ISCTE UNIVERSITY INSTITUTE OF LISBON

IUL School of Social Sciences

Department of Political Economy

# THE IMPACT OF THE ACQUISITION OF FINTECH COMPANIES IN BANK STOCK PRICES

Dissertation submitted as partial requirement for the conferral of
*Master in Monetary and Financial Economics,*

By
Gonçalo Pais Ribeiro Pinto Lopes

Supervisor:
Professor Diptes Chandrakante Prabhudas Bhimjee, PhD
Department of Economics, ISCTE Business School

June 2020

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# RESUMO

A Revolução Tecnológica tem alterado de forma significativa a maneira como as pessoas interagem umas com as outras, tal como tem mudado a maneira como várias indústrias têm operado nas últimas décadas. Nesta Dissertação é estudada a indústria financeira, que é umas das principais indústrias que tem sido objecto de uma transformação digital.

O objetivo desta Dissertação é analisar e estudar os impactos que as Fintech têm nas já estabelecidas empresas financeiras, com especial ênfase para os bancos Europeus, bem como analisar se existe alguma categoria específica de empresa Fintech que tenha um impacto mais significativo na cotação bolsista da empresa compradora. A presente Dissertação emprega a metodologia quantitativa de estudos de eventos, analisando como uma fusão ou aquisição (F&A) de uma empresa Fintech por uma empresa financeira afeta a cotação bolsista da empresa compradora. A presente Dissertação usa dados financeiros de alta frequência dos mercados, sendo possível, através da metodologia descrita, analisar se existe um efeito positivo e significante na cotação bolsista da empresa compradora.

Os resultados empíricos da presente Dissertação permitem concluir que a aquisição de empresas Fintech apresenta impactos positivos e significativos na cotação bolsista das empresas compradoras, sejam bancos europeus ou outras empresas presentes na indústria financeira. Quanto à categoria de Fintech, os resultados mostram que as Fintech do tipo "Bancos Digitais" são as que têm o maior impacto positivo e significante, enquanto que as do tipo "Software" são as que têm o maior impacto negativo e significante. A robustez do modelo é igualmente testada e os resultados finais demostram que os resultados são globalmente estáveis.



**Classificação JEL:** G14, G21, G20, G34, G15, Y40

**Palavras-chave:** Estudo de Evento, Fintech, Bancos, Indústria Financeira, Fusões e Aquisições (M&A), Mercado Bolsista, Cotações Bolsistas.

# ABSTRACT

The Technology Revolution has been changing the way people interact with each other, as well as changing the way several industries operate for the last decades. This Dissertation studies banking industry, which is one of the major industries that is undergoing a digital transformation.

The objective of the following Dissertation is to analyze and study what impact does Fintech have on the already-established financial companies, with a special emphasis on European banks, as well as analyzing whether there is some specific type of Fintech company more capable of impacting more significantly the share price of the acquirer.. With the use of the event study methodology, it was possible to analyze how a merger or acquisition (M&A) of a Fintech company by a financial company affects the share price of the acquirer. The present Dissertation uses financial market data to understand if there is a positive significant effect on the share price of the acquirer when if a Fintech M&A event occurs.

The empirical results of this Dissertation allow us to conclude that the acquisition of Fintech companies have a positive and significant impact in the share price of the acquirer, both European banks as well as other financial companies. In regard to the type of Fintech, the results show that the "Digital Banking" type of Fintech is the one which has the most positive and significant impact, while "Software" has the most negative and significant impact. The robustness of the model was tested, and the results show that the results are globally stable.



**JEL Classification:** G14, G21, G20, G34, G15, Y40

**Keywords:** Event Study, Fintech, Banks, Financial Industry, Merger & Acquisitions (M&A), Stock Market, Share Prices.

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# GLOSSARY

| | |
|---|---|
| ACSAR | Average cumulative standardized abnormal return |
| AR | Abnormal return |
| CAR | Cumulated abnormal return |
| CMRM | Constant mean return model |
| MM | Market return model |
| M&A | Mergers and Acquisitions |
| SAR | Standardized abnormal return |

# 1. Introduction

Technology has been changing the way people interact with each other, as well as changing the way several industries have been operating for the last decades. The banking industry is one of the major industries that is currently facing a digital transformation; Presently, Fintech companies are entering the industry at a fast pace, taking out market share from traditional banks. In order to cope with the pace of technological changes, banks and non-bank companies are trying to stay ahead of the competition by forming partnerships with Fintech companies or even by acquiring them. In the most recent years, a big development and appearance of new Fintech companies has been witnessed, which provides new and innovative solutions for their customers. In order to remain competitive, Banks must adapt their strategies, and one such adaptive strategy addresses the acquisition of these new companies. As a result, some acquisitions may be very beneficial for the acquirer while others are not. One way of trying to understand if these acquisitions are beneficial for the acquirers is to analyze the impact these deals have on the acquirers' share price. So, taking into consideration the stock market's reaction, it is possible to understand whether shareholders and the market recognize that these acquisitions are good investments or not.

At the time of writing, and to the best of knowledge, only two previous academic researches similar to this Dissertation's research topic were available. Hornuf et al. (2018) innovatively analyzed the impact of Fintech partnerships with banks and concluded that publicly announced partnerships have a negative impact on the bank's value for short-term windows. However, it is in the long-term that investors perceive these investments as worthwhile. Furthermore, the study also concludes that "digital banks" are the banks that benefit the most, probably because they are more capable of absorbing fintechs' knowledge and technical expertise.

The second related research is conducted by Dranev et al. (2019) and addresses the acquisition of fintech companies worldwide, in order to determine whether it is associated with a positive reaction from investors. This research concludes that fintech M&A positively influences the stock returns of the companies acquiring fintech firms in the short-term.

Consequently, the main goal of this Dissertation is to analyze whether Fintech M&A has a positive and significant impact on the acquirers' share price after the deal is announced and to further analyze which type of Fintech company has the biggest impact, whether positive or negative, in the acquirer's share price. This research does have distinct improvements in comparison to previous academic literature on this subject as it addresses the specific case of European financial companies, especially European banks. To the best of knowledge, this Dissertation constitutes the first research to analyze which type of Fintech company has a greater impact on the shareholders share price.

The present Dissertation employs an event study methodology involving stock market data. By using an event window from the day of the announcement up to five (5) days after, as well as two different models (the CMRM and the MM), the findings suggest that Fintech M&A have a positive and significant impact on the share of the acquirers.

The present Dissertation's findings suggests that Fintech M&A have a positive impact on the share price of the acquirer firm, either for a European bank or for a European non-bank, which further prompts the conclusion that, in the context of profit maximization strategies and corresponding wealth creation, European banks should invest more in Fintech companies as they have the potential to technologically change how banks operate. The findings herein obtained are globally stable and have been subjected to stringent robustness checks.

This Dissertation is structured as follows:

- The first chapter, the Introduction, provides a general overview about this Dissertation's core theme and its main goals;
- The second chapter addresses the topic's literature review and the important research questions herein addressed;
- The third chapter provides a detailed overview regarding the methodology used in this Dissertation, as well as an overview about the data collected;
- The fourth chapter provides an extensive overview on the findings obtained, including a critical analysis and discussion;
- Finally, the fifth and last chapter, presents a brief overview of the main important results and conclusions of this Dissertation, as well as some operational limitations, and further provides recommendations for future researches.

# 2. Literature Review

This chapter describes the existing academic literature related to the research topics of Fintech, Fintech acquisitions, and Fintech partnerships with the traditional financial sector.

## 2.1 Definition of Traditional Banking

In the last decades, technology has been changing the way people interact with each other, as well as changing the way several industries operate. The banking industry is one of the major industries that hasn't witnessed significant exogeneous technological (i.e. motivated by the Internet Revolution) changes for the last five (5) decades. Today, Fintech companies are entering the financial industry at a very fast pace, appropriating market share from traditional banks.

A simple definition of traditional banks can be described as following: "A bank is an institution whose current operations consist in granting loans and receiving deposits from the public" (Freixas & Rochet, 2008). This simple definition highlights banks' intermediation role between savers and borrowers.

Furthermore, according to Chiorazzo et al. (2018), traditional banking can be further defined by four specific banking characteristics: "i) loans made to individual persons or businesses that are held in portfolio rather than securitized (relationship loans); ii) funding based on transactions, savings and small time deposits rather than purchased funds (core deposits); iii) revenue generated from net interest margins, deposit service charges, and fiduciary services fees rather than non-interest income from trading, brokerage, investment banking, insurance, securitization or other less traditional financial services (total traditional income); and iv) in-person customer contact rather than arms-length telephone, mail or online interactions (branch intensity)" (Chiorazzo et al., 2018: pp. 238).

## 2.2 Definition of Fintech

Fintech is a new terminology that is gaining popularity in the financial industry for the past years and originates from the merger of two words: Financial Technology. The term Fintech is earning recognition since new companies (mainly Fintech startups) are trying to enter and compete against big traditional financial players in the financial industry, in an attempt to modernize and bring competition to the financial services industry. Although no consensus has been reached towards a universal definition of Fintech, there have been some attempts to define this term more precisely.

Thakor (2019) defines Fintech as “the use of technology to provide new and improved financial services” (Thakor, 2019: pp. 1), while, according to Barba Navaretti, et al. (2017), “Fintech refers to the novel processes and products that become available for financial services thanks to digital technological advancements” (Barba Navaretti et al., 2017: pp. 4).

On a more theoretical note, the Financial Stability Board defines fintech as “technologically enabled financial innovation that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services” (This definition was also adopted by the Basel Committee on Banking Supervision). The last concept, more precisely “the provision of financial services”, is crucial to define Fintech companies, since most of them are entering the industry to offer the same services as traditions financial institutions, except for two specificities: i) fintech companies charge much lower fees or they don’t even charge fees at all; and ii) almost all Fintech firms do not provide in-person customer contact.

## 2.3 The onset of Fintech

The Internet Revolution has led to the development of the financial markets, allowing them to operate under new circumstances and leading to lower costs for financial transactions. By the 1990s, the financial industry changed and evolved to an electronic based industry (e-finance), where the population accessed their financial accounts (e.g., banking, insurance, stock trading, etc.) via internet (Lee & Jae Shin., 2018). This evolution led the banking industry to change its business models and adapt to the digitalization of services, leading to the reduction of physical locations of bank branches and the downsizing of bank staff. More recently, and with the exponential growth associated with smartphones users, banking has gradually evolved to “online-banks”, and financial institutions started allowing their customers to not only access their accounts online, but also to do all transactions they needed online and instantly (Lee & Jae Shin., 2018).

Although these transformations have happened in the last 30 years, the term ‘Fintech’ had already appeared in 1972, when Bettinger (1972) described Fintech as “an acronym which stands for financial technology, combining bank expertise with modern management science techniques and the computer” (Bettinger, 1972). The change was eminent for some bankers; however, for several decades the entire financial industry did not see significant developments. Traditionally, the quality of financial innovation and patents in the financial industry was very low for decades (Lerner et al., 2015), and has only started increasing since the 1970s (Lerner, 2002). Therefore, the lack of tech-related financial innovation processes has been one of the main reasons for the appearance of the fintech concept.

Thakor (2019) stated that one of the main reasons for the emergence of fintech companies is related to the fact that the unit cost of financial intermediation hasn’t changed in over a century. This line of argumentation is backed up by a study done in 2014 which has estimated that the unit cost of financial intermediation in the U.S.A. has remained at about 2% of the total assets over the past 130 years (Philippon, 2015).

As a result, fintech companies started appearing after the Subprime Crisis in 2008 in order to cut costs, reduce prices and commissions, and improve the quality of financial services, while “creating a more diverse and stable financial landscape (The Fintech Revolution, 2015)” (Lee & Jae Shin., 2018, pp: 35). The promise of cheaper financial services aims to improve social wellbeing, achieve economies of scale, and improve competition within the financial industry (Lee & Jae Shin., 2018).

Recent empirical studies such as Andreas Fuster et al. (2019) have further provided evidence that fintech has improved the productivity of mortgage lending. Moreover, Chen et al. (2019) presents evidence that investments in Fintech innovation generate considerable returns to their investors and shareholders.

## 2.4 Fintech and Banking: Cooperation or Rivalry?

In the media, FinTech is considered "disruptive", "revolutionary" and armed with "digital weapons", that will "tear down" barriers and traditional financial institutions (World Economic Forum, 2017)" (Barba Navaretti et al., 2017: pp. 2).
There is still scant academic literature addressing the interaction between Fintech companies and Banking. Whether they should cooperate, compete, or form alliances is not clear yet, but one thing is certain: the pressure on traditional financial institutions has led them to start investing in new ways to prepare themselves for a new banking paradigm or to participate in strategic partnerships with Fintechs. For the majority of researchers, Banks and Fintechs should cooperate in the long run (Barba Navaretti et al., 2017). Although banks have been threatened by Fintechs, they have accepted these competitors and are able to cooperate with them (Lee & Jae Shin., 2018).

"Empirical evidence suggests that banks have been keen to enhance their profitability through financial innovation (Scott et al., 2017)" (Hornuf, et al., 2018:pp. 7), which should give enough reasons for traditional financial institutions to invest in Fintech companies that could provide them new technology and better ways to offer financial products. Cooperation between them can bring traditional financial institutions to the front row of financial innovation without demanding for inhouse modernization (Lee & Jae Shin., 2018). Another line of argumentation advanced by these authors argues that Fintech customers are mostly millennials (young people between 18 and 35 years old) living in big cities and having an above-average income. This income streams are mostly favorable for Fintech companies, thus prompting the need for traditional banks to invest and cooperate with Fintech companies (Barba Navaretti et al., 2017).

There are several reasons for Fintechs and Banks to cooperate. The following table provides some benefits to Fintechs and Banks when forming a coalition/partnership:

**Table 1** - Benefits for Fintech and Banks

| Benefits for Fintech | Benefits for Banks |
|---|---|
| Fintech may gain admission to a bigger database of banks' customers. | Banks can achieve a competitive advantage while investing in Fintech knowledge, as they have a less expensive method of delivering financial services. |
| Fintechs are recent entrants to the financial industry, therefore they may benefit from banks' years of experience and expertise when dealing with regulators and financial regulation. | Banks can get exclusive access to use a specific application that can enhance their efficiency, improving their market competitiveness. |
| Gain access to a banking license, which in some cases may be very expensive; and gain access to a wider pool of financial resources. | Banks can grow their range of products and services on offer with product-related partnerships. |
| Banks have already established economies of scale, which the Fintechs can benefit from. | Access to a broader younger customer base. |

Source: (Hornuf et al., 2018).

Currently, one of the main issues is the tension between stability and competition. Fintechs bring more competition to the financial industry and provide services with more efficiency than traditional banks. However, they will not replace banks, and banks have the means to adopt these innovations in order to provide the same services and products in a new, more efficient way. Ultimately, Fintech will progressively converge towards the business models of traditional financial institutions (Barba Navaretti et al., 2017).

## 2.5 Different categories of Fintech

Fintech companies are appearing at a fast pace in the market and, as a result, competition among them is also increasing substantially. In order to differentiate themselves, Fintech companies have been developing unique business models and have been focusing on particular markets and segments within the financial industry. As the Fintech revolution goes on, customers have been changing the way they use and save their money (Vasant Dhar & Roger M. Stein., 2017).

In the present Dissertation, we have identified five main fintech business models, covering five of the most important types of Fintech segments. These are: i) Digital Banking; ii) Capital Markets & Trading; iii) Payments; iv) Lending; and v) Insurance.

### 2.5.1 Digital Banking

Digital Banking is the digitalization of traditional banking services and products. There are already Fintech companies which have access to banking licenses and provide the same services and products as traditional banks, but with a significant difference: everything is done through a mobile application and there are no physical branches (Chiorazzo et al., 2018). A client can open online bank accounts, deposit, withdraw or transfer money, apply for financial products, manage her/his loans, pay bills, or simply check accounts within this app and normally with much lower or no fees at all (Thakor, 2019).

For example, the most famous digital banks are the UK-based Revolut and Monzo and the Berlin-based N26[1].

### 2.5.2 Capital Markets & Trading

Fintech is changing the way people trade and manage their investments. According to Lee et al (2018), one of the most promising areas for Fintech to thrive is within the domain of investments, foreign exchange, and trading. Traditional banks typically have high commission fees and transaction fees which investors and traders need to bear. As a result, fintechs which are focused in this financial segment allow their customers to buy and sell stocks, commodities, ETF's, bonds, derivatives, and foreign currency without transactions costs or with very low fees. Some fintechs also allow traders to interact with each other, allowing for the possibility to share knowledge and even to replicate portfolios from other traders (basically the investor has

[1] Check websites: Revolut, Monzo, N26

the option to copy the trades of popular traders). Most recently, some investment fintechs already have a "robot-advising" service, which "provide digital financial advisory based on mathematical rules or algorithms with minimal human intervention" (Thakor, 2019).

There are several benefits related to these fintechs. Having the possibility of being able to buy financial products with no fees maximizes the return for investors. Furthermore, the possibility to exchange different currencies allows investors and companies to reduce costs associated with foreign currency transactions. More recently, some fintechs have also started offering the possibility of buying/selling cryptocurrencies like Bitcoin or Ethereum.

Fintechs operating in this sector include Robinhood, eToro and coinbase[2].

### 2.5.3 Payments

The payments business model is one of the most popular among Fintech companies and the market segment that presents multiple opportunities for fintechs. As it is one of the most used services on a daily basis, fintechs can acquire customers the fastest by lowering costs with ease, and, accordingly, companies are constantly trying to enter in this segment. For Thakor (2019), the greatest possibility for the Fintech disruption is within the payments services and with cryptocurrencies. The said author describes that virtual currencies allow transactions to be processed on a P2P basis, without the actual need for a banking system. This allows for a faster and cheaper transaction structure, which ultimately benefits consumers.

Furthermore, Lee et al (2018) have divided the payment fintechs into two different segments: i) consumer & retail payment; and ii) wholesale & corporate payment; and the Basel Committee on Banking Supervision goes further and divides these two segments into sub-segments. Within retail payments, the transactions occur mainly via mobile wallets, peer-to-peer (P2P) transfers, and digital currencies; while within the wholesale segment transactions occur via B2B point of sale, FX wholesale, and digital exchange platforms. The mobile payments sector is becoming very popular as it is user-friendly, convenient, and safe for the user (Bank for International Settlements, 2018).

[2] Check websites: Robinhood, eToro, coinbase.

### 2.5.4 Lending

The lending business model in Fintech relates to two different types of lending: i) P2P consumer lending; and ii) P2P business lending. P2P lending "is the loaning of money to individuals and businesses through online services that directly match lenders with borrowers without using an intermediating bank" (Thakor, 2019). The P2P platforms act as the intermediary, but do not invest in the loan itself. The lender can choose who he will borrow the money to, and benefit from higher or lower interest rates, depending on the credit score of the borrower. By having cost-effective software and by not being involved in the loans (no need to meet central banks capital requirements), P2P lending fintechs can offer lower interest rates. These fintechs also provide investors with an attractive remuneration for their investments, especially in times when market interest rates are very low.

Jagtiani and Lemieux (2018) provide evidence in support of the argument that fintech lenders are able to provide credit in market segments where there is low credit supply, where there are less bank branches, and where the local economy is more challenging for traditional banks. The authors further state that fintech lenders may give less creditworthy borrowers access to credit, which banks wouldn't be willing to serve in the first place.

### 2.5.5 Insurance

Insurance Fintech, also known as InsurTech, is the segment of Fintech that operates in the insurance sector. Lee et al (2018) explain that InsurTechs enhance the relationship between the insurer and the customer. By using data analytics to enhance risk more precisely and broadening its customer base, it benefits both the insurer and the customer, by reducing the costs with managing risk and by calculating the premiums more precisely.

For Thakor (2019), InsurTech will be able, with the help of big data, to use information from personal gadgets to assess individual risk more precisely, rewarding low-risk behaviours and penalizing high-risk behaviours, which will lead to more fair premiums. In the long run, the author defends that these fintechs will also provide more opportunities for insurance companies to insure more sophisticated types of risks.

## 2.6 Previous research on the impact in share prices of Fintech M&A

The present Dissertation focuses on critically analyzing the impact of the acquisition of fintech companies in bank stock prices. Hornuf et al. (2018) innovatively analyzed the impact of Fintech partnerships with banks. This research is focused only on partnerships between banks and fintechs in Canada, France, Germany, and the United Kingdom, considering the time window between January 2007 and January 2018. The authors chose these four countries because "they have the highest GDPs in the Comprehensive Economic and Trade Agreement (CETA) area and represent different financial systems". For these authors, partnerships can be in the form of acquisition or product-related collaborations without acquisition. These authors have gathered data from 400 banks which had formed 500 partnerships with Fintechs, the majority being product-related collaborations. Moreover, Hornuf et al. (2018) conduct an event study to assess whether the partnerships of banks with Fintechs have a significant impact on the market valuation of the banks. This research concludes that publicly announced partnerships have a negative impact on the bank's value for short-term windows. The authors state that "alliances with fintechs are not perceived as a worthwhile effort to gain competitive advantage with regard to digitalization" (Hornuf et al., 2018: pp. 25). However, the authors further state that it is only in the long-term that investors perceive these investments as worthwhile, especially if the bank follows a digitalization approach. Furthermore, the study also concludes that "digital banks" are the banks which benefit the most, probably because they are more capable of absorbing fintechs' knowledge and technical expertise.

In addition, Dranev et al. (2019) addresses Fintech M&A worldwide. This research addresses the financial sector, more specifically the acquisition of fintech companies worldwide, in order to determine whether it is associated with a positive reaction from investors. Using data from global (i.e., multinational) companies, this academic research encompasses 178 M&A deals in the three largest developed markets: i) U.S.A.; ii) Canada; and iii) Europe; and the two largest emerging markets: iv) India; and v) China. This innovative research addresses the 2010-2017 period.

For this purpose, the authors measure the reaction of the market to these M&A deals by using event study methodology in order to assess the abnormal returns following the dates of the announcements. This research concludes that fintech M&A positively influences the stock returns of the companies acquiring fintech firms in the short-term but does not have a significant effect in the long-term for the acquirer. This research also concludes that the stock returns are higher when the acquiring company is from a developed country rather than an emerging country, which leads to the idea that "companies from developed countries operate in an environment that helps to implement the target's technology" (Dranev et al., 2019: pp. 361-362). Finally, the research also concludes that when the acquiring company belongs to the financial sector, the effect on cumulative abnormal return from companies belonging to this sector has a significant positive effect, which is higher than companies from other sectors. The authors explain this finding through "the greater synergy effect of integration between core financial businesses and fintech services" (Dranev et al., 2019: pp. 361-362).

**Table 2** - Previous studies

| Authors and Year of Publication | Methodology | Sample Description | Main Results |
|---|---|---|---|
| Dranev, Y., Frolova, K., & Ochirova, E. (2019) | Event Studies Methodology | 178 M&A deals across 5 markets for 2010-2017 | Fintech M&A has a positive impact on the stock price of the acquirer |
| Hornuf, L., F. Klus, M., Lohwasser, T., Schwienbacher, A. (2018) | Event Studies Methodology | 500 bank - fintech partnerships across 4 countries from 2007 to 2018 | Alliances have negative impact in the short-term, but banks benefit in the long run |

It is worth mentioning that, at the time of writing, and to the best of knowledge, no other empirical studies related to the acquisition of Fintechs has been published, and, more specifically, there is no further empirical evidence about the impact in the share price of acquirers of Fintech companies.

## 2.7 Literature gap and extension

As the topic of Fintech is very recent, there aren't many researches about the specific topic associated with the present Dissertation's academic research question. In previous research, the corresponding authors have mentioned that the lack of data on M&A deals doesn't allow for stronger conclusions. Moreover, and to the best of knowledge, no research has been conducted with M&A deals dated after January 2018. Lastly, no research has been conducted based solely on the specific case of European acquisitions. Both studies above presented are similar to a certain extent, the main difference being that one takes into consideration acquisitions on a global scale, while the other incorporates collaborations between Fintechs and Banks.

As a result, this Dissertation contributes to the existing academic and banking literature in at least two ways. First, this study aims to analyze how the market reacts to the announcement of the acquisition of a fintech company, with special attention to European banks as the acquirer. Second, this is the first paper to analyze, per type of Fintech, the market reaction to the announcement of the acquisition of a fintech company. Again, to the best of knowledge, no previous research has been conducted on this second point.

Hence, with the above-mentioned literature as background, the present Dissertation aims to expand the empirical knowledge on this fundamental topic, focusing on whether the acquisitions of fintech companies have impact on the stock price of the acquirer, regardless of the fact that the latter might be related to the financial industry or not. As such, the present research will address the following research sub-questions (RQ's):

***RQ 1:*** *Does investment in Fintech companies increase the share price of the acquirer firm?*

***RQ 2:*** *If the acquirer firm is a traditional bank, does the investment in Fintech companies increase the share price of the acquirer?*

***RQ 3:*** *Should traditional banks invest in or acquire Fintech companies?*

***RQ 4:*** *Is it more likely that a company that acquires or invests in a Fintech company becomes more attractive to investors?*

***RQ 5:*** *Which type of Fintech has the ability to impact more or less the share price of the acquirer firm?*

# 3. Methodology & Data

## 3.1 Event Study Methodology

The present Dissertation adopts the event study methodology, which, for example, typically allows researchers to address the impact(s) of a particular event on the share price of the company affected, using financial market data. Accordingly, researchers can scrutinize and understand whether there is an abnormal reaction in the stock price of the affected company, allowing to infer whether the event is impactful (i.e., significant) or not.

Dolley (1933) published the first event study article, which addressed the effects of stock splits on share prices. Nevertheless, this innovative study was conducted with a method which lacked some information. The traditional method presently used nowadays was only much later introduced by Ball and Brown (1968) and by Fama, Fischer, Jensen and Roll (1969). These authors changed the way event studies were conducted by considering the earnings information (Ball and Brown, 1968) and subsequently by controlling the confounding events (Fama et al., 1969).

Most recently, McWilliams and Siegel (1997) (two of the most cited authors in the event studies area) have inferred that, in an event study, three (3) assumptions are essential: i) market efficiency; ii) unanticipated event;, and iii) isolation of confounding effects. Market efficiency implies that, if markets are efficient, then the information available is already reflected in the stock prices. The second assumption implies that the event must be unanticipated, so that the market couldn't have had previous information about the said event, leading to immediate reactions in the market as the event occurs – making it an efficient market (as described in the first assumption). Therefore, we should expect reactions from the market only on the dates of the announcements. The third assumption heeds the researcher to make sure that there are no confounding effects during the event window. This may have a significant influence in the companies' financial performance as it can be overlapping with the particular event a researcher is actually addressing.

Notwithstanding, there is no exact way of conducting an event study, but Mackinlay (1997) has presented a very efficient general guidance on how to conduct an event study in seven (7) steps, using a sample of firms for which stock prices are observed. These steps, which can be extrapolated to other types of event studies, are the following:

1. The need to define the event of interest, as well as the event window (e.g., the period which companies stock prices are studied)

2. The need to define the selection criteria for the inclusion of samples (e.g., companies) in the study

3. In order to study the impact of a specific event, it is necessary to calculate the abnormal returns. These can be assessed with the help of various modelling options, more specifically, using the two most widely used models, i) the Constant Mean Return Model and ii) the Market Return Model

4. Then, the researcher needs to define a clear estimation window, in which the parameters are estimated (e.g., abnormal returns and the cumulative abnormal returns). The estimation window is defined, normally, before the announcement date, whereas the event window comes after, so that there is no influence of the event in the estimation of the parameters in the estimation window

5. The fifth stage consists on testing the sample for the abnormal returns (AR) and cumulative abnormal returns (CAR), defining the null hypothesis and the procedures for combining the individual company abnormal returns. Then, the estimation of the statistical significance of the abnormal returns is also conducted.

6. Empirical findings are estimated and discussed

7. Interpretation and conclusion associated with the said findings are also presented

It is worth mentioning that, after concluding this 7-step guidance, the conclusions pertaining to the results are only valid when the researcher has conducted the analysis in a right manner, being able to accurately identify the findings (e.g., in the case of Mackinlay (1997), the abnormal returns) associated with the event. The present Dissertation will thus follow a procedure quite similar to Mackinlay (1997).

## 3.2 Modelling Abnormal Returns and Parametric Tests

In order to study and analyse the market reaction to each one of the mergers or acquisitions presented in our Dissertation, we needed to calculate the Cumulative Abnormal Returns (CARs). To achieve this result, the following steps must also be implemented (following the procedure quite similar to Mackinlay (1997)):

We start by calculating the Abnormal Returns (ARs), using formula 1:

$$AR_{it} = R_{it} - E(R_{it}|X_t) \quad (1)$$

Where:

$AR_{it}$= Abnormal Returns for time period t

$R_{it}$= Actual Returns for time period t

$E(R_{it}|X_t)$= Normal returns for time period *t*

In order to calculate the normal returns, we estimate two statistical models: i) the Constant Mean Return Model; and ii) the Market Model.

The Constant Mean Return Model (CMRM) is the simplest model of the two. In this model, we assume that the expected return $E[R_{it}]$ is constant, and it is assessed by calculating the mean of $R_{it}$ from the estimation window with $T$ days:

$$E[R_{it}] = \frac{1}{T}\sum_{t=1}^{T} R_{it} \quad (2)$$

The abnormal return of company $i$ on day $t$ ($AR_{it}$) can be calculated the following way:

$$AR_{it} = R_{it} - E[R_{it}] \quad (3)$$

Alternatively, the Market Model (MM) uses market data to predict the returns of a stock price $i$. In this case, the normal return is defined as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \quad (4)$$

Where:

$R_{it}$= Return of a security $i$

$R_{mt}$= Actual Return
$\alpha_i$= intercept term
$\beta_i$= systematic risk
$\varepsilon_{it}$= zero mean error term

In this model, the Abnormal Return of the company $i$ on day $t$ ($AR_{it}$) can be calculated in the following way:

$$AR_{it} = R_i - (\alpha_i + \beta_i R_{mt}) \tag{5}$$

This last methodology provides a potential improvement over the CMRM, by eliminating actual returns that are related to market variations, and not related to the specific company. As a result, the variance of the abnormal return is lower, and the results are more accurate. In this Dissertation we will later explain how this methodology actually changes the empirical results between both models.

The advantage of using the MM will also depend on the value of the $R^2$ of the regression: the higher the $R^2$, the lower the variance of the abnormal returns – leading to a more accurate model to explain this specific event. In this Dissertation, both models are calculated and analysed since its quite useful to compare both the CMRM and the MM models.

To test the null hypothesis of no abnormal returns, $AR_{it}$ is divided by the standard deviation of the Abnormal Returns of company $i$ from the estimation window:

$$t_{AR_i} = \frac{AR_{it}}{SD_{AR_i}} \tag{6}$$

where Standard Deviation is:

$$SD_{AR_{it}} = \left[\frac{1}{T-2}\sum_{t=1}^{T}(AR_{it})^2\right]^{0.5} \tag{7}$$

and the significance level has $T-2$ degrees of freedom.

In order to combine the inferences of all events, the abnormal returns must be aggregated. This aggregation is based across two dimensions – through time and across the sample's companies. First, and as MacKinlay (1997) describes, we need to calculate the aggregation through time.

This means that we have to calculate the cumulative abnormal returns. This approach aggregates all measured effects of the event on the stock price of company $i$, and is calculated as follows:

$$CAR_i = \sum_{T=1}^{K} AR_{it} \tag{8}$$

The significance of the $CAR_i$ can be tested as:

$$t_{CAR_i} = \frac{CAR_i}{SD_{CAR_i}} \tag{9}$$

where Standard Deviation of CAR is:

$$SD_{CAR_i} = \left(k \times SD_{AR_i}^2\right)^{0.5} \tag{10}$$

where:

$SD_{AR_i}^2$= variance of residuals from the estimation window

Additionally, to calculate the aggregation across different stock prices of different companies, another concept is presented – the Standardized Abnormal Return (SAR). This process allows each abnormal return to have the same variation, by dividing the abnormal return by its standard deviation:

$$SAR_{it} = \frac{AR_{it}}{SD_{it}} \tag{11}$$

with $SD_{it}$ being:

$$SD_{it} = \left\{SD_{AR_i}^2 \times \left[1 + \frac{1}{T} + \frac{(R_{mt} - \overline{R_m})^2}{\sum_{t=1}^{T}(R_{mt} - \overline{R_m})^2}\right]\right\}^{0.5} \tag{12}$$

Where:

$SD_{AR_i}^2$= Residual variance

$R_{mt}$= Market return on day $t$

$\overline{R_m}$ = Average return on the market portfolio

The standardized abnormal returns can then be cumulated over the time period of the event window and can be calculated as follows:

$$CSAR_i = \left(\frac{1}{k^{0.5}}\right) \sum_{t=1}^{k} SAR_{it} \tag{13}$$

By assuming that the values of $CAR_i$ are independent and identically distributed when $CAR_i$ is divided by its standard deviation, its values are identically distributed. The average effect of the event on all companies in the sample on day t is given by the average standardized cumulative abnormal returns (ACSAR), which it is calculated as:

$$ACSAR_t = \frac{1}{n} \times \frac{1}{SD_{CSAR}} \sum_{i=1}^{n} CSAR_{it} \tag{14}$$

where $SD_{CSAR}$ is:

$$SD_{CSAR} = \left[\frac{(T-2)}{(T-4)}\right]^{0.5} \tag{15}$$

To test the hypothesis that $ACSAR_t$ is significantly different from zero, this can be estimated as follows:

$$Z_{ACSAR} = ACSAR_t \times n^{0.5} \tag{16}$$

If $ACSAR_t$ is statistically significant, it is possible to conclude that the event had an impact on the stock price of the n companies.

The aggregation of abnormal returns assumes that there are no overlaps between the event windows, which allow for the aggregation of the abnormal returns without having problems related to a zero covariance. In this Dissertation, the zero-covariance problem does not apply, as the event windows of all the companies comprised in the sample are different.

## 3.3 Non-parametric tests

Most of the event studies done by researchers rely on parametric tests. However, according to Arnold R. Cowan, "a disadvantage of parametric statistics is that they embody detailed assumptions" (Arnold R. Cowan, 1992: pp. 1). As a result, non-parametric tests are an alternative test to perform in an event study. Non-parametric do not require so many restrictions about return distributions as parametric tests. According to Cowan (1992), the sign test is one of the most used tests in event studies. The second most popular non-parametric test is the rank test. According to Corrado (1989), the rank test has more power in detecting the abnormal returns than the common parametric tests. These tests are used in event studies to verify the results; therefore, they may be used to provide robustness checks for the parametric tests.

Cowan (1992) has studied both non-parametric tests and has concluded that, although the rank test is generally more powerful than the generalized sign test, when the event window is greater than 1 day the power of the test decreases rapidly. As the event study performed in this Dissertation has an event window of six (6) days (i.e. (0,5[3])), the generalized sign test is better suited for this Dissertation as a robustness check.

Cowan (1922) describes a developed version of the sign test: the generalized sign test. The sign test is a binomial test that evaluates whether the frequency of positive abnormal returns amounts to 50% of the total amount of returns. The developed version from Cowan (1992) adapts the frequency to the amount of positive abnormal returns in the estimation period, instead of assuming a fraction of 50%. As a result, this test serves to check whether the number of companies with positive cumulative abnormal returns in the event window is greater than the expected number in the absence of abnormal returns, this meaning a period unaffected by the event.

The expected number is based on the fraction of positive abnormal returns in the estimation period:

$$\hat{p} = \frac{1}{n}\sum_{j=1}^{n}\frac{1}{T}\sum_{t=1}^{T} S_{jt} \tag{17}$$

[3] The event window (0,5) means that it starts on the day of the announcement (day zero (0)) and goes up to five (5) trading days after.

And

$$S_{jt} = \begin{cases} 1 & if\ AR_{jt} > 0 \\ 0 & otherwise \end{cases} \tag{18}$$

Where T is the estimation window

The generalized sign test uses the normal approximation to the binomial distribution with parameter $\hat{p}$. It is calculated as:

$$Z_G = \frac{w - n\hat{p}}{\lfloor n\hat{p}\,(1-\hat{p})\rfloor^{\frac{1}{2}}} \tag{19}$$

Where

$w$= number of stocks in the event window for which the cumulative abnormal return is positive

Under the null hypothesis, there is no difference between the proportion of positive returns in the event window and its proportion of positive returns in the estimation window.

## 3.4 Estimation and Event Window

In previous sections, it was defined that the estimation window is used for the expected returns' calculation. In this study, we have addressed our estimation window based on Mackinlay (1997), which has defined a window encompassing 250 trading days prior to the event date.
As McWilliams and Siegel (1997) have described, the selection of the event window is complex. First, the size of the event window must be choosen in order to capture the abnormal returns of the event without including any confounding effects. Second, it is important to analyze the day prior to the event day, as some information may be leaked out of the companies and, as investors may not react immediately to the announcements, the event window may also include the day after the event date. Third,  the event window can be extended to understand whether the event has had a prolongued significant abnormal return. In this Dissertation, it has been decided to analyze only one event window. The chosen event window starts at the day of announcement until 5 days after the event (0,5). A further decision was also undertaken not to include any day prior to the announcement day as we are analysing the day of the announcement (whether announced by the companies themselves or not). As a result, there aren't as many opportunities for leaked information to be taken advantage of by certain financial market participants in the marketplace. The academic literature available does not provide a concrete

manner of choosing the right event window, and therefore we have chosen the event window (0,5) in order to capture the day of the announcement plus one trading week of window, in order to capture the short-term effects on the analysed stock prices.

## 3.5 Hypothesis

Based on previous literature, M&A events between companies and Fintech companies are typically expected to have a significant positive impact on the share price of the acquirer. Furthermore, it is also expected that acquirers that are present in the banking industry will witness a more significant impact on their share price than acquirers present in other (i.e., non-banking) industries.
Lastly, and relating to the type of Fintech acquired, no previous literature has been found, meaning that no expected returns can be predicted, as the present Dissertation quite innovatively addresses this specific issue.

## 3.6 Confounding Events

It is imperative that the findings obtained are only influenced by the event(s) being studied, without having any external influence by another confounding event. As almost all companies in the database below are related to large European banks or other companies, there is some degree of probability that some results might be affected by confounding effects. In order to eliminate these confounding events, George Foster (1980) suggests the elimination of the abnormal returns of the day of the confounding events for the companies that exhibit them.
In this Dissertation, the confounding events are further identified in the validation section.

## 3.7 Data

The data collection was done through the use of the Zephyr database (from Bureau Van Dijk), which contains information on more than 1.6 million M&A deals and potential deals all over the world. For this Dissertation, the following search and selection criteria were employed:

1. Time period: from 01/12/2007 and up to and including 12/10/2019, in order to retrieve data from the last peak of economic activity until 12/10/2019 (according to business cycle dating procedures proposed by the NBER);
2. Completed and announced acquisitions;
3. European listed acquirer;
4. Acquirer must be in an industry in one of the following US SIC codes: 60 – Depositary institutions, 61- Non-depositary credit institutions; 62- Security and commodity brokers, dealers, exchanges and services; 6712- Offices of bank holding companies; 6722- Management investment offices, open-end;
5. Target company must be in an industry in one of the following US SIC codes: 60 - Depository institutions, 61 - Non-depository credit institutions, 62 - Security and commodity brokers, dealers, exchanges and services, 63 - Insurance carriers, 64 - Insurance agents, brokers, and service, 67 - Holding and other investment offices, 7371 - Computer programming services, 7372 - Prepackaged software, 7373 - Computer integrated systems design, 7374 - Computer processing and data preparation and processing services, 8711 - Engineering services, 872 - Accounting, auditing, and bookkeeping services, 8741 - Management services, 8742 - Management consulting services;

Search and selection strategy criterion 5 was chosen in line with the research article of Dranev et al. 2019 (pp. 353-364), which have identified those US SIC codes as the ones that better describe fintech companies.

After using the above-mentioned search and selection strategy, information on more than 2,500 deals is retrieved, and a further refinement strategy step is further implemented. Then, all these 2,500 deals were individually researched in Crunchbase[4] and in their own websites, in order to check if these target companies are fintech companies or not. The intermediate tally comes to a further selection of 189 deals, of which 102 deals involved a bank as the acquirer.

After that, the Bloomberg L.P. database and the Wall Street Journal database were employed to retrieve the historical share prices of each acquirer, in order to proceed with our analysis on the impact of the stock price. After eliminating some acquired companies for which we could not find any market data or that had any other measurement errors, we came to a final tally for our sample, comprising 144 deals, of which 99 involved a bank as the acquirer. The "non-bank"

[4] Crunchbase website

type of acquirer relates to a company which is present on, at least, one of the US SIC codes in search and selection strategy criterion 4. This database might be to a certain extent slightly limited, as the present Dissertation only tries to explain how a fintech M&A impacts the share price of a European company present in one of the *specific* industry codes shown in search strategy criteria 4. Notwithstanding, this constitutes the outcome of the stringent search and selection process employed by the present Dissertation.

The final database used in this dissertation can be seen in Table 10 (Appendix A).

# 4. Empirical Findings

The goal of the present Dissertation is to analyse whether banks (and other companies) that incur in Fintech M&A as acquirers do benefit from the corresponding acquisitions. 144 observations were analysed, and through the chosen event window, many of them have individual positive significant abnormal and cumulative abnormal returns. Nevertheless, we need to understand the effect of all events in a group way.

In this chapter, we will present the individual ARs and CARs as well as several studies of Fintech M&A grouped. The group studies are divided into the following segments: i) all events combined; ii) differentiation between banks and non-banks companies; iii) by percentage of acquisition; and lastly, iv) by different types of Fintech companies.

## 4.1 Individual Events

As there are 144 observations in our database, analysing each and every one of them individually is not possible as it would be very time-consuming and wouldn't add much value to this Dissertation. Nevertheless, it still makes sense to present a brief overview of all individual CARs for both models (CMRM and MM) in the following table:

**Table 3** - Brief summary of CAR's for both models: CMRM and MM, for the event windows (0,5).

| Event Window | Positive CARs | | | Positive Significant* CARs | | | Negative Significant* CARs | | |
|---|---|---|---|---|---|---|---|---|---|
| | CMRM | MM (1) | MM (2) | CMRM | MM (1) | MM (2) | CMRM | MM (1) | MM (2) |
| (0,5) | 76 | 63 | 69 | 6 | 6 | 6 | 2 | 3 | 5 |

** At a 5% significance. Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later.*

This table shows us how many positive CARs there are within the 144 observations, how many of them are positive and significant, and how many are negative and significant, using both models: CMRM and MM. In respect to the latter, it is important to note that two (2) different Market Models are employed for a simple reason: as the present research unfolds, this Dissertation initially uses market model 1 (MM (1)) taking into consideration the MSCI World Index as the benchmark. In contrast to the evolution of this index, the share prices of

European banks have nevertheless been declining since 2008, and our choice to use this index as a benchmark in the market model is not entirely efficient. As a solution to this research issue, a second market model (here represented as MM (2)) is complementarily employed. This second model uses the Euro Stoxx Banks index as a benchmark, but only for the observations that have a bank as the acquirer. While the MSCI World Index has an average daily return of 0.018% since 2008, the Euro Stoxx Banks index has an average daily return of -0.023% for the same period. For the remaining chapters of this Dissertation, market model 2 is adopted, as it is the only market model that makes more sense in the research context of the present Dissertation.

We can easily observe from the table above that the CMRM shows more positive CAR's than both market models. This is explained by the fact that the CMRM includes the price returns that are related to the variation in the market's return. In this case, the CMRM produces more positive CAR's than negatives, proving that the overall markets are growing (on average).

MM (2) shows more positive CAR's than MM (1), which is the result of the adaptation of the second market model by the appropriate benchmark. On the other hand, the negative significant CAR's are also higher in MM (2) than in MM (1) and CMRM. This particular case could be explained by the importance of the event for the shareholders of the acquirers. As a result, we tried to differentiate the type of event by percentage of acquisition. If we take into consideration only the observations which resulted in the acquirer owning 50% or more of the Fintech company, the table changes significantly. The following table is based on the CAR's for 42 observations in both models:

**Table 4** - Brief summary of CAR's for both models: CMRM and MM, for the event window (0,5), but only for acquisitions of at least 50% of the Fintech company.

| Event Window | Positive CARs | | Positive Significant* CARs | | Negative Significant* CARs | |
|---|---|---|---|---|---|---|
| | CMRM | MM | CMRM | MM | CMRM | MM |
| (0,5) | 28 | 22 | 2 | 4 | 0 | 0 |

** At a 5% significance. Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later.*

As can be observed from the Table 4, there are no negative significant CAR's when a deal is realized for, at least, 50% of a Fintech company's' ownership. Although positive CAR's continue slightly lower in the MM than the CMRM, it is in the positive significant CAR's that we see the biggest differences: i) MM displays double the number of positive significant CAR's than the CMRM; and ii) no model presents negative significant CAR's.

## 4.2 All events grouped

In contrast to analysing the events individually, we now proceed with the analysis of the overall impact of all events combined. In Table 5, we show the different significance levels for both different models and for two scenarios: (1) all 144 observations together, regardless of the percentage of acquisition; and (2) only the observations which resulted in the acquirer owning 50% or more of the Fintech company (i.e. 42 observations):

**Table 5** - Summary of ACSAR's for both models: CMRM and MM, for the event windows (0,5) and for both scenarios: all 144 observations and for acquisitions of at least 50% of the Fintech company.

| | | CMRM | | | MM | | |
|---|---|---|---|---|---|---|---|
| Observations | Day | ACSAR | Z | | ACSAR | Z | |
| All 144 obs. | 0 | -0,0557914 | -0,8821401 | | -0,0236887 | -0,3745512 | |
| | 1 | 0,0312678 | 0,49438738 | | -0,0123486 | -0,1952478 | |
| | 2 | 0,09346547 | 1,47781883 | | 0,00370642 | 0,0586036 | |
| | 3 | 0,11399075 | 1,80235194 | * | -0,0095761 | -0,151412 | |
| | 4 | 0,08946446 | 1,41455727 | | -0,0329688 | -0,5212827 | |
| | 5 | 0,17886327 | 2,82807658 | *** | 0,00090132 | 0,01425117 | |
| Sub-sample of 42 obs. | 0 | 0,09406902 | 1,48736181 | | 0,16577349 | 2,62110902 | *** |
| | 1 | 0,40811106 | 6,45280243 | *** | 0,23098067 | 3,65212506 | *** |
| | 2 | 0,42118455 | 6,65951247 | *** | 0,16198284 | 2,56117352 | ** |
| | 3 | 0,60758497 | 9,60676196 | *** | 0,26454981 | 4,1828998 | *** |
| | 4 | 0,62735373 | 9,91933347 | *** | 0,2305107 | 3,64469413 | *** |
| | 5 | 0,84441393 | 13,3513565 | *** | 0,26157128 | 4,13580503 | *** |

*Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later. The z test determines whether the null hypothesis of no ACSAR is equal to zero, is rejected or not.*

*Rejects the null hypothesis at the 10% significance level
** Rejects the null hypothesis at the 5% significance level
*** Rejects the null hypothesis at the 1% significance level

Starting with all 144 observations, the MM, ACSAR values are either positive or negative and very close to zero. Furthermore, none of the values are statistically significant after the event occurs. In respect to CMRM, almost all ACSAR values are positive (apart from the day zero

(0)). Additionally, on day three (3) and day five (5), both ACSAR values are positive and statistically significant at 10% and 1% level, respectively.

These results are rather somewhat conclusive. As already mentioned before, this particular case could be explained by the importance of the event for the shareholders of the acquirers. If we take into consideration only the observations which resulted in the acquirer owning 50% or more of the Fintech company, the results change significantly. The elimination of the not very relevant observations (for acquisitions below the 50% threshold) yields a final database of 42 observations.

In this case, it's easy to observe that in the MM, all ACSAR values are positive and statistically significant at 1% level (with the exception of day two (2), which is statistically significant at 5% level). With reference to CMRM, and in line with the MM, all ACSAR values are positive and almost all are statistically significant at the 1% level, with a sole exception for day zero (0). In the day of the announcement, the ACSAR is positive, however it is not statistically significant.

In summary, the differentiation of the events by percentage of acquisition is very important to obtain good and conclusive results, taking into consideration the controlling power of acquisitions above the 50% threshold. Although the results for all 144 observations were not conclusive, we can still observe evidence in the CMRM that Fintech acquisitions have positive impacts in the share price of the acquirer. However, the smaller observation database yields the best conclusions. Both models (CMRM and MM) show clear evidence of a positive impact from Fintech acquisitions, yielding a novel finding.

Consequently, it is possible to state that Fintech acquisitions positively affect the acquirer's market stock price when the said acquisitions surpass the 50% threshold of management control (an important benchmark for corporate control).

In order to verify the robustness of the parametric results, the following table 6 shows the results of the non-parametric test and tries to establish a connection to the parametric tests.

**Table 6 -** Summary of results of the non-parametric test, the Generalized Sign Test, for both models: CMRM and MM, for the event windows (0,5) and for both scenarios: all 144 observations and for acquisitions of at least 50% of the Fintech company.

| Observation | Event Window | Generalized Sign Test CMRM | | Generalized Sign Test MM |
|---|---|---|---|---|
| All 144 obs. | (0,5) | 0,909519 | | -0,3505 |
| Sub-sample of 42 obs. | (0,5) | 2,304003 | ** | 0,395052 |

*Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later.*

*Rejects the null hypothesis at the 10% significance level
** Rejects the null hypothesis at the 5% significance level
*** Rejects the null hypothesis at the 1% significance level

The generalized sign test above shows that only in the CMRM and for the observations which resulted in the acquirer owning 50% or more of the Fintech company, the proportion of positive returns in the event window is statistically different from its proportion of positive returns in the estimation window at 5% confidence level. Regarding the MM, there are no signs of differences between the event window nor the estimation window.

Although the results between parametric and non-parametric tests may be not consistent, these differences can be explained because the generalized sign test does not take into consideration the magnitude of the values. In sum, it is still possible to state that Fintech acquisitions positively affect the acquirer's market stock price, when the said acquisitions surpass the 50% threshold of management control.

## 4.3 All events divided by type of acquirer

In order to be able to answer to this Dissertation's main research question, we will analyse the events group by type of acquirer: either i) non-banks or ii) banks, in order to distinguish between both groups and determine whether Fintech acquisitions do influence the share prices of European banks.

**Table 7** - Summary of ACSAR's for both models and divided by type of acquisition and type of acquirer.

| | | CMRM | | | MM | | |
|---|---|---|---|---|---|---|---|
| Observation | Day | ACSAR | Z | | ACSAR | Z | |
| (i) All 45 Non-Banks obs. | 0 | -0,1213063 | -1,9180204 | * | -0,0952837 | -1,506568 | |
| | 1 | 0,01600984 | 0,25313773 | | -0,0094619 | -0,1496064 | |
| | 2 | 0,3478145 | 5,49943007 | *** | 0,15443153 | 2,44177689 | ** |
| | 3 | 0,58734616 | 9,28675814 | *** | 0,29397238 | 4,64811142 | *** |
| | 4 | 0,70400671 | 11,1313234 | *** | 0,30839004 | 4,87607473 | *** |
| | 5 | 0,89893374 | 14,2133904 | *** | 0,34108113 | 5,39296612 | *** |
| (ii) All 99 Banks obs. | 0 | -0,026012 | -0,4112854 | | 0,00885449 | 0,14000184 | |
| | 1 | 0,03820324 | 0,60404632 | | -0,0136607 | -0,2159939 | |
| | 2 | -0,0221477 | -0,3501863 | | -0,064805 | -1,024657 | |
| | 3 | -0,1011708 | -1,5996509 | | -0,1475527 | -2,3330135 | ** |
| | 4 | -0,1898729 | -3,0021546 | *** | -0,1881319 | -2,974627 | *** |
| | 5 | -0,1484415 | -2,3470661 | ** | -0,1537259 | -2,4306193 | ** |
| (iii) Sub-sample of 24 Non-Banks obs. | 0 | 0,13378096 | 2,11526264 | ** | 0,23041423 | 3,6431688 | *** |
| | 1 | 0,33094353 | 5,2326767 | *** | 0,21852238 | 3,45514225 | *** |
| | 2 | 0,32359323 | 5,11645821 | *** | 0,12606946 | 1,99333323 | ** |
| | 3 | 0,56205801 | 8,88691742 | *** | 0,24095769 | 3,80987555 | *** |
| | 4 | 0,71901473 | 11,368621 | *** | 0,23157985 | 3,66159897 | *** |
| | 5 | 1,0468114 | 16,5515415 | *** | 0,32032425 | 5,06477116 | *** |
| (iv) Sub-sample of 18 Banks obs. | 0 | 0,04111977 | 0,65016071 | | 0,12083858 | 1,91062566 | * |
| | 1 | 0,5110011 | 8,07963675 | *** | 0,29299922 | 4,63272442 | *** |
| | 2 | 0,55130631 | 8,71691814 | *** | 0,26646302 | 4,21315021 | *** |
| | 3 | 0,6682876 | 10,5665547 | *** | 0,31557646 | 4,9897019 | *** |
| | 4 | 0,50513907 | 7,98695006 | *** | 0,25125218 | 3,97264581 | *** |
| | 5 | 0,57455064 | 9,0844432 | *** | 0,21705925 | 3,43200811 | *** |

*Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later. The z test determines whether the null hypothesis of no ACSAR is equal to zero, is rejected or not.*

*Rejects the null hypothesis at the 10% significance level
** Rejects the null hypothesis at the 5% significance level
*** Rejects the null hypothesis at the 1% significance level

Accordingly, Table 6 is divided into four scenarios. We have either: (i) all 45 non-bank observations regardless of the percentage of acquisition; (ii) all 99 banks observations regardless of the percentage of acquisition; (iii) 24 non-banks observations which resulted in the acquirer owning 50% or more of the Fintech company; or (iv) 18 banks observations which resulted in the acquirer owning 50% of more of the Fintech company.

Starting with all observations, regardless of the percentage of acquisition (i.e. (i) and (ii)), a difference between non-banks and banks observations is observed. While non-banks observations have positive and significant ACSAR values after the second (2) day for both models (CMRM and MM), bank observations show the opposite: almost all ACSAR values are negative and some are event negative and significant ACSAR values for both CMRM and MM.

In the MM, ACSAR values for non-banks observations are almost all positive, except for days zero (0) and one (1). Furthermore, all values after the second (2) day are statistically significant at 1% level, apart from the second day which is significant at 5% level. In respect to CMRM, almost all ACSAR values are positive (apart from the day zero (0)). Additionally, on days two (2) to five (5), ACSAR values are positive and statistically significant at 1% level. In CMRM, there is also another curious result: on the day of the announcement, the impact of the event in the share price is negative and statistically significant at 10%. Nevertheless, these results show that the Fintech acquisitions positively impacts the share price of non-bank acquirers, but only after the second day after the announcement day.

For bank observations, the results are completely different, suggesting innovative findings in the link between Banks and Fintechs. Both models show that in general, ACSAR values are negative, with some exceptions in both models (day zero (0) in MM and day one (1) in CMRM). In addition, in MM the ACSAR values after day three (3) are also statistically significant 5% or 1% level, showing that there is a significant negative effect on the share price of the bank acquirer. CMRM shows almost the same results, although the negative effects are significant only after day four (4). These innovative results show that Fintech acquisitions negatively impact the share price of the acquirer bank. However, this demonstration, once again, prompts the need to distinguish the analysed events by percentage of acquisition.

When analysing the observations which resulted in the acquirer owning 50% or more of the Fintech company, the results for non-banks are quite similar, while the results for banks change considerably.

In Table 6, case (iii), in the MM, ACSAR values for non-banks observations are all positive, which is somewhat better than the results with all observations. Now we also have positive and significant values for the day zero (0) and day one (1). Furthermore, all values are statistically significant at 1% level, apart from the second day which is significant at 5% level. In respect to CMRM, all ACSAR values are also positive. Additionally, all ACSAR values are statistically significant at 1% level, except for day zero (0) which is significant at 10% level. In sum, it is possible to conclude that these results show that the Fintech acquisitions affects positively the share price of non-bank acquirers.

For bank observations, the results are completely different than the ones with all observations included (Table 6, case (iv)). In MM, we can easily observe that all ACSAR values are positive and statistically significant at 1% level, with the exception of the day of the announcement which is significant at 10% level. Similarly, CMRM shows almost the same results, although on the day of the announcement the ACSAR value is not statistically significant. This outlier result on the day of the announcement in both models can be explained by the exact moment of the announcement of the acquisition. It is possible that some acquisitions are only announced after the end-of-day (EOD), after markets' closing hour, meaning that the effect on their share price is only reflected on the day subsequent to the announcement day. Nevertheless, these results prove that Fintech acquisitions positively impacts the share price of European banks as acquirers, when controlling positions are at stake.

In summary, the differentiation of the events by percentage of acquisition is very important to obtain efficient and conclusive results. Overall, the share price of non-bank observations is positively impacted, either by observations which resulted in the acquirer owning 50% or more of the Fintech company, or by other type of acquisitions. However, when the non-bank company acquires more than 50% of the Fintech company, the results are more effective, and the share price is positively impacted starting right away on the day of the announcement.

On the other hand, the findings for bank observations are somewhat different. In this case, the differentiation between percentage of acquisition is crucial to have more clear and effective conclusions. When not taking into consideration the percentage of acquisition, the results show that the Fintech acquisition negatively impacts the share price of the acquirer bank, and the values are even statistically significant after the second or third day after the announcement date (depending on the type of model). Yet, if the European bank acquires more than 50% of the Fintech company, the corresponding findings are considerably more efficient, demonstrating that Fintech acquisitions positively impact the share price of the acquirer bank, with a statistically significance at the 1% level after the day of the announcement.

In order to verify the robustness of the parametric results, the following table 8 shows the results of the non-parametric test and tries to establish a connection to the parametric tests.

**Table 8 -** Summary of results of the non-parametric test, the Generalized Sign Test, for both models: CMRM and MM, for the event windows (0,5) and divided by type of acquisition and type of acquirer.

| Observation | Event Window | Generalized Sign Test CMRM | | Generalized Sign Test MM | |
|---|---|---|---|---|---|
| All 45 Non-Banks obs. | (0,5) | 2,264947 | ** | 0,138172 | |
| All 99 Banks obs. | (0,5) | -0,37955 | | -0,50633 | |
| Sub-sample of 24 Non-Banks obs. | (0,5) | 2,903588 | *** | 0,022862 | |
| Sub-sample of 18 Banks obs. | (0,5) | 9,129606 | *** | 6,235785 | *** |

*Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later.*

*Rejects the null hypothesis at the 10% significance level
** Rejects the null hypothesis at the 5% significance level
*** Rejects the null hypothesis at the 1% significance level

In the table above we can see that the results are, again, somewhat heterogeneous. For the non-bank type of acquirer and in both types of acquisition, the generalized sign test is only significant in the CMRM, which is in line with the results of the parametric test. In contrast, in the MM the test is not significant in either one of the types of acquisition, which shows some discrepancy between the parametric and the non-parametric tests. This inconsistency between the parametric and non-parametric tests can be, once again, explained by the fact that this test does not take into consideration the values' magnitude, but only the sign.

On the other hand, when the type of acquirer is a Bank, the results of the non-parametric test are very consistent with the results of the parametric tests. We can easily observe that the results are only significant when the event results in the acquirer owning 50% or more of the Fintech company, and with a significance at the 1% level. These results are very coherent and consistent with the results obtained in the parametric tests and show a very good robustness of the overall research design of the model.

## 4.4 All events divided by type of Fintech acquired

In order to be able to fully answer this Dissertation's research question five (5), the analysis of the events group by type of Fintech acquired is also implemented. The events have been divided into several types (i.e., business lines) of Fintech. Nevertheless, only the types which had, at least, 10 observations were taken into consideration. These resulted in 5 different categories: i) Digital Banking; ii) Lending; iii) Payments; iv) Software; and v) Trading. Table 7 shows the ACSAR values for these types of Fintech companies:

**Table 9** - Summary of ACSAR's for both models and divided by type of Fintech acquired.

| | | CMRM | | | MM | | |
|---|---|---|---|---|---|---|---|
| Observation | Day | ACSAR | Z | | ACSAR | Z | |
| Digital Banking | 0 | 0,42867295 | 6,77791446 | *** | 0,69720772 | 11,023822 | *** |
| | 1 | 1,95581829 | 30,9242024 | *** | 1,33119739 | 21,0480789 | *** |
| | 2 | 1,44791031 | 22,8934722 | *** | 0,79972978 | 12,6448381 | *** |
| | 3 | 1,61051494 | 25,464477 | *** | 0,72656023 | 11,4879259 | *** |
| | 4 | 1,02056741 | 16,1365877 | *** | 0,29704277 | 4,69665861 | *** |
| | 5 | 1,50022729 | 23,7206763 | *** | 0,43141449 | 6,82126208 | *** |
| Lending | 0 | -0,0330316 | -0,5222748 | | -0,0554773 | -0,8771731 | |
| | 1 | -0,0395435 | -0,6252376 | | -0,0363787 | -0,5751972 | |
| | 2 | 0,05120678 | 0,80965025 | | 0,0130264 | 0,20596549 | |
| | 3 | 0,02522342 | 0,39881728 | | 0,00154119 | 0,02436839 | |
| | 4 | 0,02638228 | 0,41714048 | | -0,0024219 | -0,0382929 | |
| | 5 | 0,00581139 | 0,09188619 | | -0,0191645 | -0,3030173 | |
| Payments | 0 | -0,1595961 | -2,5234367 | ** | -0,0843249 | -1,3332937 | |
| | 1 | -0,0708507 | -1,1202479 | | 0,0649628 | 1,02715211 | |
| | 2 | -0,2895718 | -4,5785317 | *** | -0,0383982 | -0,6071287 | |
| | 3 | -0,3570021 | -5,6446994 | *** | 0,03765125 | 0,59531851 | |
| | 4 | -0,2255671 | -3,5665292 | *** | -0,0042532 | -0,0672488 | |
| | 5 | -0,0037342 | -0,0590432 | | 0,10043437 | 1,58800682 | |
| Software | 0 | -0,1812225 | -2,8653797 | *** | -0,111701 | -1,7661484 | * |
| | 1 | -0,1601288 | -2,5318583 | ** | -0,1417012 | -2,2404919 | ** |
| | 2 | -0,3062085 | -4,8415807 | *** | -0,2776053 | -4,3893255 | *** |
| | 3 | -0,2786812 | -4,4063363 | *** | -0,3437843 | -5,435707 | *** |
| | 4 | -0,4544923 | -7,1861537 | *** | -0,3882688 | -6,1390681 | *** |
| | 5 | -0,3854752 | -6,0948973 | *** | -0,3636096 | -5,749173 | *** |
| Trading | 0 | -0,0373473 | -0,5905123 | | -0,0191927 | -0,3034626 | |
| | 1 | 0,32495 | 5,13791056 | *** | 0,11191742 | 1,76956978 | * |
| | 2 | 0,50073326 | 7,91728796 | *** | 0,25415833 | 4,01859602 | *** |
| | 3 | 0,61446523 | 9,7155483 | *** | 0,35677204 | 5,64106132 | *** |
| | 4 | 1,08520798 | 17,1586448 | *** | 0,53118265 | 8,39873515 | *** |
| | 5 | 0,79579982 | 12,5827 | *** | 0,37789751 | 5,97508421 | *** |

*Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later. The z test determines whether the null hypothesis of no ACSAR is equal to zero, is rejected or not.*

*Rejects the null hypothesis at the 10% significance level
** Rejects the null hypothesis at the 5% significance level
*** Rejects the null hypothesis at the 1% significance level

As can be observed from the Table 7, the only type of Fintech that doesn't show any statistical significance for either models is 'Lending'. Furthermore, the ACSAR values are both positive and negative, depending on the day of observation.

The remaining types of Fintech companies ('Digital Banking'; 'Payments'; 'Software'; 'Trading') are all statistically significant, whether positive or negative, except for the Payments type in the market model.

'Software' ACSAR's values are all negative and all statistically significant. In the MM, day zero (0) is statistically significant at 10% level, day one (1) at 5% and the remaining days at 1% level. In the CMRM, the results are similar, excepting for day zero (0) which is significant at 1% level. This type of Fintech is the one which shows the greatest and more extended negative effect associated with the event.

'Payments' also shows negative ACSAR values in the CMRM, and some are even statistically significant at 5% or 1% level (day zero and days 2 to 4, respectively), however in the MM, this type of Fintech has mixed values between positive and negative and none is statistically significant, so that the final appreciation regarding the impact of the event is less grounded.

On the other hand, 'Digital Banking' ACSAR's values are all positive and all statistically significant at 1% level, being therefore the type of Fintech that shows the greatest and extended positive effect associated with the event. The second type of Fintech with the greatest effects is 'Trading'. This type of Fintech shows positive ACSAR's values for both models, except for the day of the announcement. However, after day one (1), the results are all statistically significant at 1% level.

Overall, 'Digital Banking' is the type of Fintech that has the highest positive impact on the share price of the acquirer firm, while 'Software' is the one that has the highest negative impact on the share price of the acquirer firm. Most likely, this can be explained by the generation of revenues for the acquirer. While 'Digital Banking' potentially generates new customers and a new revenue stream, 'Software' development will have an impact on the cost-structure of the company that acquires. This could potentially be more risky and generate more costs than savings for the acquirer.

In order to verify the robustness of the parametric results, the following Table 10 shows the results of the non-parametric test and tries to establish a connection to the parametric tests.

**Table 10 -** Summary of results of the non-parametric test, the Generalized Sign Test, for both models and divided by type of Fintech acquired.

| Observation | Event Window | Generalized Sign Test | | | |
|---|---|---|---|---|---|
| | | CMRM | | MM | |
| Digital Banking | (0,5) | 0,008944 | | -0,00537 | |
| Lending | (0,5) | 1,818821 | * | -0,17271 | |
| Payments | (0,5) | -0,61723 | | 0,770334 | |
| Software | (0,5) | -1,00652 | | -2,0359 | ** |
| Trading | (0,5) | 0,918193 | | 1,39449 | |

*Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later.*

*Rejects the null hypothesis at the 10% significance level
** Rejects the null hypothesis at the 5% significance level
*** Rejects the null hypothesis at the 1% significance level

Relating to the type of Fintech acquired, the results of the non-parametric test point to a more ambivalent interpretation of the findings. The Generalized Sign Test is only significant in two cases: for the 'Lending' type in the CMRM at 10% level of significance and for the 'Software' type in the MM at 5% level. 'Software' is the only type of Fintech which has consistent results between both types of tests, therefore we can firmly conclude that 'Software' is the one that has the highest negative impact on the share price of the acquirer firm. Regarding all the other types, the inconsistency between both the parametric and non-parametric tests can be, once again, explained by the fact that this test does not take into consideration the values' magnitude, but only the sign.

## 4.5 Robustness Tests

As previously mentioned in the "Methodology & Data" of the present Dissertation, in order to ensure the correct validity of the methodology, three (3) assumptions must be respected: i) market efficiency; ii) unanticipated event; and iii) isolation of confounding effects. In the following sub-sections these assumptions will be validated.

### 4.5.1 Market efficiency

The first assumption analyses whether the markets react immediately after the announcement of the deal, or whether the markets have a delayed reaction to the event's announcement.
The results of our event window (0,5)[5] show mainly positive significant reactions from investors. The following Table 11 represents a summary of ACSAR's for both models and divided by type acquirer for the most relevant type of acquisitions (i.e. acquisitions of 50% or more of the Fintech company), which correspond to the final 42 observations and, accordingly, the most relevant results of our Dissertation:

**Table 11** - Market efficiency

| | | CMRM | | | MM | | |
|---|---|---|---|---|---|---|---|
| Observation | Day | ACSAR | Z | | ACSAR | Z | |
| 24 Non-Banks obs. | 0 | 0,13378096 | 2,11526264 | ** | 0,23041423 | 3,6431688 | *** |
| | 1 | 0,33094353 | 5,2326767 | *** | 0,21852238 | 3,45514225 | *** |
| | 2 | 0,32359323 | 5,11645821 | *** | 0,12606946 | 1,99333323 | ** |
| | 3 | 0,56205801 | 8,88691742 | *** | 0,24095769 | 3,80987555 | *** |
| | 4 | 0,71901473 | 11,368621 | *** | 0,23157985 | 3,66159897 | *** |
| | 5 | 1,0468114 | 16,5515415 | *** | 0,32032425 | 5,06477116 | *** |
| 18 Banks obs. | 0 | 0,04111977 | 0,65016071 | | 0,12083858 | 1,91062566 | * |
| | 1 | 0,5110011 | 8,07963675 | *** | 0,29299922 | 4,63272442 | *** |
| | 2 | 0,55130631 | 8,71691814 | *** | 0,26646302 | 4,21315021 | *** |
| | 3 | 0,6682876 | 10,5665547 | *** | 0,31557646 | 4,9897019 | *** |
| | 4 | 0,50513907 | 7,98695006 | *** | 0,25125218 | 3,97264581 | *** |
| | 5 | 0,57455064 | 9,0844432 | *** | 0,21705925 | 3,43200811 | *** |

*Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later. The z test determines whether the null hypothesis of no ACSAR is equal to zero, is rejected or not.*

*Rejects the null hypothesis at the 10% significance level
** Rejects the null hypothesis at the 5% significance level
*** Rejects the null hypothesis at the 1% significance level

[5] Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later.

Both banks and non-banks have a positive reaction from the investors on day zero (0) – the day of the announcements of the deals – in both models, the CMRM and the MM. In the MM, the most relevant model, both banks and non-banks investors reactions were positive and significant at a 10% and 1% significance level, respectively. On the other hand, the CMRM shows slightly less efficient results: while non-banks reactions are positive and significant at a 5% significance level, banks reactions are not significant. However, these are still positive and the reaction of investors *on day zero* is, in all cases, positive. Furthermore, and more importantly, all these findings are also significant at a 1% significance level, in the days following the announcement date[6].

Consequently, these presented findings do not reject the assumption of market efficiency.

### 4.5.2 Anticipation

As previously explained, this assumption implies that the event must be unanticipated, so that the markets couldn't have had previous information about the said event. This fundamental assumption leads to the expectation that reaction from the markets only occurs on the dates of the announcements – this would be how markets in a perfect economic world would operate. However, sometimes shareholders might have access to information before it is announced to the markets. In order to ensure that this question has been properly addressed, we have performed a simulation with a particular event window: (-1,5) (i.e. from the day before of the announcement day up to 5 days after the announcement date).

After analysing these results, it is possible to conclude that no statistical significance was obtained for the day prior to the announcement date, meaning that the markets have only reacted after the announcement date, as can be confirmed in the table below, where the results for Day -1 are not statistically significant for both models:

**Table 12** - Summary of ACSAR's for both models for a different type of event window: (-1,5), in order to check for the Anticipation assumption.

[6] Except for the 5% for Day 2 for the non-banks' response in the MM model,

| | | CMRM | | | MM | | |
|---|---|---|---|---|---|---|---|
| Observation | Day | ACSAR | Z | | ACSAR | Z | |
| All 42 obs. | -1 | 0,00676897 | 0,10702685 | | -0,0164093 | -0,2594532 | |
| | 0 | 0,10200813 | 1,61289009 | | 0,1064119 | 1,68251987 | * |
| | 1 | 0,41705401 | 6,59420283 | *** | 0,18003109 | 2,84654151 | *** |
| | 2 | 0,41615637 | 6,58000999 | *** | 0,12622627 | 1,99581254 | ** |
| | 3 | 0,60392839 | 9,54894634 | *** | 0,22494741 | 3,55673092 | *** |
| | 4 | 0,62504062 | 9,88275988 | *** | 0,20021358 | 3,16565466 | *** |
| | 5 | 0,84350488 | 13,3369832 | *** | 0,23267211 | 3,67886905 | *** |

*Event Window (0,5) is the range of days being studied, starting at the day of the announcement (day zero (0)) up to five (5) days later. The z test determines whether the null hypothesis of no ACSAR is equal to zero, is rejected or not.*

*Rejects the null hypothesis at the 10% significance level
** Rejects the null hypothesis at the 5% significance level
*** Rejects the null hypothesis at the 1% significance level

### 4.5.3 Confounding Events

The third sub-section of the assumptions relates to the presence of confounding events with the event window of the methodology. To check whether there are any confounding events, we were able to cross-check the event windows with the information available in the acquirers' website, in order to verify that no other relevant events took place in those same event windows. After carefully and individually analysing all 42 final observations on a case-by-case basis, we concluded that there aren't any possible confounding events. A major explanation for this might have to do with the fact that there are few relevant fintech events taking place in the markets[7], which reduces the likelihood of fintech-related events being affected by other similar events.

[7] In comparison with the length of the event window considered throughout the present Dissertation.

# 5. Conclusion

The goal of the present Dissertation is to analyse whether banks (and other companies) that incur in Fintech M&A as acquirers do benefit from the corresponding acquisitions. We use financial market data from European financial companies, with a special emphasis on European banks. The results of this event study methodology are conclusive, allowing for the analysis of how a merger or acquisition (M&A) of a Fintech company by a financial company affects the share price of the acquirer.

In order to analyze how a M&A event of a Fintech company actually impacts the share price of the acquirer, an event study methodology is used involving stock market data. By using an event window from the day of the announcement up to five (5) days thereafter, as well as two different models (the CMRM and the MM), the robust findings suggest that Fintech M&A has a positive and significant impact on the share of the acquirers. For financial companies (excluding banks), Fintech M&A has a positive and significant impact on the share price of the non-bank acquirer after the second day following the announcement. However, if the acquisition results in the acquirer owning 50% or more of the Fintech company, the findings show that the impact on the share price of the acquirer is positive and significant starting from the very first day of the deal announcement. Furthermore, European banks also observe a positive and significant impact on its share price after a M&A event, but only if the acquisition results in the acquirer bank owning 50% or more of the Fintech company. These findings demonstrate that the importance of the event for the shareholders of European banks is a key determinant for a better performance associated with the corresponding share prices.

Furthermore, by analyzing the events by type of Fintech acquired, the findings demonstrate heterogeneous reactions from the markets to the deals. 'Digital Banking' is the type of Fintech that has the highest positive impact on the share price of the acquirer firm, while 'Software' is the segment that has the highest negative impact on the share price of the acquirer firm. Moreover, 'Trading' also has a positive and significant impact on the share price of the acquirer firm, while 'Lending' and 'Payments' do not show any conclusive results.

The positive findings presented in this Dissertation lead to the conclusion that investment in Fintech companies does increase the share price of the acquirer firm, either for a European bank or for a non-bank, which further prompts the conclusion that, in the context of profit maximization strategies and corresponding wealth creation, European banks should invest more in Fintech companies as they have the potential to technologically change how banks operate.

The present Dissertation greatly expands Dranev et al. (2019), in which 178 M&A deals across 5 periods covering the 2010 – 2017 period were analysed. The results showed that Fintech M&A has a positive impact on the stock price of the acquirer, although this Dissertation specializes in addressing the specific case of European financial companies, especially European banks. Furthermore, our database of events is much larger and complete for the European market, since, in Europe, most of the Fintech M&A events happened after the year of 2017.

This research does have distinct improvements in comparison to previous academic literature on this subject, although some limitations associated with this Dissertation should nevertheless be acknowledged. First, this study only relates to the European financial market, deliberately setting aside other geographies where other Fintech M&A might also occur. Second, this Dissertation specifically focuses only on one specific industry: the financial industry. Third, this Dissertation only takes into consideration events in which Fintech companies are acquired, although there have been some cases of companies, namely banks, that seek to implement partnerships with Fintech companies instead of acquiring them.

For further research, our suggestions include: i) expanding existing databases for partnerships and other type of relationships between financial companies and Fintech companies (other than M&A), as it would be very interesting to analyse whether only acquisitions have positive impacts in the share price of the acquirer or whether other types of partnerships also positively impact the share prices of the acquirers; ii) it would also be interesting to address how non-European banks' shareholders react to Fintech M&A, addressing the impact to other important geographies and then even comparing the results between geographies; iii) lastly, future research could also be extended to other industries in order to understand how Fintech companies can impact industries other than the financial industry.

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# 7. Appendices

## Appendix A

**Table 13** - Dissertation Database

| Acquirer | Announcement Date | Type of Fintech acquired | Type of Acquirer |
|---|---|---|---|
| ALANDSBANKEN ABP (1) | 19/12/2014 | Payment | Bank |
| ALANDSBANKEN ABP (2) | 27/09/2018 | Investment | Bank |
| AVANZA BANK HOLDING AB | 25/10/2018 | Lending | Bank |
| BANCA IFIS SPA | 15/05/2018 | Asset Management | Bank |
| BANCA POPOLARE DI SONDRIO SCPA | 13/02/2019 | Asset Management | Bank |
| BANCO BILBAO VIZCAYA ARGENTARIA | 02/11/2010 | Digital Banking | Bank |
| BANCO BILBAO VIZCAYA ARGENT (2) | 20/08/2014 | Digital Banking | Bank |
| BANCO BILBAO VIZCAYA ARGENT (3) | 19/11/2014 | Software | Bank |
| BANCO BILBAO VIZCAYA ARGENT (4) | 27/07/2015 | Digital Banking | Bank |
| BANCO BILBAO VIZCAYA ARGENT (5) | 07/03/2016 | Digital Banking | Bank |
| BANCO BILBAO VIZCAYA ARGENT (6) | 21/02/2017 | Payment | Bank |
| BANCO BILBAO VIZCAYA ARGENT (7) | 07/03/2018 | Digital Banking | Bank |
| BANCO BILBAO VIZCAYA ARGENT (8) | 08/03/2018 | Digital Banking | Bank |
| BANCO BILBAO VIZCAYA ARGENT (9) | 22/07/2019 | Digital Banking | Bank |
| BANCO BILBAO VIZCAYA ARGEN (10) | 24/09/2019 | Digital Banking | Bank |
| BANCO DE SABADELL SA | 17/02/2014 | Financial Planning | Bank |
| BANCO DE SABADELL SA (2) | 10/09/2019 | Lending | Bank |
| BANCO SANTANDER SA | 30/10/2009 | Software | Bank |
| BANCO SANTANDER SA (2) | 18/12/2018 | Trading | Bank |
| BANKINTER SA | 19/07/2018 | Software | Bank |
| BARCLAYS PLC | 17/04/2008 | Software | Bank |
| BARCLAYS PLC (2) | 01/03/2011 | Trading | Bank |
| BARCLAYS PLC (3) | 14/01/2013 | Digital Banking | Bank |
| BARCLAYS PLC (4) | 30/08/2013 | Clearing House Software | Bank |
| BARCLAYS PLC (5) | 12/04/2016 | Software | Bank |
| BARCLAYS PLC (6) | 12/10/2016 | Trading | Bank |
| BARCLAYS PLC (7) | 10/04/2018 | Trading | Bank |
| BARCLAYS PLC (8) | 31/07/2018 | Software | Bank |
| BARCLAYS PLC (9) | 02/08/2018 | Trading | Bank |
| BARCLAYS PLC (10) | 21/01/2019 | Lending | Bank |
| BARCLAYS PLC (11) | 12/02/2019 | Lending | Bank |
| BARCLAYS PLC (12) | 08/04/2019 | Payment | Bank |
| BARCLAYS PLC (13) | 16/05/2019 | Software | Bank |
| BARCLAYS PLC (14) | 28/05/2019 | Software | Bank |
| BNP PARIBAS SA (2) | 23/04/2008 | Software | Bank |

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|---|---|---|---|
| BNP PARIBAS SA (3) | 30/07/2015 | Digital Banking | Bank |
| BNP PARIBAS SA (4) | 05/10/2018 | Digital Banking | Bank |
| COMDIRECT BANK AG | 08/04/2009 | Trading | Bank |
| COMMERZBANK AG | 23/09/2014 | Software | Bank |
| CREDIT SUISSE GROUP AG (2) | 20/01/2016 | Digital Banking | Bank |
| CREDIT SUISSE GROUP AG (3) | 23/05/2017 | Payment | Bank |
| DANSKE BANK A S | 16/05/2018 | Trading | Bank |
| DANSKE BANK A S (2) | 17/12/2018 | Lending | Bank |
| DANSKE BANK A S (3) | 25/04/2019 | Software | Bank |
| DEUTSCHE BANK AG | 20/01/2010 | Financial Planning | Bank |
| DEUTSCHE BANK AG (2) | 01/11/2010 | Financial Planning | Bank |
| DEUTSCHE BANK AG (3) | 18/02/2015 | Lending | Bank |
| DEUTSCHE BANK AG (4) | 16/03/2015 | Payment | Bank |
| DEUTSCHE BANK AG (5) | 03/04/2017 | Asset Management | Bank |
| DEUTSCHE BANK AG (6) | 28/12/2017 | Trading | Bank |
| DEUTSCHE BANK AG (7) | 19/04/2018 | Trading | Bank |
| DEUTSCHE BANK AG (8) | 24/08/2018 | Factoring | Bank |
| DEUTSCHE BANK AG (9) | 15/11/2018 | Payment | Bank |
| DEUTSCHE BANK AG (10) | 27/11/2018 | Investment | Bank |
| DEUTSCHE BANK AG (11) | 18/09/2019 | Payment | Bank |
| HSBC HOLDINGS PLC | 25/01/2016 | Others | Bank |
| HSBC HOLDINGS PLC (2) | 09/06/2016 | Payment | Bank |
| HSBC HOLDINGS PLC (3) | 29/09/2016 | Investment | Bank |
| HSBC HOLDINGS PLC (4) | 23/03/2017 | Software | Bank |
| HSBC HOLDINGS PLC (5) | 30/05/2018 | Factoring | Bank |
| HSBC HOLDINGS PLC (6) | 02/08/2018 | Software | Bank |
| HSBC HOLDINGS PLC (7) | 09/07/2019 | Software | Bank |
| ING GROEP NV | 14/04/2009 | Factoring | Bank |
| ING GROEP NV (2) | 30/09/2015 | Software | Bank |
| ING GROEP NV (3) | 14/10/2015 | Software | Bank |
| ING GROEP NV (4) | 31/03/2016 | Others | Bank |
| ING GROEP NV (5) | 23/06/2017 | Factoring | Bank |
| ING GROEP NV (6) | 04/10/2017 | Lending | Bank |
| ING GROEP NV (7) | 03/12/2018 | Lending | Bank |
| INTESA SANPAOLO SPA | 19/12/2016 | Lending | Bank |
| INTESA SANPAOLO SPA (2) | 05/04/2017 | Software | Bank |
| LLOYDS BANKING GROUP PLC (2) | 20/12/2016 | Asset Management | Bank |
| NATIONAL BANK of GREECE SA | 27/01/2009 | Financial Planning | Bank |
| NATIXIS SA | 08/11/2016 | Financial Education | Bank |
| NATIXIS SA (2) | 08/11/2016 | Digital Banking | Bank |
| ROYAL BANK of SCOTLAND GROU (2) | 01/11/2018 | Digital Banking | Bank |
| ROYAL BANK of SCOTLAND GROU (3) | 31/12/2018 | Digital Banking | Bank |
| ROYAL BANK of SCOTLAND GROU (4) | 07/01/2019 | Payment | Bank |
| SKANDINAVISKA ENSKILDA BANKEN A | 31/08/2017 | Payment | Bank |
| SKANDINAVISKA ENSKILDA BANK (2) | 07/02/2019 | Payment | Bank |
| SOCIETE GENERALE SA | 24/04/2008 | Lending | Bank |

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|---|---|---|---|
| SOCIETE GENERALE SA (2) | 07/07/2016 | Asset Management | Bank |
| SOCIETE GENERALE SA (3) | 06/03/2017 | Software | Bank |
| SOCIETE GENERALE SA (4) | 05/07/2017 | Digital Banking | Bank |
| SOCIETE GENERALE SA (5) | 25/07/2017 | Digital Banking | Bank |
| SOCIETE GENERALE SA (6) | 20/10/2017 | Lending | Bank |
| SOCIETE GENERALE SA (7) | 26/10/2017 | Financial Planning | Bank |
| SOCIETE GENERALE SA (8) | 10/09/2018 | Financial Planning | Bank |
| STANDARD CHARTERED PLC | 12/12/2008 | Payment | Bank |
| STANDARD CHARTERED PLC (2) | 20/08/2015 | Digital Banking | Bank |
| STANDARD CHARTERED PLC (3) | 12/06/2019 | Software | Bank |
| SWEDBANK AB | 10/05/2017 | Software | Bank |
| SWEDBANK AB (2) | 15/02/2019 | Software | Bank |
| SWEDBANK AB (3) | 28/05/2019 | Software | Bank |
| SYDBANK A S | 11/11/2013 | Software | Bank |
| TF BANK AB | 06/11/2017 | Clearing House Software | Bank |
| UBS AG | 12/10/2015 | Trading | Bank |
| UNICREDIT SPA | 14/03/2016 | Lending | Bank |
| WUSTENROT & WURTTEMBERGISCHE AG | 10/01/2017 | Software | Bank |
| 1PM PLC | 28/07/2015 | Payment | Non-Bank |
| 3I GROUP PLC | 22/05/2008 | Financial Planning | Non-Bank |
| ARAGON AG | 17/12/2007 | Software | Non-Bank |
| BREWIN DOLPHIN HOLDINGS PLC | 27/05/2011 | Digital Banking | Non-Bank |
| CARDTRONICS PLC | 01/07/2016 | Payment | Non-Bank |
| CMC MARKETS PLC | 08/03/2017 | Software | Non-Bank |
| CNP ASSURANCES SA | 15/02/2018 | Asset Management | Non-Bank |
| DAIMLER AG | 13/04/2017 | Digital Banking | Non-Bank |
| DEUTSCHE BORSE AG | 19/02/2010 | Financial Planning | Non-Bank |
| DEUTSCHE BORSE AG (2) | 05/07/2011 | Lending | Non-Bank |
| DEUTSCHE BORSE AG (3) | 12/02/2014 | Financial Planning | Non-Bank |
| DEUTSCHE BORSE AG (4) | 20/11/2014 | Others | Non-Bank |
| DEUTSCHE BORSE AG (5) | 26/07/2015 | Software | Non-Bank |
| DEUTSCHE BORSE AG (6) | 31/08/2018 | Others | Non-Bank |
| DEUTSCHE BORSE AG (7) | 18/09/2018 | Software | Non-Bank |
| DEUTSCHE BORSE AG (8) | 31/12/2018 | Asset Management | Non-Bank |
| DEUTSCHE BORSE AG (9) | 09/04/2019 | Payment | Non-Bank |
| ERNST RUSS AG | 12/07/2017 | Trading | Non-Bank |
| FRONTOFFICE NORDIC AB | 12/07/2017 | Payment | Non-Bank |
| GLI FINANCE LTD | 16/07/2013 | Others | Non-Bank |
| GLI FINANCE LTD (2) | 05/05/2015 | Payment | Non-Bank |
| GLI FINANCE LTD (3) | 28/06/2016 | Trading | Non-Bank |
| GRUPPO MUTUIONLINE SPA | 04/03/2013 | Trading | Non-Bank |
| HELIAD EQUITY PARTNERS GMBH & C | 07/06/2016 | Trading | Non-Bank |
| IG GROUP HOLDINGS PLC | 24/09/2008 | Trading | Non-Bank |
| INTRUM JUSTITIA AB | 25/02/2015 | Others | Non-Bank |

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|---|---|---|---|
| INVESTEC PLC | 30/03/2010 | Software | Non-Bank |
| JUPITER FUND MANAGEMENT PLC | 05/03/2014 | Others | Non-Bank |
| JUPITER FUND MANAGEMENT PLC (2) | 19/11/2018 | Investment | Non-Bank |
| KBC SECURITIES NV | 30/04/2013 | Investment | Non-Bank |
| LONDON STOCK EXCHANGE GROUP PLC | 09/03/2012 | Lending | Non-Bank |
| LONDON STOCK EXCHANGE GROUP (2) | 27/02/2019 | Asset Management | Non-Bank |
| LONDON STOCK EXCHANGE GROUP (3) | 03/06/2019 | API Banking | Non-Bank |
| OSTERREICHISCHE POST AG | 10/10/2018 | Software | Non-Bank |
| POSTE ITALIANE SPA | 26/09/2019 | Software | Non-Bank |
| SCHRODER INVESTMENT MANAGEMENT | 14/11/2016 | Software | Non-Bank |
| SCHRODERS PLC | 02/11/2010 | Software | Non-Bank |
| SCHRODERS PLC (2) | 25/03/2013 | Trading | Non-Bank |
| SCHRODERS PLC (3) | 25/06/2014 | Lending | Non-Bank |
| SCHRODERS PLC (4) | 10/11/2016 | Investment | Non-Bank |
| SCHRODERS PLC (5) | 31/05/2018 | Lending | Non-Bank |
| TELEFONAKTIEBOLAGET LM ERICSSON | 11/12/2017 | Lending | Non-Bank |
| TELEFONAKTIEBOLAGET LM ERIC (2) | 31/01/2018 | Asset Management | Non-Bank |
| TELENOR ASA | 12/10/2010 | Software | Non-Bank |
| TP ICAP PLC | 16/09/2019 | Investment | Non-Bank |