain as of June 2022*. https://www.statista.com/statistics/775523/ratio-from-blackberry-from-the-banks-in-spain/.

Statista, (2021, December 31). *Number of employees in the banking sector in Spain from 2010 to 2021*. https://www.statista.com/statistics/765375/employment-in-the-banking-sector-spain/.

Statista. (2022, September 15). *FinTech-Spain*. https://www.statista.com/outlook/dmo/FinTech/spain#transaction-value.

Staykova, K. S., & Damsgaard, J. (2016). Adoption of mobile payment platforms: Managing reach and range. *Journal of theoretical and applied electronic commerce research*, *11*(3), 65-84.

Stiroh, K. J. (2006). A portfolio view of banking with interest and noninterest activities. *Journal of Money, Credit and Banking, 38*(5), 1351–1361.

Stock, J.H. (1988). Estimating continuous-time processes subject to time deformation: an application to postwar US GNP. *Journal of the American Statistical Association, 83*(401), 77-85.

Stoneman, P. (1986). Technological difussion: the viewpoint of economic theory. *Ricierche Economiche, 4*, 585/606.

Stoneman, P. (2002). *The Economics of Technological Diffusion*. Oxford: Blackwell.

Stoneman, P., & Diederen, P. (1994). Technology diffusion and public policy. *The Economic Journal, 104*(425), 918-930.

Stubbart, C. I., & Knight, M. B. (2006). The case of the disappearing firms: empirical evidence and implications. Journal of Organizational Behavior: *The International Journal of Industrial, Occupational and Organizational Psychology and Behavior, 27*(1), 79-100.

Swartz, E., Money, A., Williams, B., & Remenyi, D. (1998). Doing research in business and management: an introduction to process and method. *Doing Research in Business and Management*, 1-320.

Switzer, L., & Picard, A. (2015). Idiosyncratic volatility, momentum, liquidity, and expected stock returns in developed and emerging markets. *Multinational Finance Journal*, *19*(3), 169-221.

Tai, C. S. (2000). Time-varying market, interest rate, and exchange rate risk premia in the US commercial bank stock returns. *Journal of Multinational Financial Management*, *10*(3-4), 397-420.

Tang, C., Huang, T., & Wang, S. (2018). The impact of Internet of things implementation on firm performance. *Telematics and Informatics, 35*(7), 2038-2053.

Tasker, S. C. (1998). Bridging the information gap: Quarterly conference calls as a medium for voluntary disclosure. *Review of Accounting Studies, 3*(1), 127-167.

Tauni, M., Fang, H., & Iqbal, A. (2016). Information sources and trading behavior: does investor personality matter? *Qualitative Research in Financial Markets, 8*(2), 94-117.

Tinic, S. M., & West, R. R. (1986). Risk, return, and equilibrium: A revisit. *Journal of Political Economy, 94*(1), 126-147.

Tobin, J. (1958). Liquidity preference as behavior towards risk. *The review of economic studies, 25*(2), 65-86.

Tolley, E., Ulin, P., Mack, N., Robinson, E., & Succop, S. (2016). *Qualitative methods in public health: a field guide for applied research*. John Wiley & Sons.

Toma, S., Chiriţă, M., & Şarpe, D. (2012). Risk and uncertainty. *Procedia Economics and Finance*, 975-980.

Trocin, C., Hovland, I.V., Mikalef, P., & Dremel, C. (2021). How Artificial Intelligence affords digital innovation: A cross-case analysis of Scandinavian companies. *Tech. Forecast. and Soc. Change, 173*, 121081.

Tuli, F. (2010). The basis of distinction between qualitative and quantitative research in social science: Reflection on ontological, epistemological and methodological perspectives. *Ethiopian Journal of Education and Sciences, 6*(1).

Turner, C. M., Startz, R., & Nelson, C. (1989). A Markov model of heteroskedasticity, risk, and learning in the stock market. *Journal of Financial Economics, 25(*1), 3-22.

Tushman, M. L., and O'Reilly III, C. A. (1996). Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review, 38*(4), 8-29.

Umar, M., Rizvi, S., & Naqvi, B. (2021). Dance with the devil? The nexus of fourth industrial revolution, technological financial products and volatility spillovers in global financial system. *Technological Forecasting and Social Change, 163*(120450).

Upadhyay, A., & Zeng, H. (2017). Cash holdings and the bargaining power of R&D-intensive targets. *Review of Quantitative Finance and Accounting*, *49*, 885-923.

SIFMA. (2022, November 5). *US Corporate Bond Issuance*. Research. https://www.sifma.org/resources/research/us-corporate-bonds-statistics/.

Usai, A., Fiano, F., Petruzzelli, A. M., Paoloni, P., Briamonte, M. F., & Orlando, B. (2021). Unveiling the impact of the adoption of digital technologies on firms' innovation performance. *Journal of Business Research*, *133*, 327-336.

Vartanian, P. (2018). Is There a Possibility of Diversification Between Commodities and Ibovespa? Analysis of Volatility Transmission (2000–2016). *Analysis of Volatility Transmission (2000–2016)(December 16, 2018)*.

Vee, D. C., Gonpot, P. N., & Sookia, N. (2011). Forecasting Volatility of USD/MUR Exchange Rate using a GARCH (1, 1) model with GED and Student'st errors. *University of Mauritius research journal*, *17*, 1-14.

Vendrame, V., Guermat, C., & Tucker, J. (2018). A conditional regime switching CAPM. International *Review of Financial Analysis, 56*, 1–11.

Viguerie, S. P., Calder, N., & Hindo, B. (2021). 2021 Corporate longevity forecast. *Innosight, May*.

Visconti-Caparrós, J., & Campos-Blázquez, J. (2022). The development of alternate payment methods and their impact on customer behavior: The Bizum case in Spain. *Technological Forecasting and Social Change, 175*, 121330.

Vives, X. (2019). Competition and stability in modern banking: A post-crisis perspective. International *Journal of Industrial Organization, 64*, 55-69.

Volti, R. (2009). *Society and Technological Change* (7th ed.). New York: Worth Publishers.

Wagner, A., & Rosen, W. (2014). Spaces of the possible: universal Darwinism and the wall between technological and biological innovation. *Journal of the Royal Society Interface, 11*(97, 20131190).

Wang, R., Liu, J., & Luo, H. (2021). FinTech development and bank risk taking in China. *The European Journal of Finance*, *27*(4-5), 397-418.

Wang, Y., Xiuping, S., & Zhang, Q. (2021). Can FinTech improve the efficiency of commercial banks?—An analysis based on big data. *Research in international business and finance*, *55*, 101338.

Watanabe, C., Hur, J.Y., & Lei, S. (2006). Converging Trend of Innovation Efforts in High Technology Firms Under Paradigm Shift—a Case of Japan's Electrical Machinery. *Omega, 34*, 178-188.

Weber, M. (2015). Rational and social foundations of music. *The Routledge Reader on the Sociology of Music*, 59-64.

Wedig, G. J. (1990). How Risky is R and D? A Financial Approach. *The Review of Economics and Statistics*, 296-303.

Wei, S. X., and Zhang, C. (2006). Why did individual stocks become more volatile? The Journal of Business, 2006, 79(1), 259-292.

West, K. (1984). Speculative Bubbles and Stock Price Volatility. In Memo No.54, Financial Research Center. Princeton, N.J.: Princeton University.

West, K. (1988). Dividend innovations and stock price volatility. *Econometrica: Journal of the Econometric Society*, 27-61.

Wiener, J. B. (2004). The regulation of technology, and the technology of regulation. *Technology in Society, 26*(2-3), 483-500.

Wiśniewska, M., & Wyłomańska, A. (2017). Garch process with GED distribution. In *Cyclostationarity: Theory and Methods III: Contributions to the 9th Workshop on Cyclostationary Systems and Their Applications, Grodek, Poland, 2016* (pp. 83-103). Springer International Publishing.

World Economic Forum. (2016, June 23). *These are the top 10 emerging technologies of 2016*. https://www.weforum.org/agenda/2016/06/top-10-emerging-technologies-2016.

World Economic Forum. (2017, January). *Realizing human potential in the Fourth Industrial Revolution: An agenda for leaders to shape the future of education, gender and work*. In *World Economic Forum*. https://www3.weforum.org/docs/WEF_EGW_Whitepaper.pdf

World Economic Forum. (2024). *Global Risks Report 2024*. World Economic Forum. https://www.weforum.org/agenda/2024/01/global-risk-report-2024-risks-are-growing-but-theres-hope/.

Wu, L., Lou, B., & Hitt, L. (2019). Data analytics supports decentralized innovation. Manag. *Science, 65*(10), 4863-4877.

Xu, Y., Malkiel, B.G. (2003). Investigating the behavior of idiosyncratic volatility. *The Journal of Business, 76*(4), 613-645.

Yahoo Finance. (2022, April 6). Historical Prices. https://finance.yahoo.com/quote/history.

Yahoo Finance. (2020, November 15) Historical Data. 13 Week Treasury Bill (^IRX) https://finance.yahoo.com/quote/%5EIRX/.

Ying, W., Jia, S., & Du, W. (2018). Digital enablement of blockchain: Evidence from HNA group. *International Journal of Information Management, 39*, 1-4.

Yu, D., & Hang, C. (2010). A reflective review of disruptive innovation theory. International Journal, 12(4), 435-452.

Yu, L., Liu, X., Fung, H.-G., & Kin, W. (2020). Size and value effects in high-tech industries: The role of R&D investment. *The North American Journal of Economics and Finance, 51,* 100853.

Zakoian, J. (1994). Threshold heteroskedastic models. Journal of Economic Dynamics and control, 18(5), 931-955.

Zetzsche, D. A., Buckley, R. P., Barberis, J. N., & Arner, D. W. (2017). Regulating a revolution: From regulatory sandboxes to smart regulation. *Fordham J. Corp. & Fin. L.*, *23*, 31.

Zolas, N., Kroff, Z., Brynjolfsson, E., McElheran, K., Beede, D. N., Buffington, C., ... & Dinlersoz, E. (2021). *Advanced technologies adoption and use by us firms: Evidence from the annual business survey* (No. w28290). National Bureau of Economic Research.

Zuckerman, E., & Rao, H. (2004). Shrewd, crude or simply deluded? Comovement and the internet stock phenomenon. *Industrial and Corporate Chang, 13(1),* 171-21