The Impact of the changing market, caused by Covid-19, on FinTech M&A

Erasmus School of Economics, Erasmus University

Master Thesis – MSc. Financial Economics

Submission date: 12/08/2022

Student name: M.S.J. Larsson

Student number: 452517

Thesis supervisor: Dyaran Bansraj

Co-reader: xxx

Abstract

Covid-19 had a big influence globally where lots of sectors were affected by the virus. Because of the pandemic, many industries changed, presumably for good. One of the trends that was caused by the pandemic is the accelerated digitization. The FinTech sector profited significantly from this accelerated trend and saw huge market growth. Previous papers regarding the abnormal returns for FinTech deals found significant positive returns (Sahi, 2017; Dranev et al., 2019; Tanjung, 2020; Lindner, 2021). However, this paper is interested in the influence of Covid-19 on the FinTech market. Using event study methodology and OLS regression analysis, this paper examines if, and how Covid-19 influenced the abnormal returns surrounding the announcement of an acquisition of a financial technology company in the United States. The total sample used in this paper contains 922 acquisitions of which 236 involve a deal where the target is a FinTech. This paper also looks at the effect of the method of payment and industry relatedness on the acquisition performance of FinTech deals. Brown & Ryngaert (1991), Moeller et al. (2004), and Alexandridis et al. (2010) have previously found negative returns for deals where the acquisition is fully financed with stock. This paper however, finds a positive influence of stock-financing on the performance of FinTech deals, which is more in line with Signori & Vismara (2017), who find that using stock as a means of financing an M&A deal can lead to favorable acquisition terms. Martynova & Renneboog (2006), and Tuch & Sullivan (2007) found that non-diversifying deals are more likely to find operating synergies, in contrast this paper finds negative returns for deals where the FinTech acquirer operated in either the Financials or Information Technology sector. This could be caused by the war of talent (Frick et al., 2021l Mullen, 2022) or because of the difficulty to integrate a FinTech firm (Lopez, 2022). This paper also uses additional control variables that are found to be determinants of the acquirer's gains. Size and Relative Deal Size are added to the regression. Size has a significant negative effect on the short-term performance, which is in line with previous literature (Bruner, 2004; Moeller et al., 2004). Relative Deal Size has a significant positive effect on the short term-performance, this is also in line with the findings in previous literature (Asquit et al., 1983; Moeller et al., 2004; Chen & Tan, 2011). Lastly, this paper looks at whether the effect is more pronounced in FinTech subsectors. A significant positive effect was found for the eCommerce & Marketing Tech subsector. The significant positive effect was even more pronounced when the deal was announced in the post-covid era.

JEL classification: G01, G29, G34

Keywords: FinTech, M&A, stock-financed acquisitions, industry relatedness, value creation, Cumulative Abnormal Return (CAR)

Table of Contents

1. Introduction

The Great Depression of 1929, the 1973 OPEC oil price shock, the 1997 Asian crisis and the 2007-2008 financial crisis are among the most well-known global economic crises in history. Many papers have been written about the short-term and long-term consequences of these events, but it is still very hard to predict the upcoming of a new economic crisis. No one could have predicted that Covid-19 would have such a large impact on our lives when it first appeared, but in February 2020, a global economic recession broke out. The first major sign of the recession was a massive drop in the stock market, with major indices dropping 20 to 30 percent in late February and early March. The drop in believe in the financial market was also seen in other markets than the stock market. Covid-19 influenced the mergers and acquisitions (M&A) market as well, with worldwide monthly deal volume dropping 45 percent between December 2019 and June 2020 (Bosker et al., 2020).

During the first phase of the epidemic, the amount of money spent in sectors as retail trade, hotels, and restaurants, plummeted drastically. This was the result of global regulations such as the closure of stores, restaurants, and clubs due to the spreading virus. People were also forced to work from home because offices were closed, forcing businesses to adjust to the new world order. Meanwhile, the demand for services that can be provided remotely or that address the issue of diminishing human contacts, such as ICT and delivery services, expanded substantially. In a matter of three months, the pandemic reduced hotel demand by 63%, whereas ICT demand increased by a similar percentage. The repercussions appeared to be driven by supply shortages caused by social isolation and lockdown measures, as well as demand shocks as consumers stayed at home, with demand shocks dominating for the majority of sectors. The severity of shifts in demand differs greatly depending on how the government responds to the pandemic.

The global financial economy recovered during the second phase of the outbreak. The stock market had already fully recovered by the end of 2020, with the S&P 500 hitting 115% of its pre-covid peak on February 19, 2020 (Wen & Arbogast, 2021). The markets were adapting and customer demands adapted with them. One of the most important market changes during the pandemic was the accelerated global digitization with global digital customer interactions worldwide increasing from 36% to 58% between December 2019 and July 2020 (LaBerge et al., 2020). The pandemic resulted in a digital tidal wave where you have to become more digital before the wave hits (Veldhuijsen & De Lange-Snijders, 2020; Woodford, 2021). One of the markets that benefited greatly from the accelerated digitization was the FinTech market. The digitization lead to an increase of 21% to 26% in the relative daily downloads of finance-related mobile applications. This would roughly equate to an aggregate increase of over 900 million app downloads over the protracted COVID period, that would have likely not occurred in the pandemic's absence (Fu & Mishra, 2020; Fu & Mishra, 2022).

FinTech includes both technology-enabled enterprises that provide financial services and entities that provide technological services directly to firms in the Financials sector (Weeks, 2016). To include this technology into your service offerings, you must either develop it from scratch or purchase a FinTech company. Numerous financial institutions aspire to buy fintech firms due to their potential to decrease expenses, enhance business processes, resolve difficult IT issues, and mitigate cybersecurity concerns.

M&As are a significant landmark in the development of a company and have far-reaching effects on its shareholders, stakeholders, and future performance. The primary objective of M&As is the creation of synergies that can, in turn, facilitate corporate growth, increase market power, boost profitability, and increase the wealth of shareholders. Therefore, M&As should constitute projects with a positive net present value (Alexandridis et al., 2010). While corporations seek value-creating transactions, their shareholders observe closely and develop opinions about the transaction.

Takeover activity is found to have a huge correlation with high stock market valuations, such as during the second phase of the pandemic. These finding were also presented in Schleifer & Vishny (2003) and Rhodes-Kropf & Viswanathan (2004) who found that merger waves result from managerial timing of market overvaluations of their firms. Gort (1969) and Mulherin (1996) had a different opinion, they found that merger waves result from shocks to an industries' economic, technological, or regulatory environment. Harford (2005) adds to these findings that there also must be high capital liquidity. In the second phase of the pandemic high valuations, high capital liquidity and shocks that require a large scale reallocation of assets were all present, thus providing an ideal environment for a new merger wave. This indeed took place with worldwide M&A activity breaking records in the first half of 2021 (EY, 2021).

According to past literature, M&A has a mixed short-term impact on firm stock returns because investors may evaluate M&A benefits differently following the announcement (Agrawal et al., 1992). According to Berkovitch and Narayanan (1993), synergy objectives drive M&A, which arise when target and acquirer management participate in a Only if it boosts both sides' shareholder wealth. Some M&A study indicates the acquiring company's returns are negative or nil (Fuller et al., 2002), while other papers find post-acquisition anomalous returns are positive yet insignificant (Beitel et al., 2004; Goergen and Renneboog, 2004).

With Covid-19 causing an accelerated digitization, which in turn led to an increase of the FinTech market, it will be interesting to look at the FinTech M&A market. Many companies needed to innovate and become more digital to keep up with customer demands, you could either achieve this by developing a digital product in house or by acquiring a firm that already has digital solutions in place. With the high valuations in place, one could argue that this will lead to a negative reaction of acquirer stockholders to M&A deals. Bouwman et al. (2007) wrote a paper about the acquisition performance of M&As during high-valuation periods and low-valuation periods. They found that buyers during high-valuation markets significantly outperform buyers during low-valuation markets in the short run, with a reversal in returns in the long-run.

"Do the changing markets, caused by Covid-19, have any influence on the cumulative abnormal returns surrounding the announcement of M&A deals in FinTech in the U.S.?"

I found that FinTech acquisitions that were announced post-covid had significantly higher returns than FinTech deals announced pre-covid. The effect of Fintech M&A on the performance of the acquiring firm is evaluated using an event study and OLS regression analysis. Since North America is the largest FinTech market, with twice as many fintech companies as APAC, and accounts for more than half of yearly deals (Accenture, 2016; Ketabchi, 2019), we collect data on completed M&As in the Financials and Information Technology sector between 1-1-2016 and 1-1-2022 by public companies in the United States. Transaction data is drawn from the Thomson Reuters database, abnormal returns surrounding the announcement of an M&A is found using the DataStream event study tool and the firm characteristics of the acquirer and target are searched for in the Compustat database. The final sample consists of 1,469 M&A deals, of which 353 deals that are classified as FinTech deals. To further improve this research the FinTech targets are also categorized in 9 different subcategories to examine if certain effects are more pronounced in subcategories.

Other variables affecting acquisition performance are also examined. When the buyer of a FinTech trade is in a similar industry (finance or IT), anomalous returns are lower. Previous research found good returns for non-diversified buys (Martynova & Renneboog, 2006; Tuch & Sullivan, 2007). The war for talent causes acquirers to focus on talent acquisition rather than synergies (or lack thereof). When employees leave following an acquisition, this will negatively effect deal returns (Frick et al., 2021; Mullen, 2022). FinTech integration issues are another possibility. FinTechs frequently focus on one solution, making integration with a large organization offering several options problematic (Lopez, 2022). Another finding is that FinTech acquisitions financed with stock result in higher returns for acquirer stockholders. These positive effects do not remain significant throughout all models and also have a lower significance when using other dependent variables. These findings go against previous literature that found a negative relation between stock financed deals and announcement returns (Lane & Yang, 1983; Travlos (1987); Franks, Harris & Mayer, 1988; Baker & Wurgler, 2002). They are however in line with the findings of Signori & Vismara (2017) who found that using stock as a means of financing a deal could lead to more favorable terms. They found this mostly for IPOs who want to make use of their liquid stocks to purchase firms. Since the U.S. provided a record high number of IPO deals in 2020, this could provide an explanation for the positive effects of stock financed deals on CAR found in this paper.

Lastly, this paper finds that acquisitions of firms in the eCommerce & Marketing Technology subsector leads to significant positive announcement returns. This effect is even more pronounced post-covid. The findings could be explained due to the growing market of this subsector. E-commerce sales went up significantly in the post-covid era where the implementation of ecommerce also got a boost (Perez, 2020).

This paper contributes in various ways to the current body of literature. Schaffers (2021), Gaytandzhiev (2021) researched the acquirer shareholder return for financial institutions that acquire FinTechs. Schaffers found no statistical evidence that these deals lead to superior wealth creation, Gaytandzhiev (2021) found that these deals are value decreasing except for minority acquisitions. Sahi (2017), Dranev et al. (2019), Tanjung (2020), and Lindner (2021) examine the performance of all acquirers and find positive short-term average anomalous returns. My paper looks the most like the Lindner (2021), this paper also looks at the short term returns surrounding the announcement of a U.S. FinTech deal. This paper found no abnormal returns that were significantly larger than those of acquisitions involving targets in the Financials and Information Technology sector. Also, a positive effect of industry relatedness, compared to my negative effect, is found and the effect of the acquisition premium paid is looked at. My paper adds to this literature by being the first study to examine the effect of the changing world industries, caused by Covid-19, on the relative performance results of FinTech M&A compared to non-FinTech M&A.

The classification of FinTechs in this research is the second contribution of this paper. While other publications have categorized FinTechs as enterprises working in both the financial and IT sectors, this study devotes more time to identifying organizations as FinTechs. I have devoted considerable effort in classifying FinTechs under nine subcategories: BPO, Digital Lending, Financial Media & Data Solutions, HR & Payroll Tech, Investments & Capital Markets Tech, Payment, Security Technology, and eCommerce & Marketing Tech. Lastly, this paper adds to past research by analyzing the extent to which payment method and industry relatedness impact the returns of Fintech acquirers relative to non-FinTech acquirers. Even though some of these variables were also employed as control variables in prior works about FinTech abnormal returns, these past papers were undertaken at a time when technology advancement, innovation, and digitization are dissimilar to the present. Due to business model innovation, fresh organizational structures, and their limited physical presence, the high-tech characteristics of target enterprises profoundly alters M&A deal dynamics. On top of that the Covid-19 financial crisis had huge implications for the M&A market.

The remainder of this paper is structured as follows. Chapter 2 presents an overview of the relevant literature on financial crises, FinTech, and M&A. In chapter 3 the data collection methodology is explained, this chapter also elaborates on how the FinTech deals were subcategorized. Chapter 4 discusses the methodology that is used in this paper. Chapter 5 presents the results of the regression analysis and the interpretation of these results. Chapter 6 discusses several limitations of this study and chapter 7 concludes the paper while also making suggestions for further research.

2. Theoretical Framework

2.1 Covid-19 phase 1: Financial Crisis

The Great Depression of 1929, caused by a reduction in money supply, the 1973 OPEC oil crisis, caused the announcement of an oil ban of the OPEC members, the 1997 Asian crisis, caused by the instable exchange rates in the East Asian countries, and the Financial Crisis of 2007-2008, caused by the collapse of the U.S. housing bubble were all the start of a global financial crisis that lasted for years.

The start of the Covid-19 pandemic many institutions and researchers predicted a new global financial crisis. The World Bank (2020) estimated that the world economy would contract by 5.2 percent in 2020, the deepest recession since World War II. These economic consequences were a consequence of governments, who took strict measures to ensure the virus's containment in their country in order to preserve the population's health. Some of the measures put in place include non-essential business closures, event cancellations, and work-from-home rules (Velthuijsen & De Lange-Snijders, 2020). Even though these strict containment measures were effective in containing the spread of the coronavirus disease and limiting fatalities, the Great Lockdown measures resulted in significant short-term economic losses and a decrease in global economic activity not seen since the Great Depression (Deb et al., 2020). As a result, governments and central banks must take steps to mitigate the economic impact of these actions. The government policies also influenced the stock markets. While the stock market was at an all-time high on 19 February 2020, the growing fears of the impact of the pandemic led to a drop of 66 percent of the S&P 500 in little over a month time.

Next to the stock market losses, there was a huge economic loss for thousands of businesses. Governments wanted virus to stop spreading so they ordered people to stay at home, as a result many businesses had to shut down. The most vulnerable companies during the crisis are weak companies which just entering the market and heavily indebted businesses which have obligations. The most impacted industries were the hospitality sector, the beauty and personal care sector, retail sector, and fitness sector (Rosenfeld, 2021). The outlook of the companies in this sector was very worrying since they had no idea how long the pandemic would last, the companies in these sector had to become innovative.. Even though there is a downturn in the market, there is a place to flourish, which means that you can make a profit if you have a good strategy. Businesses must consider how to stay afloat and which steps will keep them from declaring bankruptcy during a financial crisis (Tashanova et al., 2020).

2.2 Covid-19 phase 2: Financial recovery

The market had entirely recovered by the end of 2020, with the S&P 500 hitting 115% of its pre-covid peak on February 19, 2020. Despite this, the recovery has been unequal across industries. Some industries recovered quickly, while others remain below pre-COVID-19 levels. Since the initial collapse, the largest recoveries have been in information technology, consumer discretionary products, and materials, with index values at 133 percent, 130 percent, and 124 percent of pre-crisis levels, respectively. The outbreak benefitted many corporations in the information technology sector, including Amazon and Microsoft (Wen & Arbogast, 2021).

The market was changing because of the Covid-19 induced policies. Within a few months, the pandemic altered the business practices of corporations across all industries and geographies. One of the biggest changes caused by the Covid-19 pandemic was the digitization of the world. In order to survive the COVID-19 crisis and remain competitive, businesses must innovate. The pandemic resulted in a huge digital tidal wave. Even if the tide was rising, if you weren't digital before the wave hit, you had to do something to become more digital (Woodford, 2021; Velthuijsen & De Lange-Snijders, 2020). McKinsey issued a survey July 2020 where they asked companies how they dealt with the changing market. The companies in the survey found that they had to meet many new demands of clients which caused them to accelerate the digitization of supply-chain and customer interactions by 3 to 4 years while digital or digitally enabled products in their portfolios accelerated by 7 years. Most executives that reacted to the survey found that digital initiatives funding has increased more than anything else (LaBerge et al., 2020).

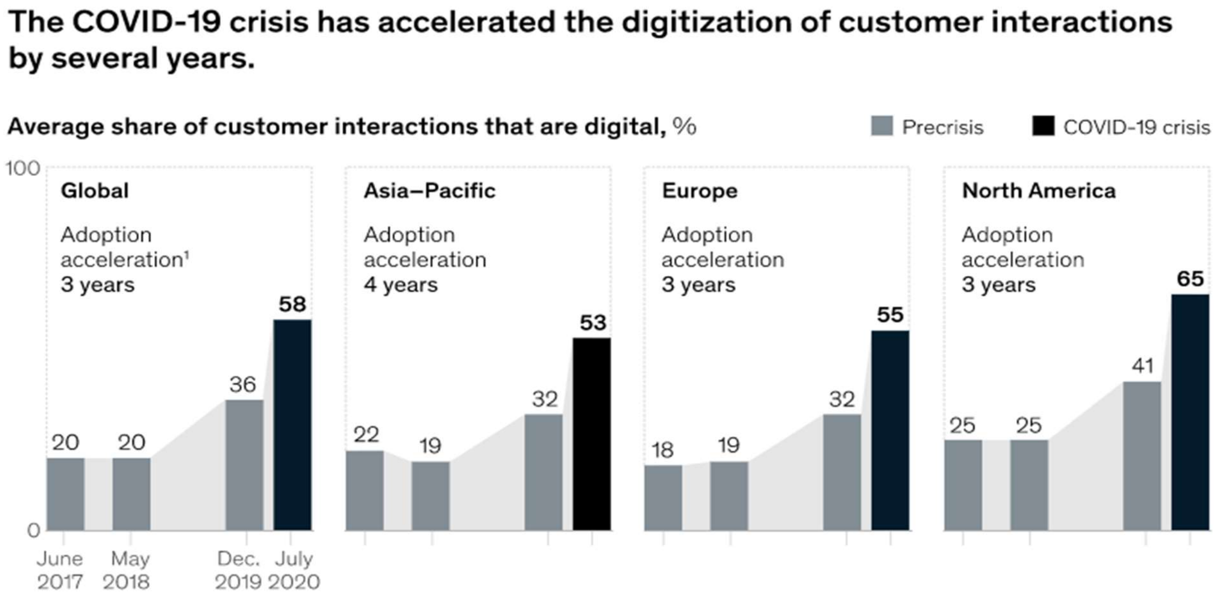

Figure 1: increase in digital interactions
This figure shows he increase in digital customer interactions worldwide. The table shows the increase from June 2017 until July 2020 for Europe, Asia-Pasific, and North America. *Source: (LaBerge et al., 2020).*

As is shown in figure 1, there has been a huge increase in digital interactions worldwide. The biggest increase in digital is in North America where it increased with 24% in half a year. The digitization was most pronounced in professional services, financial services, and healthcare and pharma. One of the markets that benefited the most from the digitization wave following Covid-19 was the FinTech market. The digitization lead to an increase of 21% to 26% in he relative daily downloads of finance-related mobile applications (Fu & Mishra, 2020; Fu & Mishra, 2022).

2.3 Financial Technology

"FinTech" is an acronym for "Financial Technology" and was devised by John Reed, who worked at Citicorp at the time, at the beginning of the 1990s. The term was formed in the context of a “Smart Card Forum” consortium that attracted leaders from the financial services and high technology industry (Kutler, 1993).

The precursors of FinTech could be seen as the first automated teller machine (ATM), installed in Arlington, Ohio in 1959 (the first in Europe was installed by Barclays Bank in London in 1967), the change from trading in person to electronic trading, introduced by NASDAQ in 1971, Citibank and Chase Manhattan's introduction of home banking in 1981, the launch of online banking facilities in 1994 by Stanford Credit, and the Norwegian Fokus Bank's first provision of mobile banking in 1999 (Arner et al., 2015).

There is a variety of description as to the term FinTech in academic research with no general agreement between the researchers. According to Gulamhusinwala et al. (2015), FinTech enterprises are connectors of novel business models and technologies that are intended to activate, improve, and disrupt the financial services sector. According to Arner et al. (2015), the word "FinTech" does not refer to any specific industry or business strategy. Rather, the term refers to all products and services that have their origins in the financial services industry. According to Puschmann (2017), FinTech is an umbrella word that encompasses innovative financial solutions enabled by technology, as well as start-up companies that deliver these solutions and traditional financial service providers like banks and insurers. The S&P global also provided an explanation of how they believe FinTech should be defined. FinTech includes both technology-enabled enterprises that provide financial services and entities that provide technological services directly to companies in the Financial sector (Weeks, 2016).

2.4 Mergers & Acquisitions

Acquisitions, according to Fuller et al. (2002), are among the most significant corporate finance events, both for a company and for the economy. Extensive research shows that when a takeover is announced, shareholders of target corporations benefit significantly and value is created (i.e., combined bidder and target returns are positive). The primary acquisition objective is synergy creation, resulting in corporate growth, improve market power, boost profitability, and increase shareholder wealth. Therefore, M&As should constitute projects with a positive net present value (Alexandridis et al., 2010).

2.4.1 M&A activity and merger waves

M&A activity has been proven to have a strong relationship with high stock market prices. Researchers like Shleifer & Vishny (2003) and Rhodes-Kropf & Viswanathan (2004) construct models in which merger waves are caused by managerial timing of their businesses' market overvaluations. More neoclassical hypotheses for merger waves, dating back to Gort (1969) and more recently investigated by Mitchell & Mulherin (1996), contend that merger waves are caused by changes in an industry's regulatory, economic, or technological environment.

Harford (2005) discovered that merger waves form in response to unique shocks in industries that necessitate asset reallocation. He also determined that sufficient capital liquidity is required to allow asset reallocation. To cause a wave to propagate, there must be an increase in capital availability and a decrease in financing limitations, both of which are associated with high asset prices. According to variables analyzing cash liquidity and market valuations, the apparent association between high stock market values and merger waves has been misattributed to behavioral misvaluation factors. Rather, the link is fueled by increased capital liquidity (lower transaction costs) associated with an economic boom. As a result, the rationale for merger waves is self-evident: in order to generate a significant volume of transactions, merger waves require both an economic motive for transactions and relatively low transaction costs. Even if sector shocks do not cluster in time, the effect of this macro-level liquidity component causes industry merger waves to cluster.

2.4.2 Covid-19 and the M&A market

Historically, there has been a strong relationship between M&A activity and the evolution of stock prices and risk, as measured by implied volatility. Between 2000 and 2019, merger and acquisition volume and the MSCI World index correlated approximately 80 percent (Kengelbach et al., 2020). As you would expect M&A volume followed the MSCI World index with worldwide monthly deal volume dropping by almost 50 percent from December 2019 to June 2020 (KPMG, 2020).

Kooli & Son (2021) found that in the beginning of Covid-19 everyone held off acquisitions. They first wanted to understand what consequences the pandemic would have on their business. Taking stock of which measure could be taken and short term liquidity were given more priority than identifying acquisition opportunities. Selling companies also had great uncertainty because valuations and fundability were unclear. After two months many companies had secured liquidity and had a plan for the coming year. The financial markets normalized, so investors saw opportunities for exits on favorable terms and companies became available again for acquisition.

As is seen in chapter 2.3.1 of this paper, merger waves are driven by high stock valuation, shocks to an industry's economic, technological, or regulatory environment, and high capital liquidity.

The market changes caused by the Covid-19 pandemic caused a huge merger wave where valuations hit all-time highs. Throughout 2021, the benchmark S&P 500 added 27 percent and reported 70 record-high closes, which is the second-most ever (Valetkevitch, 2022).

Due to Covid-19 a shift in the spending nature of consumers took place. Because vacation budget was left over and restaurants were closed. Therefore people could save more where parts of these savings were invested through the stock market, but also through private equity. In the 5 months preceding April 2021, investors put more money in stocks than the twelve years preceding (Cox, 2021). The amount of money available has been enormous for years which is a continuing trend as a result of the major monetary stimulus programs in the U.S. and Europe. Slot (2021) quoted Maurice Dercks, M&A-specialist at Deloitte, who said the following: "In this day and age, raising money for growth and acquisitions is relatively easy, and not just for private equity. We see the number of initial public offerings - whether through a SPAC or not - increasing rapidly and private debt funds gaining market share. As a result, the availability but also the price of financing has suffered little from the corona crisis. This means that companies that have the ambition to accelerate their growth with new equity or debt now have the momentum to do so. And for companies that now have the wind at their backs, that applies even more." The high capital liquidity is also influenced by the interest rates that are extremely low.

The combination of the high stock valuations, high capital liquidity, and the changing industry's economic, technological, and regulatory environment provides for a perfect environment for a merger wave to take place.

Worldwide M&A activity broke records in the first half of 2021, with deals worth more than 2.6 trillion US dollars. This was also extremely high in comparison with the five-year average preceding the Covid-19 crisis, which was 1.6 trillion US dollars. The majority of these M&A activities was situated in North America which saw a total deal worth of 1.4 trillion US dollars. The Asia-Pasific region and Europe follow North America in deal values, however they do not even record a third of the deal value that North America achieved (EY, 2021). The first half of 2022 recorded lower values, however these values are still higher than the pre-covid average, namely 2.02 trillion US dollars. The sector that drove M&A was Technology, which accounted for nearly a third of global M&A activity (McCall, 2021; EY, 2022) A big part of this M&A activity was captured in the FinTech market which saw a huge growth caused by the accelerated digitization. Global fintech investment was 210 billion US dollars, of which 83 billion US dollars was FinTech focused M&A deal value (KPMG, 2022). Because of the interesting ongoing trends in FinTech this paper looks at the deal performance of deals involving a FinTech target. Previous literature found positive short-term returns for FinTech deals (Dranev et al., 2019; Tanjung, 2020) previously found significant positive returns for FinTechs. Because of the changing markets caused by the Covid-19 pandemic, which in turn accelerated the growth of the FinTech market, I expect that deals announced post-covid will have an even more pronounced effect on deal performance. One could argue that the high valuations in the market would lead to acquirer stockholders to negatively react to M&A announcements. However Bouwman et al. (2007) researched the effect of market valuation on M&A performance and found that buyers during high-valuation market significantly outperform buyers that acquire in low-valuation markets in the short-run. However, this reverses in the long-run. The first hypothesis of this paper is therefore the following:

H1: Post-covid acquisitions have significantly higher abnormal returns for acquirer shareholders than pre-covid surrounding the announcement of a FinTech firm

2.4.3 Value creation in M&A

In order to get more interpretable results, variables that are previously found to have influenced the announcement returns are looked at.

2.4.3.1 Cash/Stock transaction

According to Shleifer & Vishny's (2003) market-driven acquisition hypothesis, stock overvaluation is a major motivator for corporations to make acquisitions. Choosing a stock-financed deal demonstrates that the acquirer's management believes its stock is overpriced (Myers & Majluf, 1984). Shareholders see stock-financed acquisitions as managers believing their equity is overvalued due to knowledge asymmetry. (Lane & Yang, 1983; Travlos, 1987; Franks, Harris & Mayer, 1988; Baker & Wurgler, 2002). Travlos (1987) understood from other publications that the proceeds from new stock offerings are typically used to finance capital expenditures, a portion of which represents corporate acquisitions; these findings could be interpreted as indirect evidence of a differential return relationship across different payment methods. He wanted to see how much of an influence the manner of payment had on the stock prices of bidding corporations when takeover proposals were announced. He discovered evidence that pure stock exchange bidding corporations caused considerable losses to their shareholders when a takeover proposal was announced (Moeller et al. (2004), Brown & Ryngaert (1991), and Alexandridis et al. (2010). Signori & Vismara (2017) however find an important link between initial public offerings and takeover activity. They find that "stock as currency" was a motive for going publicly. According to them, firms can acquire at more favorable terms using publicly traded stocks as a means of financing. Firms that go public are found to use the liquidity of their stocks to perform more stock-financed acquisitions within the 3 years of the IPO. Covid-19 first put the brakes on listings with only 388 businesses completing their IPOs during the first half of 2020. During H2 of 2020 the market completely bounced back with the value for H2 on record (Chen & Vetterli, 2021). Carnevali & Platt (2020) found the U.S. accounted for half of the IPO value worldwide, a large part of these IPOs were done by companies that seek to acquire other firms and fast-track them on to public markets (SPAC). Taking these prior publications' findings into account, I expect that using stock as a source of financing will lead to an increase in abnormal returns. The second hypothesis consists of several parts which are formulated as follows:

H2: Using stock as a means of financing a FinTech deal will result in positive acquirer shareholder returns

Wansley et al. (1987), Asquith et al. (1987), and Servaes (1991) found significantly higher bidder returns for cash offers compared to stock offers.

2.4.3.2 Leverage

Another explanation for the difference in returns between stock and cash purchases is that it is due to the variation in leverage that occurs as a result of the acquisition. A cash acquisition is typically financed by the acquirer issuing new debt, whereas a stock acquisition is a sort of new common stock issue (Yook, 2003). When a firm takes on debt to finance a cash acquisition, it increases its leverage. According to the free cash flow hypothesis, organizations with a lot of free cash flows will engage in value-destroying mergers. If a corporation incurs more debt, it must pay more interest, resulting in lower free cash flows and lower agency costs of free cash flows (Jensen, 1986). In addition, larger leverage increases the tax shield, which means that holding a higher debt has tax advantages in the sense that interest payments are deductible.

2.4.3.3 Relative Size

According to Moeller et al. (2004), Asquit et al. (1983), and Chen & Tan (2011), the bigger the relative size of an M&A transaction, the higher the bidders' announcement returns. The relative deal size is obtained by dividing deal’s transaction value by the market capitalization of the acquirer. This effect is caused by the higher acquisition premiums paid for small companies if they are compared to acquisition premiums for large firms.

2.4.3.4 Industry Relatedness

All FinTech transactions have a GIC-sector which is either Financials or Information Technology (as classified in the Eikon database). A significant driver of M&A activity is the prospect of synergies between bidder and target, which are believed to result in efficiencies and, eventually, favorable returns for shareholders (Tuch & Sullivan, 2007). Unrelated mergers are likely to yield administrative and financial synergies at best, whereas related acquisitions allow better possibility for economies of scale and scope. Martynova & Renneboog (2006) mainly find operating synergies in non-diversifying transactions. Because it is more difficult to access the performance of managers in diversified business structures, related acquisitions may provide corporate control benefits (Singh & Montgomery, 1987). It could be argued however that firms that are either in the Financials sector or the

Information Technology sector are often still diversifying when acquiring a FinTech firm. For Tech/FinTech firms the war for technology talent is becoming a bigger problem each year. That is why it is becoming an increasing reason for M&A activity involving companies in the same industry (Frick et al., 2021). I expect that buying companies will be blinded by the war for talent and therefore don't scan for synergies as carefully as before. Surveys by Bain Talent retention was discovered to be the second most important contributor to transaction success. Almost no company has been untouched by the unprecedented number of employees seeking new possibilities. These realities loom over each proposed talent-focused transaction (Mullen, 2022). Talent acquisition is rarely the main objective of a deal where the acquirer operates in a different sector. I therefore expect them to better assess an acquisition and its potential synergies, leading to better performance in comparison to FinTech acquirers from the Information Technology sector. As for Financial services companies, I also expect the returns for acquiring a FinTech company to be negative relative to acquirers that are not operating in the same industry as implementing a FinTech company in a financial services company is very difficult. One of the problems is the regulatory compliance for the financial services industry. Not all FinTechs need to comply to these rules but when they are acquired they need to comply to these rules when they integrate in the acquirers firm. Also most financial technology companies were not developed with an open mind, so integrating them with a new business for the purpose of creating synergies might be difficult since implementation costs first have to be made (Lopez, 2022). Overall I expect deals where the acquirer and target operate in the same sector to have lower returns than deals where the acquirer does not operate in the same sector. Hypothesis 3 will therefore be the following:

H3: Acquirers that operate in a related industry will have lower abnormal returns in FinTech deals than acquirers that do not operate in related industries

2.4.3.5 Tobin's Q/market-to-book ratio

Tobin's Q, also known as the Q ratio, is calculated as follows:

$$Tobin's\ Q = \frac{Total\ Market\ Value\ of\ Firm}{Total\ Asset\ Value\ of\ Firm}$$

In other words, a company's market value divided by the replacement value of its assets. The ratio indicates whether a company's stock is over or undervalued. A low ratio (between 0 and 1) indicates an undervalued stock. This would make it an appealing takeover target because purchasing the company would be less expensive than building a comparable one. A high Q (over 1) indicates that the stock of the company is overvalued. It signifies that the company is earning more than its replacement costs, which has ramifications for managerial success. It may be claimed that a company with a high Tobin's Q is efficient with its resources. According to previous research, acquiring businesses with a high Tobin's Q have significant positive abnormal returns, whereas bidders with a low Tobin's Q have significant negative abnormal returns (Sarvaes, 1991; Lang et al., 1989). The same holds true for market-to-book ratio, which is calculated by dividing a companies' total market value by their book value.

2.4.3.6 ROA/ROE

The acquirer's return on assets (ROA) is computed by dividing their net income by their total assets. Return on assets is a metric used to assess a company's profitability. High profitability, according to Jensen's (1986) free cash flow hypothesis, is linked with the take on of more investments that destroy value. Later study has corroborated these conclusions (Markides & Ittner, 1994). Profitability is controlled for to override the possibility that managers' empire-building influences the results. The same holds true for acquirer's return on equity (ROA), which is computed by dividing their net income by their equity.

2.4.3.7 Size

The size of the bidder negatively affects the abnormal returns surrounding the announcement of an M&A transaction. Large acquirers have a 2 percent lower announcement return than small acquirers, according to prior study. This size effect may be explained by the hubris theory: overconfident managers and entrenched management in large firms increase the risk that a large bidder will overpay for the target. There are strong indications that managers of large organizations may be more prone to overconfidence. Such managers may have grown the company or, if not, may have to overcome greater challenges to become CEOs than managers of small businesses (Bruner, 2004; Moeller et al., 2004).

3. Data

3.1 Sample Selection

The sample used in this study consists of data on M&A from the Thomson Reuters Deal Screener, annual financials data from Compustat and stock- and index return data from DataStream using the event study tool. This paper solely looks at deals where the acquirer and target are both U.S. companies as it would like to capture the effect of the changing markets caused by the Covid-19 pandemic. Different governments implemented different policies as a reaction to the spreading virus which resulted in different effects on markets. Galvin et al. (2018) found that winners in FinTech are primarily emerging at a regional rather than global level. The regulatory complexity within countries makes that firms invest more in regional compliance rather than launching a global effort. I argue that therefore cross-border deals are best left out of this sample. Statista researched the investments into fintech companies worldwide between 2010 and 2021 and found that the Americas accounted for nearly 80 percent of the total (Cherowbrier, 2022). As the U.S. attracted the biggest part of the investments within the Americas, I investigate the effects in this country.

The sample includes transactions exceeding 5 million USD that were announced and completed between 1-1-2016 and 1-1-2022, allowing this paper to (approximately) compare the four years preceding the Covid-19 Financial Crisis with the two years following. Transactions involving several acquiring firms were excluded from the sample due to a lack of data on the distribution of shares acquired by each entity. Following Alexandridis et al. (2010) deals where acquirers own more than 10 percent of the target's shares preceding the announcement are removed as well as deals where acquirers end up with less than 50 percent after the acquisition. This guarantees that transactions in which acquirers possess relatively big shares in targets prior to the transaction, giving them a relative advantage, are excluded from the study. Since stock price information is needed for the event study, only deals that involve public acquirers are included in the sample. Lastly, I follow Dranev et al. (2019) who selects FinTech firms from either the financial services industry (GICS: Financials) or the technology industry (GICS: Information Technology). The further screening of FinTech targets is explained in sector 3.2 of this paper.

The search leads to a sample of 1,469 M&A transactions completed by 901 unique acquirers. There are 756 deals where the target belongs to the Information Technology sector and 713 deals where the target belongs to the Financials sector. Since FinTech is an acronym for Financial Technology, we separately searched the Financials and Information Technology sectors for FinTech deals. To conduct the event analysis, the DataStream codes of the acquiring companies were required.

With the 1,469 deals the DataStream database was searched using the event study tool. With the DataStream Event Study Tool, we could find the cumulative abnormal returns surrounding the announcement of the deal. To calculate the CARs, you need to determine your estimation period, event window, and indices to compare the results with (needed for the market model CAR). In the appendix the indices used to calculate the market model CAR are presented in table 16. Filling in the event study tool template returned CARs for 1,390 deals (market model CAR as well as mean adjusted CAR). The loss of deals could be due to the lack of stock price information for the buying companies during the estimation period and event period.

For the acquirers' and targets' annual financials, the Compustat database was consulted. The following variables were collected to enable this research: Total Assets, Total Market Value, Net Income, Stockholder Equity, Total Long-Term Debt, Total Debt in Current Liabilities, Common Shares Outstanding, Closing Price Annual. These variables were in turn used to construct several additional variables like leverage, ROA, Tobin's Q, and Relative Deal Size. The calculation of these variables is discussed in the methodology part of this paper.

3.2 Fintech Classification

Dranev et al. (2019) found that core technologies behind FinTech came from the Information Technology sector. As a result, organizations with strong IT skills and aspects of their business related to IT and software development for the financial industry are considered FinTech in the scope of their research. Since there has not been a clear definition of FinTech to date (Becker & Allayannis, 2019), Dranev et al. (2019) used a combination of SIC codes. They assume that a company belongs to the FinTech industry if it belongs to a SIC code in the financial and IT sector at the same time. Newer studies regarding FinTechs also use this method of classification (Austin & Dunham, 2022; Schaffers, 2021; Lindner, 2021). I scan the targets that fall in the Financials and Information Technology sector and manually expand the screening by scanning the sites that are presented in table 17 in the appendix.

To get a better understanding of what falls under FinTech I also used the classification of the report about FinTech key sectors and trends written in S&P Global Market Intelligence (Weeks, 2016). FinTech is defined in this research as technology-enabled enterprises that provide financial services, as well as organizations that provide technology services directly to companies in the Financials market. They also divide FinTechs in 9 subcategories. The combination of Dranev et al. (2019), Weeks (2016), the sites mentioned in table 17, and the firm specific sites worked well in looking at whether the target firm could be seen as a FinTech, and if so, in which subsector it falls. The description of the subsectors based on which the FinTech targets are categorized are given in chapter 3.2.1-3.2.9. Not every subsector was well defined in Weeks (2016). Therefore, I looked for good definitions of the sub-sector and combined those with the FinTech term used in that paper to categorize target firms. It is interesting to look at the different subsectors since some of the subsectors have attracted much more attention than others. For example Insurance Technology, Payments, and Digital Lending attract much more investors than Investments & Capital Markets Tech (Woodford,2020). Thus, the outcomes of the M&A deals are also expected to differ.

3.2.1 BPO

Business Process Outsourcing (BPO) is the transfer of one or more IT-intensive firm processes to a third party, which subsequently owns, administers, and maintains the operations based on predetermined and quantifiable performance indicators. BPO offerings are classified into two types: horizontal offers (those that may be used across different industries) and vertical-specific offerings (those that demand specific industry vertical process knowledge).Think about cloud-based services, IT-infrastructure and managed hosting (Pratt & McLaughlin, 2022). In the scope of this research these companies needed to provide these technology services to companies active in the Financials sector.

3.2.2 Digital Lending

Nonbank lending that is powered by technology is referred to as digital lending. Borrowers and lenders are connected via digital lending organizations, which earn from loan connections and transaction processing. Companies employ technology to recruit platform members as well as arrange and close loans, with an emphasis on transparent communications and protocols that result in more efficient processes (Weeks, 2016).

3.2.3 Financial Media & Data Solutions

Financial Media consists of businesses that supply financial information. This includes websites that provide stock information and investment strategy articles. Investor's business daily is an illustration of such a business. They supply investors with exclusive stock listings, market data, and research to assist them earn more money. In addition, this category also includes comparison platforms. In this study, websites that compare product prices go under eCommerce. The websites that compare banks, insurers, credit card providers, loans, and asset managers fall under this category for the purposes of this study.

Data solution providers provide services to businesses in need of assistance with better data utilization. Data services include data gathering, data research, data digitalization, list building, data purification, and data entry. The data solution providers that fall under FinTech in this research provide these services to companies in the Financials sector.

3.2.4 HR & Payroll Tech

Human resources technology (HR Tech) is a broad category for software and associated hardware used to automate the HR function in firms. P ayroll and compensation, talent acquisition and management, workforce analytics, performance management, and benefits administration are all part of it. (Sutner, 2021). In the scope of this research companies that provide HR Tech, either on-premise or as SaaS product, to companies in the Financials sector are included.

Payroll Tech is a niche under HR Tech that works entirely on optimizing the payroll side of a firm. Businesses can opt to conduct their payroll manually, outsource it to a payroll service, or select a payroll software package from a customizable payroll software list. When a company uses a paid service or payroll provider, it outsources its payroll responsibilities to an outside company. Payroll software can assist speed up and streamline the process. Payroll software can also help organize a company's financial data by handling employee documentation, tax statements, recordkeeping needs, and other important files (Fallon, 2022). The companies that provide these services to firms in the Financials sector are included in the FinTech sample.

3.2.5 Insurance & Healthcare Tech

Insurtech refers to technological advances developed and applied to improve the insurance industry's efficiency. InsurTech, as opposed to FinTech, is more commonly associated with improving services for individuals than enterprises (OECD, 2017). New types of processes may improve the efficiency of intermediation and claims management (McKinsey, 2015). Since insurance falls in the Financials sector the companies that provide these innovations fall under the FinTech definition.

In the scope of this research the healthcare tech companies that are classified as FinTech are the companies that make the healthcare sector more efficient and then mostly the internal processes. Healthcare Fintech provides similar services to InsurTech companies, whereby technology is needed to handle policies, customer billing as well as claims settlement and payments. Healthcare FinTechs also provide the internal software, prescription optimization for clients, automated billing and online medical care.

3.2.6 Investments & Capital Markets Tech

In the scope of this research, this subsector entails automated investors. The disruption of traditional wealth management is one of the most active subjects in investing and capital markets technology. Robo-advisers have developed adaptive, automated technology that is revolutionizing money management. Robo-advisers are retail-focused, algorithm-driven wealth management services that utilize algorithms to assess risk tolerance and manage assets in low-cost ETF portfolios. Investors may manage their portfolios remotely thanks to their automated allocation and rebalancing capabilities (Weeks, 2016).

3.2.7 Payment

The payments sector is experiencing a dramatic transition in how payments are initiated and handled as a result of new technologies and societal norms. The major changes are in person-to-person payments, retail payments, and credit and debit card processing and settlement. Person-to-person (P2P) payments are transferred using ACH or debit/credit cards. ACH transfers eliminate card network assessment fees, making them cheaper than credit and debit card transactions. This class includes smartphone apps that employ near-field communication (NFC), QR codes, or barcodes to facilitate in-store payments (e.g. Apple pay). Payment acquirers/processors, ISOs, card networks, and issuing banks handle and settle credit and debit card transactions in the U.S. Financial technology has also influenced business-to-business (B2B), with Tech firms appearing to automate account payable procedures and remove friction between buyers and suppliers. (Weeks, 2016).

3.2.8 Security Technology

Security technology comprises of concepts, rules, and components to decrease risk, identify vulnerabilities, and give response assistance. This research focused on IT security, encompassing p rocedures, tools, and staff used to secure an organization's digital assets. Combining FinTech with security technologies yielded only cybersecurity companies. Cyber security protects a company's information and its processing or storage technology. As the frequency and sophistication of cyber-attacks grows, businesses and organizations, particularly those entrusted with preserving national security, health, or financial records, must take precautions to safeguard critical business and human data (De Groot, 2020). The companies in this category all provide their services to companies in the Financials sector.

3.2.9 eCommerce & Marketing Tech

The term “marketing technology” encompasses strategies, solutions, and technology tools utilized by a corporation in order to fulfill its marketing and commercial goals. Marketing technology is founded on the concept of marketing automation, artificial intelligence (AI), as well as on well-defined marketing strategies. In essence, marketing technology is the perfect bridge between marketing, business and technology, and it is considered as a growth hacking solution for any company that implements it (Baltes, 2017).

The purchase and sale of goods or services online, as well as the transmission of money and data to accomplish these transactions, is referred to as ecommerce. The term "ecommerce" is commonly used to refer to the online sale of physical goods, but it can also refer to any sort of economic transaction facilitated by the internet.. Whereas e-business encompasses all aspects of running an online firm, ecommerce focuses on the exchange of goods and services. (Luketvich et al., 2022). The companies in this subcategory all provided services to companies that fall in the Financials sector.

3.3 Data Treatment

To minimize the risk of outliers influencing the results, I winsorize the non-binary variables in this paper. As is used in Alexandridis et al. (2010), Relative Deal Size, as well as the CARs, are winsorized at the 1th and 99th percentiles (Dinc & Erel, 2013). To reduce the influence of outliers on the regression, the logarithmic value of the acquirer's total assets is utilized for the size variable. The percentage differences between the values for this variable are far more interesting to interpret than the absolute differences.

3.4 Final dataset

Table 1: Cleaning and merging of final dataset
Table 1 shows the cleaning and merging process of the databases. Transaction data for deals completed in the U.S. are downloaded with a sample period from 2016-2021. Only targets within the Financials and Information Technology sector are included. Finally, observations with missing values for one of our dependent, independent or control variables are dropped to get equal observations across all regressions.

Request	Operator	Description	#Observations
Thomson One (Reuters) database	Include	All Mergers & Acquisitions	n/a
Acquirer Nation (Code)	Include	United States of America	397,711
Target Nation (Code)	Include	United States of America	336,362
Acquirer Public Status (Code)	Include	Public	148,754
Date Announced	Between	01/01/2016 to 01/01/2022	15,650
Deal Value ($ Mil)	Between	5 to HI	8,417
Percent of Shares owned before Transaction	Between	0 to 10	5,947
Percent of shares owned after Transaction	Between	50 to HI	4,327
Target Sector	Include	Financials & Information Technology	1,469
Deleting deals with missing observations			921
Final sample of M&A deals			**921**
Of which Fintech			236
Of which BPO			*34*
Of which Digital lending			*16*
Of which Financial Media & Data Solutions			*21*
Of which HR Tech & Payroll Tech			*8*
Of which Insurance & Healthcare Tech			*53*
Of which Investments & Capital Markets Tech			*15*
Of which Payment			*37*
Of which Security Technology			*36*
Of which eCommerce & Marketing Tech			*16*

The final dataset in this paper includes 921 deals. Of these deals, 236 contained a FinTech target. These FinTech targets are in turned placed under one of the subcategories. Most deals fall into the Insurance & Healthcare Tech. BPO, Payment, and Security Technology follow with more than 30 deals each. The final sample of 921 deals is used in the multiple linear OLS regression in this paper.

3.5 Descriptive Statistics of final dataset

Looking at the summary statistics of the final dataset presented in table 2, a couple of things stand out. Since this paper looks at the FinTech market I will focus on the differences between the FinTech deals and the non-FinTech deals. Firstly we will look at the differences for the pre-covid deals.

For every CAR the FinTech deals provide negative mean returns compared to the non-FinTech deals. These negative mean returns however are almost zero varying between 0.1% and 0.2% while the mean of non-FinTech deals varies between 0.6% and 0.9%. What is interesting is that for non-FinTech deals there are more deals where the target and acquirer fall into the same GIC-sector with 67% for FinTech deals and 84.8% for non-FinTech deals. For the interaction of industry relatedness and FinTech a different dummy is used where the dummy equals “1” if the GIC-sector of the acquirer is either Financials or Information Technology. Even when using these two GIC-sectors, 75% of the FinTech deals have an acquirer in the same sector which is still lower than for the non-FinTech deals. Another thing that is noticeable is the difference for the amount of deals that are fully financed with stock. In FinTech deals only 3.3% of the deals are financed using only stock compared to 19.4% in non-FinTech deals. This relatively low percentage of fully financed stock deals could be explained by Thraya et al. (2019) who state that acquisitions of innovative companies with cash signify buyers’ willingness to support the target financially and to further expand its capabilities. Relative Deal Size and Size are higher for non-FinTech deals but these differences are not that big.

When looking at the descriptive of post-covid deals here are also some noticeable differences between FinTech and non-FinTech deals. First of all the table show that the CAR means go up for FinTech deals as well as non-FinTech deals where the CAR means of FinTech deals go up a lot more. The average CAR goes up between 1.7% and 2.2% for FinTech deals compared to 0.7% and 0.8% for non-FinTech deals. Post-covid you can still see that there are less deals where the target and acquirer are in the same GIC-sector for FinTech deals compared to non-FinTech deals. However, compared to pre-covid, post-covid there are less deals where the companies involved in the transaction fall in the same GIC-sector. For FinTech deals the amount of deals containing industry relatedness (where FinTech falls into both Financials as Information Technology) went down from 75% to 69.4%. For non-FinTech this went down from 84.8% to 74.7%. As for the pre-covid sample, the amount of stock deals are still lower for FinTech deals compared to non-Fintech deals. 7.1% of the FinTech deals are fully financed with stock compared to non-FinTechs 15.8%. It is interesting to see that for FinTech deals the amount of stock acquisitions went up with 3.8% compared to a decline of 3.6% for non-Fintech deals. The Relative Deal Size is the variable that stands out the most. For both FinTech as non-FinTech this variable went up post-covid compared to pre-covid. However where pre-covid Relative Deal Size was lower for FinTech deals the targets price went from 18.5% of the acquirer’s market value to 68.3% of the acquirer’s market value whereas the relative size for non-FinTech deals only went up with 8.9%. Post-Covid a decline in acquirers size is seen in both FinTech as non-FinTech deals compared to pre-covid however this is not a significant decline.

Table 2: Descriptive statistics

This table presents the descriptive statistics of all dependent, independent and control variables that are used for the analyses. The sample period is 2016-2021. The top table lists the number of observations, the mean value, and the standard deviation for all variables pre-covid where the table shows the difference between deals that are classified as FinTech (if the binary *FinTech* variable is 1) and deals that are classified as non-Fintech. The table below shows the same information for post-covid deals. Tables with the full summary statistics (including minimum, maximum and median) are in the appendix (see table 12-15).

	FinTech deals *Fintech = 1*			Non-FinTech deals *Fintech* = 0		
Variable	N	Mean	S.D.	N	Mean	S.D.
CARMM [-1,1]	151	-0.001	0.055	495	0.006	0.055
CARMM [-1,2]	151	-0.001	0.054	495	0.009	0.060
CARMM [-1,3]	151	-0.002	0.056	495	0.009	0.060
Industry relatedness	151	0.672	0.471	495	0.848	0.359
Stock	151	0.033	0.179	495	0.194	0.396
Relative Deal Size	151	0.185	0.518	495	0.209	0.321
Size	151	7.945	1.888	495	8.016	1.620
Industry relatedness*Fintech	151	0.750	0.434	495	0.000	0.000
Stock*Fintech	151	0.033	0.179	495	0.000	0.000
Covid*Fintech	151	0.000	0.000	495	0.000	0.000

	FinTech deals *Fintech = 1*			Non-FinTech deals *Fintech* = 0		
Variable	N	Mean	S.D.	N	Mean	S.D.
CARMM [-1,1]	85	0.021	0.069	190	0.016	0.068
CARMM [-1,2]	85	0.020	0.079	190	0.017	0.077
CARMM [-1,2]	85	0.019	0.083	190	0.017	0.080
Industry relatedness	85	0.471	0.502	190	0.747	0.436
Stock	85	0.071	0.258	190	0.158	0.366
Relative Deal Size	85	0.683	1.313	190	0.298	0.605
Size	85	7.473	1.657	190	7.942	1.944
Industry relatedness*Fintech	85	0.694	0.464	190	0.000	0.000
Stock*Fintech	85	0.071	0.258	190	0.000	0.000
Covid*Fintech	85	1.000	0.000	190	0.000	0.000

3.6 Correlation Matrix (pearson)

Table 3: Pearson correlation matrix
This table presents the correlation between the dependence, independent, and control variables used in the regression model. The significance of these correlations are denoted with asterisks ***p<0.01, **p<0.05, and *p<0.1.

Variable	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. CAR MM [-1,1]	1									
2. CAR MM [-1,2]	0.941***	1								
3. CAR MM [-1,3]	0.898***	0.959***	1							
4. Industry relatedness*Fintech	-0.052	-0.075**	-0.074**	1						
5. Stock	-0.117***	-0.124***	-0.130***	-0.146***	1					
6. Industry relatedness	-0.108***	-0.098***	-0.088***	0.065**	0.154***	1				
7. Relative Deal Size	0.116***	0.097***	0.103***	0.072**	0.235***	-0.130***	1			
8. Size	-0.173***	-0.165***	-0.157***	-0.045	0.134***	0.117***	-0.219***	1		
9. Fintech*Stock	0.034	0.021	0.023	0.126***	0.263***	-0.127***	0.446***	-0.081**	1	
10. Post Covid*Fintech	0.070**	0.048	0.031	0.413***	-0.070**	-0.220***	0.224***	-0.085***	0.172***	1

4. Methodology

4.1 Dependent Variable: Cumulative abnormal returns

This research employs a traditional event study approach to assess the influence of the Covid-19 crisis on FinTech M&A. However, it should be highlighted that this method only analyzes the short-term consequences of merger announcements and does not account for longer-term performance measurements Eckbo et al., 2007). Assuming that markets are efficient, the impact of transaction announcements should be instantly reflected in securities prices.

Abnormal returns are calculated close to the announcement date, which is the event date (MacKinlay, 1997). The event date is the date on which the takeover plans are made public (Bowman, 1983). As a result, the following M&A event windows are taken into account, with day 0 denoting the date of announcement: (-10,+10), (-5,+5), (-3,+3), (-2,+2), (-1,+1), (-1,+2), and (-1,+3). By integrating a few days around the event date 0, the model accounts for both ex-ante and ex-post delays in stock price changes. Furthermore, running the analysis with a large number of event windows allows for assumptions about the robustness of the observed results.

For everyday research, typical estimation periods range from 100 to 300 days (Peterson, 1989). Corrado and Zivney (1992) found that an estimation period of 100 days or more seems safe. They conducted a t-test for an estimation periods between 100 and 250 days and found that the t-test is virtually unaffected for the estimation period of 100 days compared to the others. Thus, this paper uses an estimation period that begins 110 days prior to the event and stops 11 days before the event. Abnormal returns represent the stock's actual return in excess of the expected return over the event window and is calculated as follows:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|R_{m,t})$$

$AR_{i,t}$, $R_{i,t}$ and $E(R_{i,t}|R_{m,t})$ represent abnormal, actual, and expected return of stock i on day t given the benchmark return $R_{m,t}$.

4.1.1 Market Model (Dependent variable)

I looked at the options of calculating CAR and found that the market model is potentially superior to the constant mean return approach[1]. By reducing the fraction of the return attributable to market return volatility, the variance of the abnormal return is minimized. This can then result in a greater capacity to recognize event consequences. The advantage of utilizing the market model is dependent on the R^2 of the market model's regression. The greater the R^2 value, the bigger the variance reduction of the abnormal return and the greater the gain. To be certain I also checked the t-statistics for the respective models and found that the market model had a higher significance for each different event window (see table 4). Since the market model CAR [-1,1] was the most significant, this paper uses this CAR as the dependent variable. The market model is a statistical model that compares the return on any asset to the return on the market portfolio. The expected joint normality of asset return distributions leads to the model's linear formulation. For any security *i* the market model is:

$$E(R_{i,t}) = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

$$E(\varepsilon_{it}) = 0 \qquad var(\varepsilon_{it}) = \sigma^2_{\varepsilon\,i}$$

Where $E(R_{i,t})$ is the expected period-t return on security i and $R_{m,t}$ the period-t returns on the market portfolio, respectively, and $\varepsilon_{i,t}$ is the zero mean disturbance term. The parameters α and β are estimated using ordinary least squares (OLS) regression analysis in which the returns observed in the estimation window are used.

Normally a broad-based stock index is employed for the market portfolio. Popular options include the S&P 500, the CRSP Value Weighted Index, and the CRSP Equal Weighted Index. Since I would like to check if the acquiring companies out- or underperform, indices that represent returns for the acquirers GICs sector are used. This way the results can be better interpreted. A list of the index used per GIC-sector is found in table 16 in the appendix of this paper. Combining the market model with the formula for abnormal returns leaves us with the following equation:

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t})$$

[1] The constant return model compares the returns with the mean returns of the respective company. Even though the constant mean return model is arguably the simplest model, Brown and Warner (1980, 1985) find that it frequently produces similar results to more complex models. This lack of sensitivity to the model can be attributable to the fact that selecting a more advanced model frequently does not significantly reduce the variation of the abnormal return. The model is often applied to nominal returns when using daily data.

Finally, we have to calculate the CAR. CAR is obtained by accumulating AR in the related event window between t_1 and t_2. Consequently, CAR used in this article indicates the combined future unanticipated economic gains stemming from the M&A announcements for the shareholders of the bidders. A positive (negative) CAR indicates that the market responded favorably (unfavorably) during the event window to the acquisitions. Therefore, purchase transactions produce (do not produce) acquirer shareholder value. For company i and event window t, the cumulative abnormal return is computed as follows:

$$CAR_{i(t1,t2)} = \sum_{t=t1}^{t2} AR_{i,t}$$

4.1.2 CAR t-stat

In order to test the significance of this proxy for acquisition performance found in this study, the method by Brown and Warner (1985) is used. This study averages CAR to obtain cumulative average abnormal returns (CAARs) since we have to calculate CARs significance for the whole sample.

$$CAAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i$$

The test statistic for testing H0 : E(CAAR) = 0 is given by:

$$t_{CAAR} = \sqrt{N}\frac{CAAR}{S_{CAAR}}$$

Where S_{CAAR} denotes the standard deviation of the CARs across the sample based on:

$$S_{CAAR}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_i - CAAR)^2$$

The results of these t-tests are presented below in table 4.

Table 4: CAR for different event windows
The average cumulative abnormal returns (CAARs) for various event periods are presented in this table using both the market model and the mean adjusted return model. The t-statistics are show in parentheses and statistical significance is displayed by asterisks *p<0.1, **p<0.05 and ***p<0.01.

Event window	Market model	Mean adjusted return model
CAR [-10,10]	0.72%**	0.39%
	(2.087)	(0.96)
CAR [-5,5]	1.05%***	0.89%***
	(3.92)	(2.90)
CAR [-3,3]	1.05%***	0.98%***
	(4.38)	(3.77)
CAR [-2,2]	0.95%***	0.97%***
	(4.35)	(4.08)
CAR [-1,1]	0.82%***	0.74%***
	(4.79)	(4.16)
CAR [-1,2]	0.98%***	0.92%***
	(4.58)	(3.97)
CAR [-1,3]	1.07%***	1.02%***
	(4.64)	(4.05)

4.2 Independent variables

The independent variables that are looked at in this paper are Post-Covid, Stock, and Industry relatedness. To measure how these variables impact the returns of the acquirers' stockholders, these variables are combined with the FinTech dummy.

Post-Covid is a dummy variable that equals "1" if the merger is announced after February 20 2020. This is the day after the market crash in the U.S. which in turn let to a decrease in M&A deals. Since the M&A market was impacted after that day this date will be used as a threshold. If the merger is completed before the February 20 2020 the dummy equals "0".

Stock is a dummy variable that equals "1" if the M&A transaction is entirely funded by the acquirer's stock. Otherwise the dummy is set to "0".

Industry relatedness is a dummy variable that equals "1" if the M&A transaction involves a target and acquirer that fall in the same GIC-sector. For FinTech companies this dummy is slightly different as these targets fall into both the Financials as the Information Technology sector. If the acquirer and the target do not fall in the same sector, this dummy equals "0".

FinTech is a dummy that equals "1" if the target falls into this business classification. Otherwise, this dummy equals "0". The independent variables in the regression are the interaction between FinTech and the variables explained above.

4.3 Control variables

Throughout the past few decades many variables have been found to impact the CARs around M&A deal announcement. In the literature review these variables are summed up as well as the effect that they were previously found to have on CAR. These variables are all looked at to check which ones have a significant impact on the CAR used in my dataset. The ones that have a significant effect are used as the control variables. The ones that were found to have a significant effect were Relative Deal Size, and Size. FinTech, Stock and Industry relatedness were also added as a control variable since they are needed to better interpret the interaction term.

Relative Deal Size is found by dividing the value of the transaction by the market value of the acquirer at the end of the previous year. This estimates the relative size of the target and acquirer.

Size is proxied by the natural logarithm of the acquirers' total assets. The natural logarithm is used as it is more interesting to look at the effect of percentage changes on the abnormal returns than to look at the absolute changes.

An overview of all variables that were looked at and a description of how they are calculated is placed in the appendix in table 18.

4.4 Emprical model

The empirical model utilized in this work for the regressions is Ordinary Least Squares (OLS), which is a widely used. It can process a large amount of data, provides accurate predictions and is easy to implement and interpret. The OLS model does have some drawbacks. To begin, a big dataset is required to generate reliable predictions because the model outputs are sensitive to alternative functional forms if the error term is not properly interpreted. Outliers in the model can also have a significant impact on the model's outcomes since they can act as anchors for the estimations, negatively impacting the model. Other issues with OLS regressions are looked at, such as heteroskedasticity and multicollinearity.

To determine heteroskedasticity, the White test is performed. We use heteroskedasticity-consistent standard errors since the test discovered heteroskedasticity in the data. Year fixed effects are included to adjust for time in order to account for heteroscedasticity across clusters of data. Including time dummies overcomes omitted variable bias, which can occur when some variables vary over time but are comparable across all observations in the sample are excluded (Brooks, 2014).

I also observe outliers throughout the data for the different variables that are used in the regression. Winsorizing and the natural logarithm of variables are the methods used to minimize the impact of outliers on the regression. Winsorizing is an efficient method for reducing the impact of data outliers without losing observations. Winsorizing your top by 1% means that the 99th percentile value will replace the top 1% values. Sometimes, only the values in the upper tail must be replaced, while other times, the lower bound of the distribution must also be replaced (Dinc & Erel, 2013). The natural logarithm is utilized as an additional method for addressing outliers in this article. This has two benefits in this study, as it addresses outliers and creates a variable that has a new interpretation. By calculating the natural logarithm of a numerical value, the absolute value is replaced with the percentage change.

Table 3 in the data section of this paper presents the pearson correlation matrix. Many independent variables are significantly correlated with each other so the variance inflation factors (VIFs)[2] will be calculated to check for multicollinearity. Table 11 in the appendix shows the results of the calculations. Since the values for VIF stay below 5, the significant correlation between the independent variables does not cause any problems.

4.4.1 Model Overview

The following multiple linear OLS regression model is used to check the hypothesis:

$$\begin{aligned} CAR_{-1,1} = {} & \beta_0 + \beta_1 FinTech_i + \beta_2 Industry\ relatedness_i x FinTech_i + \beta_3 Stock_i x FinTech_i \\ & + \beta_4 Post - Covid_i x FinTech_i + controls + year\ fixed\ effects + \varepsilon_{it} \end{aligned}$$

Table 4 presents the significance of the CARs and shows that market model CAR [-1,1] is the most significant CAR. CAR [-1,1] is therefore the dependent variable. The main independent variables are the interaction between the industry relatedness-, stock- and post-covid dummy and the FinTech dummy. The control variables used in this paper are the dummy variables industry relatedness and stock. Next to the dummy variables relative deal size and size are added as variables.

2 The Variance Inflation Factor (VIF) is used to test for multicollinearity as a robustness check. Because of the greater standard errors caused by multicollinearity among the independent variables, the results are less dependable and more difficult to interpret. VIF can be used to assess the extent of multicollinearity in an OLS model with multiple regression variables. Variables with a VIF greater than 5, a standard criterion, are eliminated from the regression (Hair et al., 1995; O'brien, 2007; Alin, 2010). The following formula is used to determine VIF:

$$VIF = \frac{1}{1 - R_i^2}$$

Where i is the predictor you are looking at and R is the R-squared.

4.4.2 Robustness checks

First off, market model CAR [-1,2] and [-1,3] replace CAR [-1,1] as the dependent variable to see if the effects found still hold. As a final check, the interaction variables that are found significant will be used in a regression where only the FinTech deals are taken into account.

4.4.3 Additional analysis

As an additional analysis this paper will look at whether the effect is more announced in certain FinTech sub-sectors. It is interesting to look at the different sub-sectors because of the big differences between them. If the effect of a subsector on CAR is found significant, an additional analysis will take place where the FinTech dummy in the main regression will be replaced by the sub-sector dummy.

5. Results

5.1 Main results

Table 5 presents the results for the main hypotheses in this paper. All columns use a multiple linear OLS regression where *CAR [-1,1]* is the dependent variable and different firm-, and deal characteristics as independent variables. In addition, all columns include year fixed effects, and robust standard errors are clustered at the firm level. The model is build up in 4 steps: first only the influence of the interaction term of Post-Covid and FinTech and the FinTech dummy on CAR is looked at. Then I look at the effects when I control for either industry relatedness (including interaction with FinTech) or stock deals (including interaction with Fintech). Lastly, the model with all independent and control variables is looked at. The table shows that the adjusted R-squared goes up when adding the variables, thus the final model with all variables explains the variation in the regression model better.

5.1.1 Effect of Covid-19 on abnormal returns surrounding FinTech acquisition announcement

FinTech acquisitions appear to have a small negative effect on M&A deal performance. However the small negative influence on CAR is insignificant for all 4 models. This is contradicting with the results of Dranev et al. (2019) and Schaffers (2021), who found a significant positive effect of FinTech deals on acquirer stockholder returns. I do find a significant positive effect of FinTech deals that are performed Post-Covid on the CAR. This positive influence is significant at the 5% level for model 1 and 2, and significant at the 10% level for model 4. Model 4 includes all variables and finds that a FinTech deal that is performed Post-Covid will result in a 1.3% higher CAR on average. Therefore, H_1 – stating that *"Post-covid acquisitions have significantly higher abnormal returns for acquirer shareholders than pre-covid surrounding the announcement of a FinTech firm"*- cannot be rejected. It could be that the ongoing accelerated digitization (LaBerge et al., 2020) is the reason that FinTech deals perform well in the post-covid era. It also confirms the findings in Bouwman et al. (2007) who find higher announcement returns during high-valuation markets.

5.1.2 Effect of payment method on abnormal returns surrounding acquisition announcement

Concerning the method of payment, the following is observed. Acquiring a company using only stock is found to have a negative impact on CAR. This variable is significant in both models that it is added at a 1% significance level. Using only stock as a means of financing will result in a 2.2% lower CAR. These findings are in line with the market-driven acquisition hypothesis by Shleifer and Vishny

(2003) who found that stock overvaluation is a major motivator for corporations to make acquisitions. Negative bidder returns surrounding the announcement of a takeover proposal by pure stock exchange bidding corporations were previously found by Brown & Ryngaert (1991), Moeller et al. (2004), and Alexandridis et al. (2010).

Using stock as a means of financing a FinTech deal does has a positive influence on CAR. For model 3 this effect is significant at a 10% level where the use of stock as a means of financing a FinTech deal will result in a 3.2% higher CAR. In model 4, where all variables are included, the effect of using stock as means of financing a FinTech deal will result in a 0.6% higher CAR. What is also interesting is that the significance is completely gone in model 4 whereas stock was found to have a highly significant effect on CAR. Thus H_{2a} – stating that "*Using stock as a means of financing a FinTech deal will result in positive acquirer shareholder returns"*- cannot be rejected. The results could be explained by the findings in Signori & Vismara (2017) who discover that using stock to finance a deal provides more favorable takeover conditions. In the 3 years after an IPO, corporations use their liquid shares to finance deals. Since IPOs in the U.S. achieved all-time highs in 2020, this could affect the quantity of stock-financed deals and their success. It contradicts Brown & Ryngaert (1991), Moeller et al. (2004), and Alexandridis et al. (2010), who found negative bidder returns after a stock-financed acquisition.

5.1.3 Effect of industry relatedness between target and acquiror on abnormal returns surrounding acquisition announcement

Targets and acquirers that are in the same GICs sector are classified as industry related deals. Industry relatedness has a small negative coefficient. Using a 3-day event period, the coefficient is significant at a 5% level in model 2. When the target and acquirer have the same GIC-sector, the CAR will be 1.2% lower on average. For model 4 the coefficient is insignificant. These findings are in contrast with previous papers who found that the prospect of synergies between bidder and target are a significant driver of M&A activity. These synergies are more likely to be present in related acquisitions (Singh and Montgomery, 1987; Tuch and Sullivan, 2007). Since all companies in the dataset fall either in the Financials or Information Technology sector, this paper finds that acquirer shareholders do not react positively to within industry acquisitions in these sectors. For the Information Technology sector this could partially be explained by the war for technology talent, which might cause these companies to participate in value destroying mergers in the short term in order to acquire talent for the long term (Frick et al., 2021). This war for talent is also seen in the Financials sector where it was found that 46% of the employers have difficult in filling jobs (Arellano, 2018).

The industry relatedness is slightly different for FinTech deals as FinTech companies are active in both the Financials and Information Technology sector. Therefore an acquirer is considered to be in the same sector if they fall either in the Financials or Information Technology sector, For model 2 and 4 significant negative coefficients are found. For model 2 industry relatedness in a FinTech deal leads to a 1.3% decrease in CAR, this effect is significant at a 5% level. In model 4 industry relatedness in a FinTech deal leads to a 1.7% decrease in deal performance which is significant at a 1% level. H_3 – stating that "*Acquirers that operate in a related industry will have lower abnormal returns in FinTech deals than acquirers that do not operate in related industries"*- can therefore not be rejected. This goes against the findings of Singh & Montgomery (1987) and Tuch & Sullivan (2007), who state that synergies are more likely to be present in related acquisitions. It could however be explained by the difficulty to integrate FinTech firms (Lopez, 2022) as well as the war for talent (Arellano, 2018; Frick et al., 2021).

Table 5: Main regression analysis

This table presents the results from the main regression, measuring impact of the interaction terms of FinTech with stock, industry relatedness, and Post-Covid. Column (1) is used to measure the impact of FinTech and the interaction between Post-Covid and FinTech on the CAR. Columns (2), and (3) also measure the impact of industry relatedness and stock respectively. They do so by adding the variable and the interaction term of the variable with FinTech. In column (4) the results of all firm-, and deal characteristics combined is shown. The number of observations and adjusted R-squared can be found at the bottom. All models include year fixed effects, and robust standard errors are clustered at firm level. Statistical significance is displayed by asterisk *p<0.1, **p<0.05, and ***p<0.01. T-statistics are shown in parentheses.

	Dependent variable: Acquisition Performance CAR [-1,1]			
	(1)	(2)	(3)	(4)
Stock			0.022***	-0.022***
			(0.000)	(0.000)
Industry relatedness		-0.012**		-0.005
		(0.014)		(0.281)
Relative Deal Size				0.011***
				(0.006)
Size				-0.004***
				(0.000)
FinTech	-0.004	-0.002	-0.007	-0.001
	(0.856)	(0.745)	(0.840)	(0.821)
Stock*FinTech			0.032*	0.006
			(0.089)	(0.783)
Industry relatedness*FinTech		-0.013**		-0.017***
		(0.025)		(0.003)
Post-Covid*FinTech	0.015**	0.018**	0.011	0.013*
	(0.033)	(0.022)	(0.125)	(0.095)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	921	921	921	921
Adjusted R-squared	0.004	0.016	0.017	0.057

5.2 Robustness tests

In order to determine whether the findings in the previous sections are robust, the dependent variable is replaced. CAR [-1,1] is replaced with CAR [1,2] and CAR [-1,3] while all independent variables are still the same. Table 6 presents the results for the regression using CAR [-1,2] as the dependent variable where table 7 presents the results for the regression using CAR [-1,3] as dependent variable. No significant changes are found for the influence of stock where the negative effect on CAR is even a little bit larger. For the interaction term with stock and FinTech a significant effect was found for the regression using CAR [-1,3] at a 10% level. This effect only holds in column (3) where not all variables are added. The effect becomes highly insignificant in column (4), just like in the main regression. In the model using CAR [-1,2], the interaction effect of FinTech and stock on deal performance is insignificant in both column (3) and column (4). For the effect of industry relatedness and the interaction between industry relatedness and FinTech on acquisition performance, no changes have been found in the models using CAR [-1,2] and CAR [-1,3]. The only thing that stands out is that the negative effect of the interaction between industry relatedness and FinTech on CAR is 0.5% higher in table 7 column (4) while the negative effect is 0.5% lower in table 6 column (3). Both these interaction effects are significant at a 1% level in column (4). The effects of the control variables added in column (4) are also the same in the models using CAR [-1,2] and CAR [-1,3]. The FinTech dummy still has a low negative, non-significant effect on the CAR in table 6 and table 7. For the interaction of Post-Covid and Fintech on the CAR, different findings are observed in table 6 and table 7. When using the CAR [-1,2], the effect becomes insignificant in columns (1), (3), and (4), albeit slightly insignificant. In column (2) a positive effect of 1.6% is found that is statistically significant at a 5% level. When using the CAR [-1,3], the effect becomes somewhat more insignificant for columns (1), (3), and (4). In column (2) a positive effect of 1.3% is found that is statistically significant at a 10% level. Concluding, all findings in the main regression, except for the findings on the interaction between FinTech and Post-Covid, are robust to changes in the dependent variable.

Table 6: robustness check CAR [-1,2]

This table presents the results from robustness check where CAR [-1,1] is replaced with CAR [-1,2]. The regression measures the impact of the interaction terms of FinTech with stock, industry relatedness, and Post-Covid. Column (1) is used to measure the impact of FinTech and the interaction between Post-Covid and FinTech on the CAR. Columns (2), and (3) also measure the impact of industry relatedness and stock respectively. They do so by adding the variable and the interaction term of the variable with FinTech. In column (4) the results of all firm-, and deal characteristics combined is shown. The number of observations and adjusted R-squared can be found at the bottom. All models include year fixed effects, and robust standard errors are clustered at firm level. Statistical significance is displayed by asterisk *p<0.1, **p<0.05, and ***p<0.01. T-statistics are shown in parentheses.

	Dependent variable: Acquisition Performance CAR [-1,2]			
	1	2	3	4
Stock			-0.025*** (0.000)	-0.026*** (0.000)
Industry relatedness		-0.012** (0.027)		-0.004 (0.409)
Relative Deal Size				0.010** (0.015)
Size				-0.005*** (0.000)
FinTech	-0.010 (0.721)	-0.006 (0.626)	-0.004 (0.785)	-0.007 (0.802)
Stock*FinTech			0.031 (0.136)	0.007 (0.761)
Industry relatedness*FinTech		-0.017*** (0.006)		-0.012*** (0.000)
Post-Covid*FinTech	0.011 (0.123)	0.016** (0.049)	0.007 (0.267)	0.012 (0.131)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	921	921	921	921
Adjusted R-squared	0.001	0.015	0.016	0.055

Table 7: robustness check CAR [-1,3]

This table presents the results from robustness check where CAR [-1,1] is replaced with CAR [-1,3]. The regression measures the impact of the interaction terms of FinTech with stock, industry relatedness, and Post-Covid. Column (1) is used to measure the impact of FinTech and the interaction between Post-Covid and FinTech on the CAR. Columns (2), and (3) also measure the impact of industry relatedness and stock respectively. They do so by adding the variable and the interaction term of the variable with FinTech. In column (4) the results of all firm-, and deal characteristics combined is shown. The number of observations and adjusted R-squared can be found at the bottom. All models include year fixed effects, and robust standard errors are clustered at firm level. Statistical significance is displayed by asterisk *p<0.1, **p<0.05, and ***p<0.01. T-statistics are shown in parentheses.

	Dependent variable: Acquisition Performance Car [-1,3]			
	1	2	3	4
Stock			-0.028***	-0.030***
			(0.000)	(0.000)
Industry relatedness		-0.011**		-0.003
		(0.040)		(0.557)
Relative Deal Size				0.013***
				(0.004)
Size				-0.004***
				(0.001)
FinTech	-0.002	-0.003	-0.001	-0.004
	(0.636)	(0.789)	(0.658)	(0.827)
Stock*FinTech			0.038*	0.009
			(0.085)	(0.689)
Industry relatedness*FinTech		0.016**		-0.022***
		(0.013)		(0.001)
Post-Covid*FinTech	0.008	0.013*	0.003	0.007
	(0.247)	(0.096)	(0.493)	(0.312)
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	921	921	921	921
Adjusted R-squared	0.000	0.011	0.017	0.054

Since the robustness checks did not have a clear answer for the robustness of the interaction between Post-Covid and FinTech one last robustness check is used. The robustness check is found in table 8 and presents the effect of the interaction between Post-Covid and industry relatedness on CAR. This time the dataset only includes FinTech mergers to really isolate the effect of Post-Covid on FinTech deal performance. Industry relatedness is also added in this model since the interaction between industry relatedness and FinTech was significant in our main regression and robustness checks. The effect of industry relatedness on the deal performance of FinTech acquisitions becomes insignificant in the FinTech subset for all three dependent variables used. However the effect of Post-Covid on the acquisition performance becomes highly significant in the subset. Deals announced after the 20^{th} of February 2020 have a CAR that is between 3.4% and 3.7% on average. The coefficient is significant at a 1% level. It can thus be said that the changing markets caused by the Covid-19 pandemic did have a positive effect on the acquisition performance of FinTech deals. However if the performance of these post-covid FinTech deals is compared to the deals made where the targets are non-FinTech, no conclusive remarks can be made since not all variables were significant in the regressions.

Table 8: robustness check FinTech subset
This table presents the results of the robustness test where the effect of industry relatedness and Post-Covid on CAR is looked at within the FinTech subset, where all targets are FinTech firms. The effect is looked at with CAR [-1,1], CAR [-1,2], and CAR [-1,3] being used as the dependent variables. The number of observations and adjusted R-squared can be found at the bottom. These models do not look at year fixed effects since these are partially captured in Post-Covid which we want to look at. All models use robust standard errors clustered at firm level. Statistical significance is displayed by asterisk *p<0.1, **p<0.05, and ***p<0.01. T-statistics are shown in parentheses.

	Dependent variable: Acquisition Performance CAR [-t,t]		
	[-1,1]	[-1,2]	[-1,3]
Industry relatedness	-0.004	-0.012	-0.010
	(0.721)	(0.398)	(0.466)
Post-Covid	0.036***	0.037***	0.034***
	(0.001)	(0.003)	(0.009)
Observations	318	318	318
Adjusted R-squared	0.028	0.011	0.017

5.3 Additional analysis

For additional analysis the subsectors are checked to see if the effect of FinTech on acquisition performance is more or less pronounced in the different subsectors. Table 9 shows that the industry relatedness and Post-Covid dummy have the same effect as in table 8. As for the sub-sectors, the only sector where a significant positive effect was found was in the eCommerce & Marketing Tech subsector. When a firm is acquired that falls in the eCommerce & Marketing Tech, the abnormal returns using a 3-day event window go up with 7.8% on average, which is significant at a 10% level. Using a 4-day event window the effect of acquiring a firm in this subsector results in a positive effect of 12% on average, which is significant at a 5% level. Lastly, when using a 5-day event window, the effect of acquiring a firm in the eCommerce & Marketing Tech subsector results in a CAR that is 12.4% higher on average, which is significant at a 5% level.

To check whether this result still holds, I constructed a new regression model where I checked the FinTech subset and used the same variables as in the main model except the FinTech dummy is replaced with the eCommerce dummy, which adopts the value "1" if the target firm falls in the eCommerce & Marketing Tech sub-sector. The results of this regression are shown in table 10. Interesting take-aways are that the interaction variable of stock and eCommerce does have a positive significant effect on CAR when using CAR [-1,2] and CAR [-1,3] as dependent variables. For CAR [-1,2] the use of only stock as a way of financing an eCommerce deal results in a CAR that is 18.9% higher on average, which is significant at a 1% level. For CAR [-1,3], this results in a 16.1% higher CAR, which is significant at a 1% level. Industry relatedness does not have a significant effect on the acquisition performance in eCommerce deals. The interaction effect of Post-Covid and eCommerce does have a significant positive effect. Using CAR [-1,1] as the dependent variable, the interaction results in a 9.1% higher CAR on average, which is significant at a 5% level. Using CAR [-1,2] and CAR [-1,3] as dependent variables, the interaction leads to a CAR that is 26% and 27.9% higher on average respectively, both significant at a 1% level. Another noticeable thing about this regression is that the R-squared of the models using CAR [-1,2] and CAR [-1,3] as dependent variable show much higher values than for the other models in this paper. These models explain 20.7% and 18.4% of the variance respectively.

Table 9: additional analysis with sub-sectors

This table presents the results of the additional analysis where sub-sectors are looked at. The effect of industry relatedness and Post-Covid on CAR is looked at within the FinTech subset, where all targets are FinTech firms. Also the dummy variables of all sub-sectors are added since we want to look at the effect of the sub-sector on the dependent variables used. The effect is looked at with CAR [-1,1], CAR [-1,2], and CAR [-1,3] being used as the dependent variables to also check if the results are robust for changes in the dependent variable. The number of observations and adjusted R-squared can be found at the bottom. These models do not look at year fixed effects since these are partially captured in Post-Covid which we want to look at. All models use robust standard errors clustered at firm level. Statistical significance is displayed by asterisk *p<0.1, **p<0.05, and ***p<0.01. T-statistics are shown in parentheses.

	Dependent variable: Acquisition Performance Car [-t,t]		
	[-1,1]	[-1,2]	[-1,3]
Industry relatedness	-0.002	-0.010	-0.009
	(0.858)	(0.507)	(0.564)
Post Covid	0.038***	0.040***	0.037***
	(0.001)	(0.002)	(0.005)
Business Process Outsourcing	-0.001	0.027	0.030
	(0.991)	(0.628)	(0.602)
Digital Lending	-0.018	0.013	0.026
	(0.710)	(0.813)	(0.659)
Financial Media & Data Solutions	-0.004	0.026	0.025
	(0.931)	(0.641)	(0.673)
HR & Payroll Tech	-0.021	0.007	0.016
	(0.700)	(0.911)	(0.805)
Insurance & Healthcare Tech	0.013	0.046	0.050
	(0.776)	(0.402)	(0.285)
Investments & Capital Markets Tech	0.024	0.053	0.063
	(0.622)	(0.340)	(0.280)
Payment	0.002	0.028	0.028
	(0.968)	(0.612)	(0.622)
Security Technology	-0.010	0.026	0.024
	(0.835)	(0.640)	(0.680)
eCommerce & Marketing Tech	0.078*	0.120**	0.124**
	(0.086)	(0.035)	(0.037)
Observations	318	318	318
Adjusted R-squared	0.064	0.049	0.049

Table 10: additional analysis of eCommerce & Marketing Tech

This table presents the results from the additional regression, measuring impact of the interaction terms of eCommerce with stock, industry relatedness, and Post-Covid. Size and Relative Deal Size are added as control variables. The regression looks at the outcomes using 3 different CARs as dependent variables to check for robustness of the results. The number of observations and adjusted R-squared can be found at the bottom. All models include year fixed effects, and robust standard errors are clustered at firm level. Statistical significance is displayed by asterisk *p<0.1, **p<0.05, and ***p<0.01. T-statistics are shown in parentheses.

	Dependent variable: Acquisition Performance Car [-t,t]		
	[-1,1]	[-1,2]	[-1,3]
Stock	0.029	0.032*	-0.035*
	(0.228)	(0.092)	(0.079)
Industry relatedness	-0.010	-0.020*	0.020*
	(0.226)	(0.070)	(0.077)
Relative Deal Size	0.009*	0.015**	0.017**
	(0.085)	(0.17)	(0.012)
Size	-0.004	-0.003	0.002
	(0.121)	(0.315)	(0.621)
Stock*eCommerce	0.060	0.189***	0.161***
	(0.240)	(0.000)	(0.003)
Industry relatedness*eCommerce	0.005	-0.022	0.019
	(0.812)	(0.391)	(0.477)
Post-Covid*eCommerce	0.091**	0.260***	0.279***
	(0.019)	(0.000)	(0.000)
Year Fixed Effects	Yes	Yes	Yes
Observations	236	236	236
Adjusted R-squared	0.069	0.207	0.184

6. Discussion and limitations

As with the majority of academic research, generalizability is challenging. This study used a sample of 922 M&A deals with targets in the Information Technology and Financials sector announced between the beginning of 2016 and the ending of 2021. Since this study only looks at the influence of the Covid-19 pandemic on the U.S., a study where more geographical locations were considered would present more generalizable results.

Regarding the data collection of this paper, a couple of limitations are present. Since FinTech companies are not easy to identify this study uses a combination of methods to identify companies as FinTech. Although a lot of time was spend on the classification of FinTechs, part of this identification process involves some sort of judgement call, which makes the identification process hard to reproduce. Also the post-covid sample comprises of 275 deals compared to 646 pre-covid deals. In future research it might be better to have a more equal sample for the post-covid and pre-covid period. Lastly in the classification process, all companies where FinTech or non-FinTech and the categorization in sub-sectors also placed all companies in 1 subsector. However, some companies that are seen as a FinTech also offer services in other sectors and some companies could also fall under multiple sub-sectors. For future research, only including companies that solely provide FinTech services could better capture the effect of FinTech M&A on acquirer stock performance, the same goes for the companies falling in multiple sub-categories.

Dranev et al. (2019) find significant positive CARs after FinTech acquisitions but negative CARs in the long-run. It would be in interesting to see how the long-run performance of FinTech deals performed post-covid is. Since the post-covid sample at the time of my data collection was only a year and a half of M&A deals, this was not really possible but in a year time this could be something to research. For financial institutions acquiring FinTechs could have a negative influence on the long-term performance of these deals. FinTech companies and other companies in the Information Technology sector that purchase a FinTech company for the sake of talent acquisition could also have trouble in the long-run if they struggle with retaining the employees that they acquired in the deal (Mullen, 2022; Lopez, 2022).

Lastly, it would be interesting to take a better look at the influence of the changing markets caused by the Covid-19 pandemic on the eCommerce market. This paper found that the companies that acquired firms placed in this subsector generated large short-term returns. Perez (2020) found that in the first post-covid quarter, U.S. e-commerce sales went up with 31.8% compared to the first quarter, so changes in this sector caused by the covid-19 pandemic were definitely present.

7. Conclusion

The Covid-19 pandemic had a huge impact on many markets, one of these impacts was the accelerated digitization of the world caused by the lockdown measures. While the lockdown measures brought many companies to the brink of bankruptcy, there were also a lot of winners during the pandemic. One of the sectors that benefited was the FinTech market, which is the biggest in the United States. The primary purpose of this paper was to examine how the changing markets, caused by the Covid-19 pandemic, influenced the short-term acquirer stockholder return surrounding the announcement of a FinTech M&A deal in the United States. I use a sample of 921 U.S. M&A deals announced between 1-1-2016 and 1-1-2022. The sample consists of 236 (151 pre-covid, 85 post-covid) FinTech deals and 645 (495 pre-covid, 190 post-covid) non-FinTech deals were the target was in the Financials or Information Technology sector. Since multiple factors influence the CAR surrounding a deal announcement, Relative Deal Size, industry relatedness, and stock are added as variables in the regression. Deals performed after 20 February 2020 are seen as post-covid in this paper since that was the day of the stock-market crash which simultaneously impacted the M&A market with deal volumes dropping drastically (KPMG, 2020).

The empirical evidence of the main regression in this paper shows that FinTechs have a small negative effect on the CAR, this effect is however insignificant. However, this paper finds evidence that FinTech deals that are announced post-covid result in a significantly higher return for acquirer shareholders. This finding does not hold for all models in the robustness checks where longer event-periods are looked at. When only looking at the FinTech subsample, this paper finds that deals performed post-covid had a highly significant positive effect on the acquisition performance. The higher returns for Fintech deals announced post-covid could be explained by the accelerated digitization caused by the Covid-19 pandemic (LaBerge et al., 2020).

The empirical evidence of the main regression in this paper also shows that FinTech deals where the acquirers operate in related industries result in a lower CAR. These findings are robust to changes in the dependent variable. However, when we look at the effect of industry relatedness on the CAR within the FinTech subset, the effect is still negative except the significance goes away. The findings are noteworthy, but not for all robustness checks. They contradict Martynova & Renneboog (2006) and Tuch & Sullivan (2007), who found that linked industry mergers perform better. The findings could be explained integration challenges that arise for financial services businesses that acquire FinTechs (Lopez, 2022), and the war for personnel may blind IT acquirers to buy a FinTech firm for the staff. When these employees don't join, acquisition returns are hurt (Frick et al., 2021; Mullen, 2022). The empirical evidence of the main regression in this paper lastly shows that the influence of a FinTech acquisition that is financed with the acquirer's stock has a positive influence on the acquirer's return.

The positive result is not significant in the model where all variables are added. Changing the dependent variables gives the same result were using CAR [-1,2] even resulted in no significance in all models. It is however interesting to see that stock did have a highly significant negative effect on cumulative abnormal returns where the targets are non-FinTech as is found in previous literature (Lane & Yang, 1983; Travlos (1987); Franks, Harris & Mayer, 1988; Baker & Wurgler, 2002). This positive effect found in this paper could be explained by the findings in Signori & Vismara (2017). They found that many IPOs use the "stock as currency" motive to go public since they can acquire firms at more favorable terms using publicly traded stock as a means of deal financing. Public firms mostly use stock as a means of financing in the three years following their IPO. Since 2020 presented record high numbers of IPOs in the U.S., this could have a big influence on the amount of stock financed deals and their performance (Carnevali & Platt, 2020).

Lastly, this paper performs an additional analysis where I look at whether the effects of FinTech deals are more pronounced for sub-sectors. I find a significant positive effect for the eCommerce & Marketing Tech subsector. This paper further analyses eCommerce deals by replacing the FinTech dummy in the main regression with the eCommerce dummy. The results of this regression show that deals that are performed in this sector post-covid have a highly significant positive effect on the different CARs. These results could be explained by the fact that U.S. e-commerce sales that went up significantly in the post-covid era. In the first quarter following the Covid-19 pandemic the sales went up with 31.8% compared to the previous quarter. The pandemic sped up the implementation of ecommerce significantly (Perez, 2020).

References

Abay, K. A., Tafere, K., & Woldemichael, A. (2020). Winners and losers from COVID-19: Global evidence from Google Search. *World Bank Policy Research Working Paper*, (9268).

Accenture (2016). Fintech and the evolving landscape: Landing points for the industry. Accenture Financial Services, Accenture.

Adams, C., Mathieson, D. J., Schinasi, G., & Chadha, B. (1998). International capital markets. *Developments, Prospects, and Key Policy Issues, IMF, September*, 59-67.

Agrawal, A., Jaffe, J. F., & Mandelker, G. N. (1992). The post-merger performance of acquiring firms: a re-examination of an anomaly. *The Journal of finance*, *47*(4), 1605-1621.

Alexandridis, G., Petmezas, D., & Travlos, N. G. (2010). Gains from mergers and acquisitions around the world: New evidence. *Financial Management*, *39*(4), 1671- 1695.

Alin, A. (2010). Multicollinearity. *Wiley interdisciplinary reviews: computational statistics*, *2*(3), 370-374.

Allayannis, G., & Becker, J. M. (2019). A global FinTech overview. *Darden Case No. UVA-F-1860*.

Arner, D. W., Barberis, J., & Buckley, R. P. (2015). The evolution of FinTech: A new post- crisis paradigm. *Geo. K. Int'I L., 47,* 1271.

Arellano, C. (2018). Data's role in the war for talent in financial services | McKinsey. McKinsey & Company; www.mckinsey.com. Data's role in the war for talent in financial services | McKinsey

Ashraf, B. N. (2020). Stock markets' reaction to COVID-19: Cases or fatalities?. *Research in International Business and Finance*, *54*, 101249.

Asquith, P., Bruner, R. F., & Mullins Jr, D. W. (1983). The gains to bidding firms from merger. *Journal of financial economics*, *11*(1-4), 121-139.

Austin, R. E., & Dunham, L. M. (2022). Do FinTech Acquisitions Improve the Operating Performance or Risk Profiles of Acquiring Firms?. *Journal of Economics and Business*, 106078.

Baker, M., & Wurgler, J. (2002). Market timing and capital structure. *The journal of finance*, *57*(1), 1-32.

Baltes, L. P. (2017). Marketing technology (Martech)–the most important dimension of online marketing. *Bulletin of the Transilvania University of Brasov. Economic Sciences. Series V*, *10*(2), 43-48.

Bar Am, J., Furstenhal, L., Jorge, F., & Roth, E. (2020). Innovation in a crisis: Why it is more critical than ever | McKinsey. McKinsey & Company; www.mckinsey.com. Innovation in a crisis: Why it is more critical than ever | McKinsey

Beitel, P., Schiereck, D., & Wahrenburg, M. (2004). Explaining M&A success in European banks. *European Financial Management*, *10*(1), 109-139.

Bosker, D., Zuidema, M., & Groeneveld, O. (2020). COVID-19 has a major impact on the M&A market. KPMG; home.kpmg. https://home.kpmg/nl/nl/home/insights/2020/08/covid-19- has-a-major-impact-on-the-m-and-a-market.html

Bouwman, C. H., Fuller, K., & Nain, A. S. (2009). Market valuation and acquisition quality: Empirical evidence. *The Review of Financial Studies*, *22*(2), 633-679.

Bowman, R. G. (1983). Understanding and conducting event studies. Journal of Business Finance & Accounting, 10(4), 561-584.

Brooks, C. (2014). *Introductory Econometrics for Finance*. 3rd ed. New York: Cambridge University Press.

Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of financial economics*, *8*(3), 205-258.

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of financial economics*, *14*(1), 3-31.

Brown, D. T., & Ryngaert, M. D. (1991). The mode of acquisition in takeovers: Taxes and asymmetric information. *The Journal of Finance*, *46*(2), 653-669.

Bruner, R. F., & Perella, J. R. (2004). *Applied mergers and acquisitions* (Vol. 173). John Wiley & Sons.

Carnevali, D., & {;att, E. (2020, December 28). Markets shock in 2020 gives way to IPO boom | Financial Times. Markets Shock in 2020 Gives Way to IPO Boom | Financial Times; www.ft.com. https://www.ft.com/content/af6e52d5-ec71-41c1-b021-33d81e371a17

Chen, J., & Vetterli, J. (2021, March 8). Global IPOs hit back strongly after COVID-19 crash | White & Case LLP. Global IPOs Hit Back Strongly after COVID-19 Crash | White & Case LLP; www.whitecase.com. https://www.whitecase.com/insight-our-thinking/global-ipos-hit-back-strongly-after-covid-19-crash

Chen, Z., & Tan, J. (2011). Does bancassurance add value for banks?–Evidence from mergers and acquisitions between European banks and insurance companies. *Research in International Business and Finance*, *25*(1), 104-112.

Cherowbrier, J. (2022, May 30). Global investments in fintech companies 2021 | Statista. Statista; www.statista.com. https://www.statista.com/statistics/719385/investments-into-fintech-

Conn, R. L., Cosh, A., Guest, P. M., & Hughes, A. (2005). The impact on UK acquirers of domestic, cross-border, public and private acquisitions. *Journal of Business Finance & Accounting*, *32*(5-6), 815-870.

Corrado, C. J., & Zivney, T. L. (1992). The specification and power of the sign test in event study hypothesis tests using daily stock returns. Journal of Financial and Quantitative analysis, 27(3), 465-478.

Cox, J. (2021, April 9). Investors have put more money into stocks in the last 5 months than the previous 12 years combined. CNBC; www.cnbc.com. https://www.cnbc.com/2021/04/09/investors-have-put-more-money-into-stocks-in-the-last-5-months-than-the-previous-12-years-combined.html

Damodaran, A. (2006). The cost of distress: survival, truncation risk and valuation. *Truncation Risk and Valuation (January 2006)*.

Deb, P., Furceri, D., Ostry, J. D., & Tawk, N. (2020). The economic effects of COVID-19 containment measures.

De Groot, J. (2020, June 10). What is Cyber Security? Definition, Best Practices & Examples. Digital Guardian; digitalguardian.com. https://digitalguardian.com/blog/what-cyber-security

Douglas, J. L. (2016). New wine into old bottles: FinTech meets the bank regulatory world. *NC Banking Inst.*, *20*, 17.

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

Ebrahim, R., Kumaraswamy, S., & Abdulla, Y. (2021). FinTech in Banks: Opportunities and Challenges. Innovative Strategies for Implementing FinTech in Banking, 100-109.

Eckbo, B. E., Masulis, R. W., & Norli, Ø. (2007). Security offerings. Handbook of empirical corporate finance, 233-373.

Erkens, D. H., Hung, M., & Matos, P. (2012). Corporate governance in the 2007–2008 financial crisis: Evidence from financial institutions worldwide. *Journal of corporate finance*, *18*(2), 389-411.

EY (2021). Global M&A Hits Highest Value on Record as Post-Pandemic Market Starts to Take Shape | EY - Global; www.ey.com. Global M&A hits highest value on record as post-pandemic market starts to take shape | EY - Global

Ey (2022). M&A Activity Remains Resilient in 2022, but Further Shocks Could Derail Outlook | EY - Global; www.ey.com. M&A activity remains resilient in 2022, but further shocks could derail outlook | EY - Global

Fallon, N. (2022, July 20). How to Choose a Payroll Provider - business.com. Business.Com; www.business.com. https://www.business.com/payroll/

Franks, J. R., Harris, R. S., & Mayer, C. (1988). Means of payment in takeovers: Results for the United Kingdom and the United States. In *Corporate takeovers: Causes and consequences* (pp. 221-264). University of Chicago Press.

Frick, J., George, K., & Coffman, J. (2021, September 20). The Tech Talent War Is Global, Cross-Industry, and a Matter of Survival | Bain & Company. Bain; www.bain.com. https://www.bain.com/insights/tech-talent-war-tech-report-2021

Fu, J., & Mishra, M. (2020). The global impact of COVID-19 on FinTech adoption. Swiss Finance Institute Research Paper, (20-38).

Fu, J., & Mishra, M. (2022). Fintech in the time of COVID– 19: Technological adoption during crises. *Journal of Financial Intermediation*, *50*, 100945.

Fuller, K., Netter, J., & Stegemoller, M. (2002). What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions. *The journal of finance*, *57*(4), 1763-1793.

Galvin, J., Han, F., Hynes, S., Qu, J., Rajgopal, K., & Shek, A. (2018). Synergy and disruption: Ten trends shaping fintech. McKinsey Report.

Gaytandzhiev, Plamen. (2022, January 17). *How is bank share price performance influenced by the announcement of an investment in a FinTech company?*. *Finance & Investments*. Retrieved from http://hdl.handle.net/2105/61207

Goergen, M., & Renneboog, L. (2004). Shareholder wealth effects of European domestic and cross-border takeover bids. *European Financial Management*, *10*(1), 9-45.

Golubov, A., Petmezas, D., & Travlos, N. G. (2016). Do stock-financed acquisitions destroy value? New methods and evidence. *Review of Finance*, *20*(1), 161-200.

Gopalan, S., Jain, G., & Tan, J. (2012). Breakthrough IT banking. *Mckinsey Q, 26,* 30-35.

Gort, M. (1969). An economic disturbance theory of mergers. The Quarterly Journal of Economics, 624-642.

Gulamhuseinwala, I., Bull, T., & Lewis, S. (2015). FinTech is gaining traction and young, high-income users are the early adopters. *Journal of Financial Perspectives*, *3*(3).

Hair, J. F. Jr., Anderson, R. E., Tatham, R. L. & Black, W. C. (1995). *Multivariate Data Analysis (3rd ed). New York: Macmillan.*

Haitovsky, Y. (1969). Multicollinearity in regression analysis: Comment. *The Review of economics and statistics*, 486-489.

Hansen, R. G. (1987). A theory for the choice of exchange medium in mergers and acquisitions. *Journal of business*, 75-95.

Harford, J. (2005). What drives merger waves?. Journal of financial economics, 77(3), 529-560.

Hege, U., Lovo, S., Slovin, M. B., & Sushka, M. E. (2009). Asset sales and the role of buyers: Strategic buyers versus private equity.

Holthausen, R. W., & Zmijewski, M. E. (2012). Valuation with Market Multiples: How to Avoid Pitfalls When Identifying and Using Comparable Companies 1. *Journal of Applied Corporate Finance*, *24*(3), 26-38.

Issawi, C. (1978). The 1973 oil crisis and after. *Journal of Post Keynesian Economics*, *1*(2), 3-26.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American economic review*, *76*(2), 323-329.

Kengelbach, J., Gell, J., Keienburg, G., Degen, D., & Kim, D. (2020). COVID-19's impact on global M&A.

Ketabchi, N. (2019). State of Fintech. Toptal Finance Blog; www.toptal.com. https://www.toptal.com/finance/market-research-analysts/fintech-landscape

Kohers, N., & Kohers, T. (2001). Takeovers of technology firms: Expectations vs. reality. *Financial management*, 35-54.

Kooli, C., & Lock Son, M. (2021). Impact of COVID-19 on mergers, acquisitions & corporate restructurings. Businesses, 1(2), 102-114.

KPMG (2022). Total fintech investment tops US$210 billion - KPMG Global. KPMG; home.kpmg. Total fintech investment tops US$210 billion - KPMG Global (home.kpmg)

Kutler, J. (1993). Citibank is shedding individualistic image. *American Banker.*

LaBerge, L., O'Toole, C., Schneider, J., & Smaje, K. (2020). How COVID-19 has pushed companies over the technology tipping point--and transformed business forever. McKinsey & Company; www.mckinsey.com. COVID-19 digital transformation & technology | McKinsey

Lang, L. H., Stulz, R., & Walkling, R. A. (1989). Managerial performance, Tobin's Q, and the gains from successful tender offers. *Journal of financial Economics*, *24*(1), 137-154.

Lindner, E. (2021, November 4). What is the impact of FinTech M&A on shareholder return for U.S. acquirers between 2010-2020?. Business Economics. Retrieved from http://hdl.handle.net/2105/60142

Lopez, J. (2022). 3 Challenges of Fintech Integration | FinTalk. 3 Challenges of Fintech Integration | FinTalk; www.jackhenry.com. 3 Challenges of Fintech Integration | FinTalk (jackhenry.com)

Lutkevich, B., Chai, W., & Holak, B. (2022, June 1). What is E-Commerce? Definition and Meaning. SearchCIO; www.techtarget.com. https://www.techtarget.com/searchcio/definition/e-commerce

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, *35*(1), 13-39.

Markides, C. C., & Ittner, C. D. (1994). Shareholder benefits from corporate international diversification: Evidence from US international acquisitions. *Journal of international business studies*, *25*(2), 343-366.

Martynova, M., & Renneboog, L. (2006). Mergers and acquisitions in Europe. Advances in corporate finance and asset pricing, 13-75.

Mazur, M., Dang, M., & Vega, M. (2021). COVID-19 and the march 2020 stock market crash. Evidence from S&P1500. *Finance research letters*, *38*, 101690.

McCall, J. (2021). "Acceleration of M&A activity in tech sector better than 2019 levels" experts claim; capital.com. 'Acceleration of M&A activity in tech sector better than 2019 levels' experts claim (capital.com)

McKinsey (2015), Insurance on the threshold of digitization: Implications for the Life and P&C workforce (December).

Mitchell, M. L., & Mulherin, J. H. (1996). The impact of industry shocks on takeover and restructuring activity. Journal of financial economics, 41(2), 193-229.

Modigliani, F., & Miller, M. H. (1963). Corporate income taxes and the cost of capital: a correction. *The American economic review*, *53*(3), 433-443.

Moeller, S. B., Schlingemann, F. P., & Stulz, R. M. (2004). Firm size and the gains from acquisitions. *Journal of financial economics*, *73*(2), 201-228.

Mukhopadhyay, U., Skjellum, A., Hambolu, O., Oakley, J., Yu, L., & Brooks, R. (2016). A brief survey of cryptocurrency systems. In *2016 14th annual conference on privacy, security and trust (PST)* (pp. 745-752). IEEE.

Mullen, S. (2022). The Importance of Retaining Key Talent after an Acquisition | Bain & Company. Bain; www.bain.com. The Importance of Retaining Key Talent after an Acquisition | Bain & Company

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, *13*(2), 187-221.

O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & quantity*, *41*(5), 673-690.

OECD. (2017). Technology and innovation in the insurance sector.

Perez, S. (2020). COVID-19 pandemic accelerated shift to e-commerce by 5 years, new report says – TechCrunch. TechCrunch; techcrunch.com. COVID-19 pandemic accelerated shift to e-commerce by 5 years, new report says | TechCrunch

Peterson, P. P. (1989). Event studies: A review of issues and methodology. *Quarterly journal of business and economics*, 36-66.

Pratt, M., & McLaughlin, E. (2022). What is Business Process Outsourcing? - Definition from SearchCIO. SearchCIO; www.techtarget.com. https://www.techtarget.com/searchcio/definition/business-process-outsourcing

Puschmann, T. (2017). FinTech. *Business & Information systems Engineering, 59(1), 69-76.*

Rhodes-Kropf, M., & Viswanathan, S. (2004). Market valuation and merger waves. The Journal of Finance, 59(6), 2685-2718.

Richardson, G. (2007). Categories and causes of bank distress during the great depression, 1929– 1933: The illiquidity versus insolvency debate revisited. *Explorations in Economic History*, *44*(4), 588-607.

Rosenfeld, J. (2021, March 17). The 10 Industries That Have Been Impacted the Most by COVID-19. The 10 Industries That Have Been Impacted the Most by COVID-19; finance.yahoo.com. The 10 Industries That Have Been Impacted the Most by COVID-19 (yahoo.com)

Sahi, H. (2017). Studying market reactions to Fintech companies-Acquisitions and initial public offerings in OECD Countries.

Savor, P. G., & Lu, Q. (2009). Do stock mergers create value for acquirers?. *The Journal of Finance*, *64*(3), 1061-1097.

Schaffers, Pepijn. (2021, July 2). The Impact of Fintech M&A on the Performance of Financial Institutions. Finance & Investments. Retrieved from http://hdl.handle.net/2105/57342

Schreiner, A. (2009). *Equity valuation using multiples: an empirical investigation*. Springer Science & Business Media.

Serdar Dinc, I., & Erel, I. (2013). Economic nationalism in mergers and acquisitions. *The Journal of Finance*, *68*(6), 2471-2514.

Servaes, H. (1991). Tobin's Q and the Gains from Takeovers. *The journal of finance*, *46*(1), 409-419.

Shleifer, A., & Vishny, R. W. (2003). Stock market driven acquisitions. Journal of financial Economics, 70(3), 295-311.

Signori, A., & Vismara, S. (2017). Stock-financed M&As of newly listed firms. *Small Business Economics*, *48*(1), 115-134.

Singh, H., & Montgomery, C. A. (1987). Corporate acquisition strategies and economic performance. *Strategic Management Journal*, *8*(4), 377-386.

Slot, M. (2021, May 11). "M&A-markt draait mede dankzij coronavirus overuren" - Executive Finance -. Executive Finance; executivefinance.nl. https://executivefinance.nl/2021/05/ma-markt-draait-mede-dankzij-coronavirus-overuren/

Spigt, R. What is the impact of FinTech M&A on shareholder return for US acquirers between 2010-2020?.

Sutner, S. (2021, October 1). What is HR Technology (Human Resources Tech)? SearchHRSoftware; www.techtarget.com. https://www.techtarget.com/searchhrsoftware/definition/HR-technology

Tanjung, A.S. (2020). Studying Market Reactions to Fintech Acquisitions in North America and Europe: The Impact of Fintech Classification of Target Firms on the Acquirers' Cumulative Abnormal Returns. Business Economics. Retrieved from http://hdl.handle.net/2105/51771

Tashanova, D., Sekerbay, A., Chen, D., Luo, Y., Zhao, S., & Zhang, T. (2020). Investment opportunities and strategies in an era of Coronavirus pandemic. *Available at SSRN 3567445*.

Thompson, S. B. (2011). Simple formulas for standard errors that cluster by both firm and time. Journal of financial Economics, 99(1), 1-10.

Thraya, M. F., Lichy, J., Louizi, A., & Rzem, M. (2019). High-tech acquirers and the moderating role of corporate governance. The Journal of High Technology Management Research, 30(2), 100354.

Travlos, N. G. (1987). Corporate takeover bids, methods of payment, and bidding firms' stock returns. *The journal of finance*, *42*(4), 943-963.

Tsanis, K., & Stouraitis, V. (2022). Global Fintech Market: Recent Performance and the Effect of COVID-19–Investigating the Impact of the Pandemic in the Financial Technology Sector. In External Events and Crises That Impact Firms and Other Entities (pp. 1-23). IGI Global.

Tuch, C., & O'Sullivan, N. (2007). The impact of acquisitions on firm performance: A review of the evidence. *International journal of management reviews*, *9*(2), 141-170.

Valetkevitch, C. (2022, January 4). S&P 500, Dow hit record highs on 1st trading day of 2022 | Reuters. Reuters; www.reuters.com. https://www.reuters.com/markets/europe/sp-500-dow-hit-record-highs-1st-trading-day-2022-2022-01-03/

Velthuijsen, J. W., & De Lange-Snijders, R. (2020). The impact of COVID-19 - Annual Report 2020/2021 - Our organisation - PwC. PwC; www.pwc.nl. The impact of COVID-19 - Annual Report 2020/2021 - Our organisation - PwC

Wansley, J. W., Lane, W. R., & Yang, H. C. (1983). Abnormal returns to acquired firms by type of acquisition and method of payment. *Financial management*, 16-22.

Weeks, C. (2016). An introduction to FinTech: Key sectors and Trends. *S&P Global Market Intelligence,* 1-19.

Wen, Y., & Arbogast, I. (2021, March 21). How COVID-19 Has Impacted Stock Performance by Industry | St. Louis Fed. Covid19 Impacted Stock Performance Industry; www.stlouisfed.org. https://www.stlouisfed.org/on-the-economy/2021/march/covid19-impacted-stock-performance-industry

Williams, L. (2021, June 22). Why crises are the best times to invest in innovation - Investment Monitor. Investment Monitor; www.investmentmonitor.ai. https://www.investmentmonitor.ai/tech/innovation/innovative-investing-crisis-covid

Woodford, I. (2020, August 28). European fintechs have raised over $3bn since lockdown began, but where's that money gone? Sifted; sifted.eu. https://sifted.eu/articles/european-fintech-funding-2020/

Woodford, I. (2021). Europe’s FinTech M&A ‘boom’: What the data tells us. *Sifted.* (https://sifted.eu/articles/european-ma-FinTech-data/)

Yook, K. C. (2003). Larger return to cash acquisitions: signaling effect or leverage effect?. *The Journal of Business*, *76*(3), 477-498.

Yousfi, M., Zaied, Y. B., Cheikh, N. B., Lahouel, B. B., & Bouzgarrou, H. (2021). Effects of the COVID-19 pandemic on the US stock market and uncertainty: A comparative assessment between the first and second waves. *Technological Forecasting and Social Change*, *167*, 120710.

World Bank. (2020). Global economic prospects, June 2020. The World Bank.

Zhang, D., Hu, M., & Ji, Q. (2020). Financial markets under the global pandemic of COVID-19. *Finance research letters*, *36*, 101528.

Appendix

Table 11: Variance Inflation Factor (VIF)
This table represents the results of the VIF calculations. Since all values stay below 5, which is the threshold in this paper, no variables need to be removed in the regression of the main model.

Variable	VIF	1/VIF
Stock	1.42	0.704
Industry Relatedness	4.42	0.226
Relative Deal Size	1.54	0.649
Size	4.44	0.225
FinTech	4.79	0.209
FinTech*Stock	1.36	0.735
FinTech*Industry Relatedness	1.47	0.680
FinTech*Post-Covid	1.6	0.625
Mean VIF	2.63	0.507

Table 12: Descriptive statistics pre-covid, FinTech
This table represents the summary statistics of the variables used in the main regression where the target was a FinTech firm and the announcement of the deal was before the 20th of February 2020. Number of observations, mean, median, standard deviation, minimum, and maximum are presented.

Variable	N	Mean	Median	S.D.	Min	Max
CARMM [-1,1]	152	-0.001	0.001	0.055	-0.152	0.150
CARMM [-1,2]	152	-0.001	0.001	0.054	-0.155	0.143
CARMM [-1,3]	152	-0.002	0.001	0.056	-0.167	0.137
Strategic	152	0.671	1	0.471	0	1
Stock	152	0.033	0	0.179	0	1
Relative Deal Size	152	0.185	0.045	0.518	0.000	2.911
Size	152	7.945	7.859	1.888	4.533	12.174
Strategic*Fintech	152	0.750	1	0.434	0	1
Stock*Fintech	152	0.033	0	0.179	0	1
Covid*Fintech	152	0	0	0	0	0

Table 13: Descriptive statistics pre-covid, non-Fintech
This table represents the summary statistics of the variables used in the main regression where the target was a non-FinTech firm and the announcement of the deal was before the 20th of February 2020. Number of observations, mean, median, standard deviation, minimum, and maximum are presented.

Variable	N	Mean	Median	S.D.	Min	Max
CARMM [-1,1]	495	0.006	0.004	0.055	-0.148	0.216
CARMM [-1,2]	495	0.009	0.006	0.060	-0.152	0.231
CARMM [-1,3]	495	0.009	0.006	0.060	-0.145	0.225
Strategic	495	0.848	1	0.359	0	1
Stock	495	0.194	0	0.396	0	1
Relative Deal Size	495	0.209	0.109	0.321	0.002	1.430
Size	495	8.016	7.998	1.620	4.480	12.098
Strategic*Fintech	495	0	0	0	0	0
Stock*Fintech	495	0	0	0	0	0
Covid*Fintech	495	0	0	0	0	0

Table 14: Descriptive statistics post-covid, Fintech

This table represents the summary statistics of the variables used in the main regression where the target was a FinTech firm and the announcement of the deal was after the 20th of February 2020. Number of observations, mean, median, standard deviation, minimum, and maximum are presented.

Variable	N	Mean	Median	S.D.	Min	Max
CARMM [-1,1]	85	0.021	0.018	0.069	-0.113	0.237
CARMM [-1,2]	85	0.020	0.002	0.079	-0.161	0.260
CARMM [-1,3]	85	0.019	0.008	0.083	-0.153	0.261
Strategic	85	0.471	0	0.502	0	1
Stock	85	0.071	0	0.258	0	1
Relative Deal Size	85	0.683	0.069	1.313	0.003	3.996
Size	85	7.473	7.452	1.657	3.513	10.616
Strategic*Fintech	85	0.694	1	0.464	0	1
Stock*Fintech	85	0.071	0	0.258	0	1
Covid*Fintech	85	1	1	0	1	1

Table 15: Descriptive statistics post-covid, non-Fintech

This table represents the summary statistics of the variables used in the main regression where the target was a non-FinTech firm and the announcement of the deal was after the 20th of February 2020. Number of observations, mean, median, standard deviation, minimum, and maximum are presented.

Variable	N	Mean	Median	S.D.	Min	Max
CARMM [-1,1]	190	0.016	0.007	0.068	-0.109	0.233
CARMM [-1,2]	190	0.017	0.008	0.077	-0.162	0.255
CARMM [-1,3]	190	0.017	0.010	0.080	-0.165	0.259
Strategic	190	0.747	1	0.436	0	1
Stock	190	0.158	0	0.366	0	1
Relative Deal Size	190	0.298	0.119	0.605	0.002	3.778
Size	190	7.942	7.896	1.944	3.436	12.571
Strategic*Fintech	190	0	0	0	0	0
Stock*Fintech	190	0	0	0	0	0
Covid*Fintech	190	0	0	0	0	0

Table 16: Indices used to calculate CAR

This table presents all indices that are used in the calculation of CAR. Since the CARs of the acquiring companies are calculated, a proper index of the acquirer's GIC sector is found to better interpret the results.

GIC-sector acquirer	Index
Health care	Dow Jones U.S. Health Care Index
Information Technology	Dow Jones U.S. Technology Index
Financials	Dow Jones U.S. Financials Index
Industrials	Dow Jones U.S. Industrials Index
Real Estate	Dow Jones U.S. Real Estate Index
Consumer Staples	S&P 500 Consumer Staples
Consumer Discretionary	S&P 500 Consumer Discretionary
Utilities	Dow Jones U.S. Utilities Index
Energy	S&P 500 Energy
Materials	S&P 500 Materials

Table 17: Websites used to screen for FinTech targets

This table provides an overview of all the sites that are used in this research to screen for FinTech deals. These sites were scanned for FinTech deals, FinTech companies, and more information on the FinTech market. I also checked firm-specific websites.

Company	**Main offerings (website)**
TechCrunch	American online newspaper focused on tech startup companies (techcrunch.com)
Fintechdb	Database for FinTechs with more than seventy thousand profiles (fintechdb.com)
CBInsights	Tracks disruptive startups, emerging industries and their investors (cbinsights.com)
Crunchbase	Destination for company insights from early-stage and further (crunchbase.com)
StartupTalky	Platform for startup news, industry research and reports (startuptalky.com)
Fintech Global	Provides deal updates and analysis on FinTech (member.fintech.global)
S&P Global	Primarily provides financial information and analytics (spglobal.com)
TFR	Provides information on the FinTech market, events and deals (thefr.com)
Finextra	Leading information source for the global FinTech community (finextra.com)
Business Wire	Provides text press releases from companies worldwide (businesswire.com)
NASDAQ	Provides the NASDAQ FinTech index (nasdaq.com)
IBSintelligence	Pure-play FinTech research, advisory, and media firm (ibsintelligence.com)
VMR	Provide market research (verifiedmarketresearch.com)

Table 18: description of all variables used in this paper

This table presents the description for all variables used in this paper. The variables are placed in one of the following categories: dependent variables, independent variables of interest, deal-specific control variables, acquirer-specific control variables, and target-specific variables.

Category	Name	Description
Dependent variables	CAR Mean	CAR Mean calculates the cumulative abnormal return over event windows. It is equal to the sum of daily returns in excess of expected returns (as assessed by an estimation period) across the defined event window (3-days, 4-days, 5-days, 7-days, 11-days or 21-days). This is controlled for by the mean returns.
	CAR MM	CAR MM calculates the cumulative abnormal return over event windows. It is equal to the sum of daily returns in excess of predicted returns (as assessed by an estimation period) across the event window specified (3-days, 4-days, 5-days, 7-days, 11-days or 21-days). The market model removes the fraction of the return that is related to variation in the market's return.
Independent variables of interest	Industry relatedness*FinTech	The interaction between industry relatedness and FinTech is used to check whether industry relatedness has a positive effect on the CARs in FinTech deals. The industry relatedness dummy is used slightly different for FinTechs since FinTechs operate in both the Financials as the Information Technology sector. Thus, the industry relatedness dummy equals "1" if the acquirers GIC sector is either Financials or Information Technology.
	Stock*FinTech	The interaction between stock and FinTech is used to check whether the purchase of a FinTech

		company using only stock has a negative effect on the CAR.
	Post-Covid*FinTech	Post Covid is a dummy variable that equals “1” if the merger is completed after February 20, 2020. All the major market indices closed at record highs on February 19, following which they all plunged. If the merger is completed before the 20th of February, the dummy equals "0". This dummy is interacted with the FinTech dummy to check whether Covid-19 positively impacted the announcement returns of FinTech deals post-covid compared to pre-covid. This is compared with the control group.
Deal-specific control variables	Stock	Stock is a dummy variable that equals "1" if the M&A transaction is entirely funded by the acquirer's stock. Otherwise, the dummy variable is set to "0."
	Cash	Cash is a dummy variable that equals "1" if the M&A transaction is entirely funded with cash. Otherwise, the dummy is equivalent to "0."
	Industry relatedness	Industry relatedness is a dummy variable that equals "1" if the acquirer and target in the deal operate in the same GIC-sector. The dummy equals “0” if the acquirer and target do not operate in the same GIC-sector.
	Relative Deal Size	Relative deal size is found by dividing the value of the transaction by the market value of the acquirer at the end of the previous year. This estimates the relative size of the target and acquirer.
	Year fixed effects	A dummy for each year between 2016 and 2022 is included in the regression that equals “1” if the deal was announced in that year. It equals “0” if the deal was not announced in that year. This variable is included in order to control for factors that change each year and apply to all deals.
Acquirer-specific control variables	Size	Acquirer size is proxied by the natural logarithm of the acquirers’ total assets. The natural logarithm is used as it is more interesting to look at the effect of percentage changes on the abnormal returns than to look at the absolute changes.
	Leverage	The acquirer’s leverage is calculated by dividing the long-term debt and short-term debt by the stockholders’ equity
	ROE	Return on assets is calculated by dividing the net income of the acquirer by its equity. Equity is calculated by accumulating the common shares outstanding by the price of the common shares.
	ROA	Return on assets is calculated by dividing the net income of the acquirer by its total assets.
	Market-to-book	Market-to-book is calculated by dividing the
	Tobin’s Q	Tobin’s Q is calculated by dividing the acquirers total market value by their total assets.
Target-specific variables	FinTech	FinTech is a dummy variable that equals "1" if the target falls into this business classification. Otherwise, the dummy equals "0".

Business Process Outsourcing	Business Process Outsourcing is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
Cryptocurrency	Cryptocurrency is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
Digital Lending	Digital Lending is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
Financial Media & Data Solutions	Financial Media & Data Solutions is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
HR & Payroll Tech	HR & Payroll Tech is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
Insurance & Healthcare Tech	Insurance & Healthcare Tech is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
Investments & Capital Markets Tech	Investments & Capital Markets Tech is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
Payment	Payment is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
Security Technology	Security Technology is a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".
eCommerce & Marketing Tech	eCommerce & Marketing Techis a dummy that equals "1" if the target falls into that FinTech subcategory. Otherwise, the dummy equals "0".