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What is the impact of FinTech M&A on shareholder return for U.S. acquirers between 2010-2020?

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Abstract

Given the pace of digitization in the traditional financial service sector, the emergence of new competitors and the substantial increase in FinTech M&A activity, this study investigates the impact of FinTech acquisitions on short-term U.S. acquirer returns between 2010-2020. For this purpose, 146 FinTech targets were manually identified and individually classified into six common FinTech categories. The corresponding acquirer abnormal returns are obtained using a conventional event study approach. Further, multivariate regressions controlling for deal-, acquirer- and target-specific control variables provide more detailed insights into the profitability of FinTech M&A: overall, FinTech M&A generates shareholder value for acquirers over short-term event windows (ranging from three to 21 days). However, the abnormal returns are not significantly larger than those of acquirers in a control sample (containing finance or technology-focused targets). Moreover, positive announcement returns have a negative association with the acquisition premium paid for public targets, while complementarities between acquirer and FinTech target appear to have a positive relationship with merger returns. Finally, and in contrast to underlying theory, traditional banks experience lower abnormal returns around the FinTech merger announcement date as compared to other types of acquirers.

Keywords: Mergers and Acquisitions (M&A), Financial Technology (FinTech), FinTech Categories, Event Study Methodology, Cumulative Abnormal Stock Returns (CAR)

JEL Classification: G14, G23, G34, O33

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1. Introduction

Financial technology (FinTech) M&A activity has accelerated substantially over the last decade, with five times more deals succeeding in 2018 as compared to 2010 (Ropes & Gray, 2019). Valuations keep marching higher and enormous amounts of capital are at stake. To successfully reposition themselves in a modernizing and highly competitive financial sector, incumbent executives must understand the broad impact FinTech deals may have on shareholder wealth. Hence, this paper investigates the following:

> "*What is the impact of FinTech M&A on shareholder return for U.S. acquirers between 2010-2020?*"

Extensive research on M&A and the resulting effect on shareholder value in general has been done already, with the consensus being that acquirers experience negative or at most zero abnormal returns, on average (Adnan & Hosssain, 2016; Georgen & Renneboog, 2004; Moeller, Schlingemann & Stulz, 2005). However, empirical findings diverge across industries and, in addition, depend on many deal-specific characteristics. Hence, this paper contributes to traditional M&A literature by specifically focusing on FinTech M&A – a sector that only recently started to attract investors.

Changing consumer demands and new, tech-driven financial service providers are forcing incumbents to adopt digitalization as part of their business model transformation (PwC, 2021). Especially traditional financial institutions must confront this shift in order to remain competitive (Cuesta et al., 2015). Thus, M&A may represent an effective way for established players to adapt their technological infrastructure and reposition themselves strategically. Given this specific rationale, FinTech merger returns require a separate analysis.

Further, this paper is one of very few to conduct a merger return analysis that controls for the type of FinTech target so precisely. Post-merger synergies and thus shareholder returns for acquirers partially depend on the target's business model as well as its product and service offerings (Schmidt, Drews, & Schirmer, 2018). Hence, detailed inspection and extensive manual analysis of the underlying M&A dataset is used to classify each identified FinTech target into one of the common six FinTech categories. By controlling for different FinTech types, this study provides more detailed insights into observed merger returns compared to previous research.

On top of distinguishing between FinTech categories, this research differentiates between the type of acquirer to better understand how FinTech impacts the traditional financial sector. To be precise, FinTech M&A returns experienced by banks are compared to the returns of other acquirers, ultimately highlighting potential opportunities and challenges FinTechs might convey to obsolete banking structures. Thereby, this analysis goes beyond qualitative discussions about the interaction between traditional banks and FinTech (Romānova & Kudinska, 2016; Hornuf, Klus, Lohwasser & Schwienbacher, 2018). Instead, post-merger wealth effects for banks are quantified and benchmarked against the announcement returns of other types of acquirers.

Closely related to the interaction between banks and FinTechs are synergies that may stem from complementarities of acquirer and target in general (Hornuf et al., 2018; Makri, Hitt & Lane, 2007). Again, extensive manual examination of the identified acquirer-target pairs allows for identifying potential complementary skills, resources or product and, service offerings. By analyzing how such complementarities influence FinTech merger returns, this research offers additional insights into the origin of value creation. Rather than solely reviewing the source of post-merger complementarities (as done in previous literature), a direct association between these complementarities and merger announcement returns is measured for the first time.

Nevertheless, comprehending the impact of FinTech M&A is also relevant from a social perspective because the financial industry is undergoing a paradigm shift (KPMG, 2017). Changing customer demands and preferences redefine how financial services are being delivered nowadays, with emerging technologies including blockchain, artificial intelligence (AI), and machine learning. Such innovation-driven developments redefine the financial market infrastructures, especially the payments ecosystem (DNB, 2021). Moreover, factors beyond digitization, such as the challenging low interest rates, regulatory restrictions as well as the increasing social and economic impact of COVID-19, have exacerbated the trend towards alternative financial services and providers (PwC, 2021). New players – FinTechs – have entered the market and are realigning competitive forces in the traditional financial sector. Ultimately, these transformations may even impact central banks' regulatory responsibility as well as the transmission of their monetary policies (DNB, 2021). Correspondingly, FinTech is considered the biggest disruptor of our time.

In response to the digitization of financial services, FinTech M&A activity has accelerated substantially, with more than 1,375 completed FinTech deals between 2010 and 2020 (Ropes & Gray, 2019). Over the same period, the total disclosed value of deals amounted to approximately 200 billion US dollars – a record high. Nevertheless, 92% of the analysts expect FinTech deal-making to increase even further in 2021 because advances in machine learning and AI, for example, enable new technologies across the FinTech subsectors. Ultimately, this transformation is redefining the digital future of consumers.

In the end, the conducted analysis reveals that FinTech M&A creates shareholder value for acquirers in the short run. However, the abnormal returns stemming from FinTech M&A are not significantly greater than those experienced in the chosen control sample. This may partly be explained by excessive FinTech acquisition premia which are, according to this study, negatively associated with merger announcement returns. On the other hand, complementarities between the acquirer and the FinTech target appear to be positively related to acquirer abnormal returns. Finally, traditional banks experience lower announcement returns when merging with FinTechs as compared to other types of acquirers.

To arrive at these results, this paper first discusses related literature and derives four hypotheses regarding FinTech M&A. Next, chapter three describes the event study methodology as well as the cross-sectional regression analysis that is applied. Further, it provides an overview of the incorporated dependent and independent variables. Chapter four then explains the data collection process and provides detailed insights into the final FinTech sample. In chapter five, the results of this study are summarized. Finally, chapter six concludes the paper by answering the research question, discussing the empirical findings, highlighting limitations of the conducted research, and suggesting fields for potential future research.

2. Theoretical Framework and Hypothesis Development

FinTech is a portmanteau of 'finance' and 'technology'. The term refers to companies with deep expertise in IT (including, for example, big data, artificial intelligence, distributed databases, cloud computing, cybersecurity, blockchain etc.) coupled with a focus on providing innovative services and solutions for the financial sector (Dranev, Frolova & Ochirova, 2019). To be precise, the Financial Stability Board (2021) defines FinTech as "technologically enabled financial innovation that could result in new business models, applications, processes, or products with an associated material effect on financial markets and institutions and the provision of financial services". Thus, FinTech firms may be considered the biggest disruptor of our times by transforming the way financial businesses operate, collaborate among each other, and interact with consumers (PwC, 2019).

Recently, many variations of FinTech firms have emerged and focus specifically on certain sub-sectors or functions in the financial service ecosystem. In general, FinTech business activities may be divided into the following three categories: a) transactions execution, b) funds management (deposit, lending, capital raising and investment management) and c) insurance (Navaretti, Calzolari & Pozzolo, 2018). Taking into account the dimension of the target's product and service offerings is essential as it can realign the acquirer's business strategy post-acquisition (Schmidt, Drews, & Schirmer, 2018). Further, post-merger synergies between acquirer and target as well as returns around the announcement date may be influenced.

To better grasp the dimension of the FinTech industry, CBInsights (2019) distinguishes between the type of FinTech target more precisely. Accordingly, FinTechs are classified by the services they offer to consumers (see table 1 below). The most prominent subsector is related to online/mobile payment technologies and accounts for approximately 17% of all FinTech deals (Ropes & Gray, 2019).

Table 1. Classification of different FinTech categories by CBInsights.

Notes: The overview of FinTech business areas is obtained from a 2019 CBInsights report. These classifications are based on the types of services offered to consumers and thus commonly used in the financial service sector as well as in related literature.

Classification	**Explanation**
Funds/ Wealth Management	Investment & wealth management platforms, related analytics tools; marketplace lending & alternative underwriting platforms; deposits
Blockchain/Crypto	Companies leveraging blockchain technologies for financial services
RegTech	Audit, risk, and regulatory compliance software
Personal Finance	Tools to manage bills and track personal and/or credit accounts
Payments/Billings/Money Transfers	Payments and transaction processing; card developers; subscription billing software tools
Insurance	Companies selling insurance digitally or providing data analytics and software for (re)insurers
Capital Markets	Sales & trading; analysis and infrastructure tools for financial institutions
Mortgage/Real Estate	Mortgage lending and financing platforms

When analyzing M&A literature, it becomes evident that the traditional academic consensus claims negative or at most zero abnormal returns for acquirers in response to merger announcements (Adnan & Hosssain, 2016; Georgen & Renneboog, 2004; Moeller, Schlingemann & Stulz, 2005). However, empirical results seem to depend on the industry, the market environment, the motive behind the deal, the type of acquisition as well as other deal-specific characteristics. Hence, the impact of FinTech M&A on acquirer returns might be different and thus requires a separate analysis.

In general, the trend towards digitized financial products and services is considered the primary motive for FinTech acquisitions. By introducing new technologies to the market, FinTech based business models affect the value proposition of traditional banking activities, products and processes (Butt & Butt, 2021). Consequently, these new players increase the pressure on incumbents, forcing them to adapt in order to remain competitive and stay ahead of the competition. The triggered digitization efforts have, however, proven to be beneficial and enhance the performance of established companies (Kriebel & Debener, 2020; Gal et al., 2019). To be precise, the adoption of digital technologies is associated with significant productivity gains that stem from complementarities between technologies and other types of capital, e.g., skills or firm-specific knowledge (Gal et. al., 2019). Consequently, digital transformation has become a crucial ingredient for successful, contemporary businesses - with M&A being one of the potential means to an end.

When specifically looking at M&A in the tech sector, empirical evidence suggests that acquirers of high-tech start-ups earn significant positive abnormal returns at the time of the merger announcement (Kohers & Kohers, 2000). The corresponding bidder cumulative abnormal returns (CARs) range from .69% to 1.58% over a 2-day event window. CARs are highly significant and robust, however larger for more recent time periods. Given the rapid growth of tech-based industries, markets are optimistic about the future benefits of these deals and expect synergistic gains from the targets' technological expertise. To be precise, Kohers and Kohers (2000) suggest that the positive market perception of high-tech acquisitions has intensified recently because existing fields have developed and evolved, while companies' reliance on technology has increased. Given that high-tech acquisitions lead to shareholder wealth gains around the announcement date, FinTech M&A should also be value-enhancing in the short run.

This idea is reinforced by a study focusing specifically on the FinTech sector. Accordingly, firms may create value in the rapidly changing financial environment through M&A (Dranev et al., 2019). Companies seeking to acquire FinTech start-ups may reduce their expenses, improve business processes, solve complex IT problems, and reduce cybersecurity risks. Accordingly, the authors observe a short-term, positive stock price reaction for acquirers in response to FinTech M&A deals. To be precise, they find CARs between 0.92% and 1.93% that are highly significant over multiple short-term event windows. Similarly, Tanjung (2020) finds short-term, positive wealth effects for FinTech acquirers – with CARs ranging from 1.25% up to 1.55%, depending on the considered event window.

However, one must also consider that risks are high, and the integration of FinTech targets may be cumbersome. Particularly, risks related to technology and cybersecurity concerns convey potential new hurdles for acquirers (Buckley, Arner, Zetzsche & Selga, 2019). Incumbents require new forms of systematically important infrastructure - such as data, data privacy and cloud services - to capitalize on the opportunities of the FinTech target. Further, FinTechs are said to disrupt traditional value chains and thus force acquirers to scare up additional monetary and managerial efforts to successfully integrate the target (Pollari, 2016). Finally, the lack of commonly applied regulatory standards and high monetary investments based solely on faith in technology - rather than demonstrated results - bring forth concerns regarding a potential FinTech bubble (similar to the dot-com bubble in the early 2000s) (Kovas, 2021). Ultimately, these risks may reduce positive announcement returns of FinTech acquirers.

Nevertheless, given the rather unanimous, positive empirical findings on M&A in the FinTech sector, the first hypothesis is as follows:

> **H1**: *FinTech M&As have a significant positive effect on the cumulative abnormal Returns (CARs) of the acquiring firm in the short run.*

A positive effect of FinTech M&A on acquirer returns would highlight the potential FinTech targets may convey as well as the expected post-merger synergies - as represented by revenue enhancements or cost reductions. However, to assess whether FinTech-related risks may withhold the hypothesized value creation, the findings are benchmarked against a control sample containing non-FinTech acquisitions.

To better understand the origin of potential shareholder wealth gains for FinTech acquirers, it is crucial to consider certain deal characteristics, such as the transaction value. In general, the highest acquisition premia have traditionally been paid for technology-intensive targets (such as FinTechs) when markets are enthusiastic about start-ups' future potential (Kohers & Kohers, 2001). FinTech deal volumes and values have been climbing steadily, with more than 1,375 FinTech acquisitions between 2010 and 2020 (Ropes & Gray, 2019). To be precise, five times more FinTech deals were made in 2018 as compared to 2010. Ultimately, the acceleration in M&A activity may partly explain the surge in FinTech start-up valuations (PwC, 2021). Approximately 20 U.S. FinTech start-ups achieved unicorn status in 2020, which implies a valuation of above one billion U.S. dollars for a private company. Moreover, competition on the buy-side as well as the resulting bidding wars have driven up deal premia, which are thus significantly greater for FinTech than for non-FinTech targets (Ropes & Gray, 2019; Deloitte, 2020). These excessive deal premia represent another potential risk associated with FinTech acquisitions.

Given the rising valuations of FinTech targets, it is necessary to further inspect the role of acquisition prices for M&A profitability. A study by Laamanen (2007) shows that transaction values are inversely related to shareholder returns in the short run. The operating performance of glamour targets – as represented by high market-to-book ratio – might be overstated by investors, thus increasing the likelihood of overpaying for the target's assets. Hence, high transaction values are expected to negatively influence merger returns of acquirers.

More precisely, Sirower (1994) found that the part of the transaction value that represents the acquisition premium is a key driver of merger announcement returns. The higher the deal premium, the greater the likelihood of post-merger value destruction if the extent of the expected synergies cannot be fully materialized. Therefore, high deal premia reduce bidders' post-acquisition returns. As the main rationale for these excessive deal premia, he specifies buy-side competition and bidding wars.

Similarly, Bruner (2004) concludes that the premium paid by the acquirer has a negative effect on the acquiring shareholders' returns. If the sum of the acquisition costs and the premium exceeds the potential synergistic gains, markets perceive the deal negatively. Like Sirower, Bruner highlights deal competition as an important ex-ante explanation for excessive premia and mentions that the winner's curse induces the negative stock price reaction for acquirers.

Research by multiple other economists strengthen this view and find significant, robust negative relationships between acquisition premia and short-term bidder returns. Díaz, Azofra, & Gutiérrez (2009) find that if acquirers pay a premium of above 21%, they are most likely overpaying for the target and thus experience lower returns upon deal announcement. Finally, Alexandridis et al. (2013) also quantify a negative relationship between deal premia and announcement returns for U.S. acquirers between 1990-2007.

Given the recent M&A trend, the high FinTech valuations as well as the negative impact of high deal premia on shareholder return in general, the second hypothesis assumes the following:

> **H2**: *Short-run cumulative abnormal returns (CARs) of FinTech acquirers and the acquisition premium paid have a negative association.*

The hypothesized negative relationship would suggest that more value is destroyed if acquirers overpay for the FinTech target, relative to the target's market valuation. Hence, if this can be empirically confirmed, acquirers must pay careful attention to the potential synergies and the magnitude of the associated premium to be paid.

In addition to the deal premium, the extent of the expected synergies between acquirer and target is a main determinant of M&A shareholder returns in the short-run (Bruner, 2004). Next to the return-driven motivation of financial buyers, Bruner's theory distinguishes between the following four strategic acquisition motivations, which ultimately drive the extent of potential synergies: in a complementary merger, acquirer and target compensate each other's limitations. Complementary skills, knowledge, technologies or product and service offerings are dissimilar by nature but more valuable when combined in one entity post-merger. On the contrary, in a supplementary merger the acquirer and target reinforce each other's strengths by combining substitute skills. Thirdly, a conglomerate merger represents the idea of diversification where acquirer and target are outside each other's business lines. Finally, a cogeneric merger refers to an acquisition of a firm outside of their lines of business but related in nature or action (e.g., shared resources). However, conglomeration and diversification tend to involve greater transaction costs as well as post-merger managerial difficulties. Accordingly, conglomerate and cogeneric deals tend to have lower abnormal returns around the announcement date (Bruner, 2004).

A PwC survey supports this theoretical classification of acquisition motives and focusses on the more profitable combinations, namely complementary and supplementary fit between acquirer and target (PwC, 2021b): 50% of the firms collaborating with FinTechs do so to improve existing own products and services – a supplementary fit. On the contrary, 36% wish to add complementary products or services to their existing portfolio. By combining complementary skills and resources through a FinTech acquisition, post-merger synergies may be enhanced. Correspondingly, FinTechs may be classified into two groups: either offering complementary services to common banks or offering services that are covered by traditional banks already (Romānova & Kudinska, 2016).

Further, research on the interaction between banks and FinTechs reinforces the value-creating potential of complementary tangible and intangible assets (Hornuf, et al., 2018). Accordingly, product-related collaborations with FinTechs allow the counterparty to expand their portfolio without having to invent applications or services internally. As traditional banks, for example, operate outmoded software systems – usually incompatible with modern end-user applications – they benefit from the established resources of the FinTech. On the other hand, FinTech companies benefit from their acquirer's client base and the additional capital available for technological development (PwC, 2021b). Thus, this complementarity in skills and resources may induce significant post-merger synergies, as represented by positive stock price reactions of the bank (Hornuf et al., 2018).

When applying these findings to high technology M&As in general, it becomes obvious that post-merger synergies mainly stem from technological relatedness and complementarity of acquirer and target (Makri, Hitt & Lane, 2007). To be precise, complementary scientific and technological knowledge both significantly enhance the innovative capabilities of acquirers after the merger, as represented by better quality and more novel inventions. Thus, acquirers should look for targets with skills, knowledge or technologies that are complementary to their own. The term 'complementary' here refers to a focus on different narrowly defined areas of operation within a broadly defined area of operation that is shared by both acquirer and target. The resulting boost in innovation output is expected to yield stockholder wealth gains.

Given the relationship between complementary assets, post-merger synergies and thus stock price reactions, this paper hypothesizes the following:

> **H3**: *Complementarity between the acquirer and the FinTech target (in terms of knowledge, skills or product and service offerings) are positively related to short-run cumulative abnormal returns.*

This hypothesis supports the underlying theory from Bruner, stating that a complementary fit between acquirer and target should create more shareholder value as opposed to a diversifying or cogeneric merger. Digital technology advancements, improved, novel product offerings for consumers as well as fewer regulatory restrictions may allow the acquirer to expand its range of activities, while simultaneously enhancing efficiency (Navaretti, Calzolari & Pozzolo, 2018).

Given the importance of complementarities, more detailed research has been devoted specifically to the interaction between traditional banks and FinTechs. While some analysts perceive the FinTech boom as a threat to incumbents, empirical analysis has revealed that it is rather an opportunity for established banks to expand into adjacent areas and to advance their capabilities (Ropes & Gray, 2019). Some important opportunities to consider are the improved access to financial services for previously under-served groups; better, faster and more tailored banking services; more efficient banking processes and enhanced compliance processes at financial institutions induced by Regtech (BIS, 2018).

Hence, it comes as no surprise that buying innovative FinTechs constitutes an effective way for banks to combat the increasing competition from tech-driven firms and to modernize their core business activities (Hornuf et al., 2018). Similarly, Romānova and Kudinska (2016) assert that a timely integration of FinTech may allow banks to regain a competitive advantage in the financial landscape. Even more extreme, a BBVA report (2015) concludes that the digital transformation induced by FinTechs "forces banks to address their digitization process as a matter of urgency if they are not to be left behind in a market which finds itself in the full throes of transformation."

To better understand what effect potential FinTech acquisition could have on banks, research on M&A in the banking sector is examined: on average, merged U.S. banks experience a significant post-transaction increase in profit efficiency (Akhavein, Berger & Humphrey, 1997). This improvement stems from increases in revenues as well as a risk diversification. A more recent study confirms these findings, highlighting improved cost and profit positions of banks post-merger (Al-Sharkas, Hassan & Lawrence, 2008). By taking advantage of the improved technologies, merged banks experience greater productivity growth and higher technical efficiency. Hence, there is an economic rationale for future mergers between banking and the tech industry.

The suggested link between banks and FinTechs is further examined in a paper on the effect of FinTech start-ups on incumbent retail banks' share price (Li, Spigt & Swinkels, 2017). Accordingly, funding of digital banking start-ups has a positive effect on shareholder return of U.S. retail banks, suggesting complementarity between FinTech and traditional banking, rather than substitution or disruptive innovation. Considering that most FinTechs offer similar services in a more innovative way (e.g., accepting consumer deposits, lending money, and facilitating payments), adopting a FinTech-centered strategy is paramount for mature banks in order to outstrip the competition (PwC, 2019).

However, when new FinTech players enter the financial sector, incumbents must remain critical. Vast amounts of money are at stake, while the reliability and sustainability of the FinTech business models have yet to be proven. Only recently, in 2020, the Wirecard scandal highlighted the structural weaknesses in FinTech and the resulting fragility of the emerging sector (Zeranski & Sancak, 2020). Research addresses the considerable risks associated with FinTechs as well as the resulting negative effects on the traditional financial sector. Especially cybersecurity and data privacy issues, accompanied by regulatory and legal uncertainty, call for skepticism (Ryu, 2018). Therefore, it might not be in the public interest for a FinTech business model to dominate the financial sector and to control crucial links in the financial infrastructure. By taking on FinTech related risks, M&A returns for acquiring banks can experience significant backlashes.

On the other hand, however, FinTechs may even constitute a solution to cybersecurity and money laundering issues (Thomson Reuters, 2021). Modern financial technologies have the potential to enhance transparency, help safeguard the financial system and aid banks in their anti-money laundering (AML) efforts. Blockchain technology, for example, keeps track of digital currencies, while machine learning algorithms enable more accurate decisions than humans could ever make. If banks pursue a strategic approach instead of reactive, they may stay a step ahead of criminal activity, reduce risk and provide safer services to customers. Hence, it is reasonable to expect traditional banks to invest in or even acquire AML and cybersecurity businesses.

Moreover, the intense pressure from innovative, tech-based financial services requires banks to build new capabilities in, e.g., advanced analytics, robotics, and AI. According to a McKinsey report (2019), FinTech M&A represents one of the best ways to expand skills and to create cost efficiencies (see discussion about complementarities above), which in return free up resources for internal digitization efforts. In addition, U.S. banks have recently experienced an increase in profitability and achieved stronger capital positions, ultimately allowing them to execute deals better. Therefore, it comes as no surprise that market reactions to bank-FinTech mergers have, in general, been positive in 2019 (McKinsey & Company, 2019). This, in return, suggests that investors overlook or downgrade the potential risks that FinTechs may, on the other hand, introduce to the sector.

The power of digitized banking can be observed in the leading European markets where banks experience cost-to-asset ratios that are 60%-80% lower relative to U.S. banks (McKinsey & Company, 2019). As McKinsey analysts expect banks to capitalize on the opportunities of FinTech deals successfully, they consider FinTech M&A a crucial tool for the digital transformation of U.S. banking.

Correspondingly, the paper’s fourth hypothesis stipulates the following:

> **H4**: *FinTech M&As have a larger effect on the cumulative abnormal returns (CARs) of the acquiring firm in the short run if the acquirer is a traditional bank.*

A positive effect on incumbent banks' returns would support the complementarity hypothesis, while a zero or even negative effect would emphasize the risks associated with FinTechs and suggest a disruption of the industry by the entrants. However, given the empirical findings on shareholder returns for U.S. banks, this paper assumes that investors degrade FinTech risks and instead focus on complementary skills, product and service offerings. Therefore, FinTech merger announcement returns are expected to be larger for banks as opposed to other acquirers.

3. Methodology

3.1. Event Study

To measure the short-term impact of FinTech M&A on acquirer shareholder returns, this paper adopts a traditional event study approach. Note, however, that this method measures short-term effects of merger announcements only instead of longer horizon performance measures.

Assuming efficient markets, the effect of deal announcements should be incorporated into security prices immediately. Hence, abnormal returns are calculated around the announcement date, which represents the event date (MacKinlay, 1997). In general, shorter event windows are considered superior because longer windows might be affected by other external factors, ultimately biasing the results. Hence, the following, commonly used M&A event windows are considered, with day 0 representing the announcement date: (-10,10), (-5,+5), (-3,3), (-2,+2), (-1,1), (-1,+2) and (-1,+3). By incorporating few days around the event date 0, the model accounts for potential information leakage ex-ante as well as ex-post delays in stock price adjustments. Further, conducting the analysis with multiple event windows allows for conclusions regarding the robustness of the observed findings.

Abnormal returns represent the stock's actual return in excess of the expected return over the event window and is calculated as follows:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|R_{m,t}) \tag{1}$$

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

The expected returns $E(R_{i,t}|R_{m,t})$ are calculated using the market model approach. This method is preferred to other measures of normal performance (such as the constant-mean-return model) as it factors in the correlation between stock i and the market, thus accounting for the dynamics of the market in general. This approach reduces the variance of the abnormal returns by removing the variation related to volatile market returns.

The adopted estimation window of 180 days finishes 20 days before the event in order to prevent the event from influencing the normal performance model parameter estimates (MacKinlay, 1997). Hence, the stock returns can be modelled as follows:

$$R_{i,t} = \alpha + \beta R_{m,t} + e_{i,t} \tag{2}$$

$$E\left(R_{i,t}\middle|X_{i,t}\right) = \hat{\alpha} + \hat{\beta} R_{m,t} \tag{3}$$

Where $\hat{\alpha}$ and $\hat{\beta}$ are estimated over the estimation period using OLS and $R_{m,t}$ represents the return of the S&P 500 Index on day t. The S&P 500 Index is used as a benchmark because all acquirers are listed in the U.S.

The expected return $E(R_{i,t}|R_{m,t})$ represents the return that should have materialized on day t if the event would not have occurred, i.e., if the merger would not have been announced. Correspondingly, the abnormal return of stock i on day t is calculated as follows

$$AR_{i,t} = R_{i,t} - \hat{\alpha} - \hat{\beta} R_{m,t} \tag{4}$$

However, to evaluate the robustness of the results later on, mean-adjusted abnormal returns are also obtained. This model assumes that unsystematic, firm-specific risk equals zero and that systematic, market-specific risk equals one. Although it may be the simplest model for abnormal returns, it has proven to yield similar results to those stemming from more sophisticated ones (MacKinlay, 1997). Accordingly, abnormal returns can be modelled as follows – using the same estimation window as above (-200, -20) to calculate the average return of stock i:

$$E(R_{i,t}) = \overline{R}_{i,t=-200,t=-20} \tag{5}$$

$$AR_{i,t} = R_{i,t} - \overline{R}_{i,t=-200,t=-20} \tag{6}$$

Finally, to accommodate a multiple-day event window, the cumulative abnormal return $CAR_i(t_1, t_2)$ of stock i is required. These $CAR_i(t_1, t_2)$ constitute the dependent variable in the regression analysis later (see chapter 3.2. regression analysis).

$$CAR_i(t_1, t_2) = \sum_{t=t1}^{t2} AR_{i,t} \tag{7}$$

A positive (negative) CAR implies that shareholder value is created (destroyed). However, the actual conclusion can only be drawn if the corresponding t-statistic (equation 8) significantly deviates from zero. In that case, the event had a significant, short-term effect on stock returns over the event window.

$$t_{CAR_{i,(t1,t2)}} = \frac{\overline{CAR}_i(t_1,t_2)}{\sqrt{VAR\ (\overline{CAR}_i(t_1,t_2))}} \tag{8}$$

To assess hypothesis 1 - "*FinTech M&As have a significant positive effect on the cumulative abnormal returns of the acquiring firm in the short run.*" - a one-sided t-test with the alternative hypothesis being CAAR>0 is performed. CAAR refers to the cumulative average abnormal return within the sample. The same analysis is performed with the CAARs of a control sample to evaluate FinTech M&A performance relative to non-FinTech acquisition returns over the same time horizon.

3.2. Regression Analysis

3.2.1. The Model Overview

To test hypothesis 2-4, the following multivariate regression equation is used:

$$\begin{aligned} CAR_i(t_1,t_2) = \propto &+\beta_1 Premium_i + \beta_2 Complement_i + \beta_3 Bank_i \\ &+\beta_4 CashPayment_i + \beta_5 \ln(RelativeDealSize)_i + i.year_i \\ &+\beta_6 \ln(Assets_i) + \beta_7 \ln(MB)_i \\ &+\beta_8 Public_i + \beta_9 Funds_i + \beta_{10} Capital_i + \beta_{11} RealEstate_i \\ &+ \beta_{12} RegTech_i + \beta_{13} Insurance_i + \epsilon_i \end{aligned}$$

A more detailed explanation of the incorporated variables is provided in table 2 below.

Table 2. Description of the regression variables.

Notes: The table summarizes and explains all variables included in the cross-sectional regression analysis. It distinguishes between the dependent variables, independent variables of interest and the considered control variables. Note that the reference category for the FinTech dummies is the Payments/Transaction category. For a more extensive discussion of the individual variables see sections 3.2.2 and 3.2.3 below.

Category	Name	Description
Dependent variable	**CAR**	Measures the cumulative abnormal return over one of the chosen event windows. It represents the sum of daily returns in excess of the normal/expected returns over the chosen event window (3-days, 4-days, 5-days, 7-days, 11-days or 21-days).
Independent **variables of interest**	**Premium** (Hypothesis 2)	The premium measures the acquisition price per share of the target in excess of the target's closing stock price 4 weeks prior to the original announcement date, expressed as a percentage. (note: only applicable to public targets)
	Complement (Hypothesis 3)	The Complementary dummy = 1 if the acquirer and the FinTech target have complementary skills or product and service offerings. The Complementary dummy = 0 if the acquirer and the FinTech target do not have complementary skills or product and service offerings. Instead, the merger could represent a supplementary, a cogeneric or a diversifying fit.
	Bank (Hypothesis 4)	Bank Dummy = 1 if the acquirer was a traditional bank. Bank Dummy = 0 otherwise.
Deal-specific control variables	**CashPayment**	Cash Payment Dummy = 1 if the acquisition was fully paid in cash. Cash Payment Dummy = 0 otherwise (e.g., 100% stock payment or mixture of stock and cash payment).
	Ln(RelativeDealSize)	The Relative Deal Size is the ratio of the transaction value over the market capitalization of the acquirer four weeks before the merger announcement (approximates the relative size of target and acquirer).

		The natural logarithm is used to approximate a normal distribution and reduce the effect of outliers.
	i.year	A dummy for each year between 2010 and 2020 is included and equals 1 if the deal was announced in that specific year. Hence, the model controls for factors that change each year and apply to all deals (year-fixed effects).
Acquirer-specific control variables	**Ln(Assets)**	The bidder's total assets in million U.S. dollars at the time of the announcement approximates the size of the acquirer. The natural logarithm is used to approximate a normal distribution and reduce the effect of outliers.
	Ln(MB)	The market-to-book value represents the ratio of the acquirer's market capitalization over its asset book value at the time of acquisition announcement. The natural logarithm is used to approximate a normal distribution and reduce the effect of outliers.
Target-specific control variables	**Public**	Public Dummy = 1 if the target was a public firm. Public Dummy = 0 if the target was a private firm.
	Funds	Funds management dummy = 1 if the target belongs to the business classification: funds management. Funds management dummy = 0 if the target belongs to either of the other FinTech classifications.
	Capital	Capital markets dummy = 1 if the target belongs to the business classification: capital markets (this includes blockchain and crypto currencies). Capital markets dummy = 0 if the target belongs to either of the other FinTech classifications.
	RealEstate	Real Estate dummy = 1 if the target belongs to the business classification: Real Estate and Mortgage Lending. Capital markets dummy = 0 if the target belongs to either of the other FinTech classifications.

RegTech	RegTech dummy = 1 if the target belongs to the business classification: RegTech (this includes cybersecurity). RegTech dummy = 0 if the target belongs to either of the other FinTech classifications.
Insurance	Insurance dummy = 1 if the target belongs to the business classification: "Insurance". Insurance dummy = 0 if the target belongs to either of the other FinTech classifications.

To analyze whether the acquisition premium paid has a negative association with bidder returns (hypothesis 2), it is tested whether coefficient β_1 < 0. Further, hypothesis 3 assumes a β_2>0, implying that complementarities between acquirer and target induce higher merger announcement returns for the acquirer. Finally, hypothesis 4 expects β_3>0, given that traditional banks may benefit from FinTech acquisitions to a greater extent than other acquirers. The corresponding one-sided t-tests are all performed using clustered standard errors at the firm level. Given that some acquirers perform multiple takeovers in the sample, clustered standard errors control for autocorrelation on the firm level. Finally, the model accounts for year-fixed and FinTech industry-fixed effects, i.e., risk levels and performance that differ across FinTech subsector.

3.2.2. Independent Variables of Interest

To analyze hypothesis 2 – "*Short-run cumulative abnormal returns (CARs) and the acquisition premium paid have a negative association."* – the variable "**premium**" is added to the regression model. It represents the premium of the offer price to target closing stock price 4 weeks prior to the original announcement date and is expressed in percentage terms. Given that greater deal premia increase the likelihood of overpaying for the target and potential future synergies (see hypothesis development above), a higher acquisition premium expected to reduce the $CAR_i(t_1, t_2)$. Hence, the corresponding alternative hypothesis assumes that β_1< 0 and is evaluated using a one-sided t-test and firm-level clustered standard errors.

Moreover, a "**complement**" dummy is established and used to investigate hypothesis 3: "*Complementarity between the acquirer and the FinTech target (in terms of knowledge, skills or product and service offerings) are positively related to short-run cumulative abnormal returns (CARs)*". Correspondingly, a one-sided t-test and clustered standard errors at the firm level help assess whether β_2> 0. The dummy "Complement" equals "1" if the acquirer and target focus on different narrowly defined areas of operation within a broadly defined area of operation that is shared by both (Makri, Hitt & Lane, 2007). This definition has been used as an approximation for complementarities in previous literature already. Hence, if acquirer and target, for example, both operate in the financial service sector, however only one of them focusses on technological innovation in that field, then they would complement each other. To identify such complementarities, each deal is analyzed manually, considering both industry classification codes as well as firm-specific information from company websites.

Finally, a "**bank**" dummy is created, which equals "1" if the acquirer is a traditional bank and "0" otherwise. This indicator allows the research to distinguish between abnormal returns of banks as opposed to abnormal returns of other types of acquirers. The corresponding fourth hypothesis stipulates that "*FinTech M&As have a larger effect on the cumulative abnormal returns (CARs) of the acquiring firm in the short run if the acquirer is a traditional bank*", implying that $\beta_3 > 0$. This is evaluated based on a one-sided t-test and standard errors clustered at the firm level.

3.2.3. Control Variables

Given previous M&A literature, numerous variables are said to help explain abnormal returns in the cross-sectional setting. Hence, the following deal-, acquirer- and target-specific control variables are added to the regression model, enabling more accurate and unbiased coefficient estimates of the variables of interest.

First, the payment method, i.e., whether the target was bought with cash or with stock, influences merger announcement returns. According to Bruner (2004), cash acquisitions create more shareholder value on average. On the other hand, stock purchases indicate overvaluation of the acquirer's shares and suggest that the acquirer is not fully convinced about the deal potential, therefore, willing to share the up-/ downside potential of the deal. Hence, stock payments are associated with lower CAR. The corresponding "**cash payment**" dummy equals "1" if the deal was paid fully in cash and equals "0" otherwise.

Second, the "**relative deal size**" is negatively associated with merger returns in the short run (Laamanen, 2007). Greater relative deal sizes are associate with larger and thus more complex acquisitions in terms of post-merger integration. Further, higher acquisition prices increase the likelihood of overpaying for the expected future benefits of the target and might thus decrease shareholder value. Hence, the coefficient of relative deal size is expected to be negative. In this paper, the relative deal size is measured as the transaction value (in million U.S. dollars) over the acquirer's market capitalization (in million U.S. dollars). In the regression model, the natural logarithm of the relative deal size is used to minimize the effect of outliers and approximate the distribution by a normal distribution.

Moreover, "**i.year"** refers to the year-specific dummy variables that indicate in which year the deal was announced. The incorporated year-fixed effects allow controllint for factors that change each year and apply to all deals.

To control for the size of the bidder, the book value of "**assets**" is used. As highlighted in previous M&A literature, there is a negative relationship between the value of assets and announcement CARs. According to Moeller et al. (2004), large acquirers experience a 2% lower announcement return as compared to small acquirers. The Hubris theory may explain this size effect: overconfident managers, as well as managerial entrenchment in large corporations, increase the likelihood of a large bidder overpaying for the target (Bruner, 2004). The natural logarithm of the total value of assets (also measured in million U.S. dollars) is used to minimize the effect of outliers and approximate the distribution by a normal distribution.

In addition to the book value of assets, research has revealed that the relative market valuation of the acquirer is a significant determinant of merger returns. To control for this, the market-to-book ratio ("**M/B**") of the acquirer at the time of the announcement is added to the regression analysis. Accordingly, glamour firms (with high M/B ratios) are more likely to overpay for the target and thus experience lower CARs (Bruner, 2004; Dranev et al., 2019). Hence, a negative coefficient of the M/B ratio is expected. Also here, a natural logarithmic transformation is performed to reduce the effect of outliers as well as the standard deviation of the measure.

Next, this analysis controls for the status of the target (public vs private) as it influences deal premia ex-ante. Bidders are more likely to obtain an illiquidity discount for private targets as well as a discount for larger information asymmetries with private firms (Bruner, 2004). Hence, on average, bidders gain more when acquiring a private target. The created dummy called "**public**" equals "1" for public targets and "0" for private targets.

Finally, this analysis controls for the FinTech target type by distinguishing between the six most common business areas, namely **Payments/Transactions Execution, Funds Management, Capital Markets, Real Estate/Mortgage, RegTech** and **Insurance**. The corresponding dummy variables are included in the regression, with the Payment/Transaction Dummy being the reference category. Incorporating FinTech industry-fixed effects allows controlling for differences in performance and risk level across FinTech categories.

Given that the scope of this research is limited to U.S. registered acquirers and targets, the final sample contains no cross-border deals. Thus, no control variable for cross border deals is required. Similarly, an analysis of the final sample indicates that all deals were friendly by nature. Hence, no control variable for the deal attitude is required either.

To check for the robustness of the results, later on, some of the original control variables are replaced by related measures. To be precise, “Relative Deal Size” is exchanged with “**deal size**”, which quantifies the absolute transaction value in million U.S. dollars. Further, the “**Tobin’s Q”** replaces “M/B” for robustness check purposes (Servaes, 1991). In this paper, Tobin’s Q is approximated by the equity market value over equity book value and thus underlies the assumption that the book and market value of a company’s liabilities are equal. When incorporated in the regression model, both alternative control variables are transformed to logarithmic variables for similar reasons discussed above.

Finally, whether all control variables are to be included in the model depends on the corresponding multicollinearity test. A Variance Inflation Factor (VIF) of 5 is used as a threshold indicating multicollinearity. Hence, if a variable’s VIF > 5, it is excluded from the model.

4. Data

4.1. Data and Sample Selection

This paper focuses solely on completed U.S. M&As between 2010-2020, implying that both the acquirer and the target are U.S. registered corporations. The sample begins in 2010 to exclude the effect of the last financial crisis on the U.S. banking industry (McKinsey & Company, 2019). The relevant transaction information is obtained from the Thomson One (Reuters) database using the following additional criteria:

1. the deal was announced and completed between 2010 -2020 and involved a 100% acquisition of the target by a single acquirer
2. both the acquirer and the target must be based in the U.S. (no cross-border deals)
3. the acquiring firm must be public, with shares listed on the stock exchange
4. the target operates in both the Finance and IT sector (see discussion on FinTech identification below)
5. the operating sector of the acquirer is not further restricted to obtain a wide range of different acquirers (allowing for a more apparent distinction between banks and other types of acquirers)
6. the target may be both a private or a public firm
7. the transaction value is greater or equal to 5 million USD

However, identifying FinTech targets within this sample requires detailed manual work as the FinTech industry does not have its own industry classification codes. Further, FinTech compromises a palette of different types of firms, ranging from start-ups to already established industry players. Hence, as a first filter, the following SIC codes are considered: 60 (depositary institutions), 61 (non-depository credit institutions), 62 (security and commodity brokers, dealers, exchanges, services), 63 (insurance carriers), 87 (engineering, accounting, research, management, and related services) as well as the tech-related SIC codes 7371 (computer programming services), 7372 (prepackaged software), 7373 (computer integrated systems design), 7374 (computer processing, data preparation, processing services) (Dranev et al., 2019).

Moreover, the following NAIC codes are used: 52 (finance and insurance) as well as 511210 (software publisher), 518210 (data processing, hosting, related services), 541511 (custom computer programming services), 541519 (other computer-related services). For an overview of the considered industry classification codes, see table 3 below.

Table 3. Industry classification codes.

Notes: This table summarizes the industry classification codes that are considered for identifying FinTech targets. Ideally, a FinTech firm is associated with codes from both the finance and the technology sector. However, SIC and NAIC code assignments may be imprecise/incomplete. Hence, each potential target firm is in addition analyzed manually in order to be classified as FinTech or not.

Classification Code	Category	Code	Description
SIC	Finance	60	Depositary Institutions
		61	Non-Depository Credit Institutions
		62	Security and Commodity Brokers, Dealers, Exchange Services
		63	Insurance Carriers
		87	Engineering, Accounting, Research, Management, and Related Services
	Technology	7371	Computer Programming Services
		7372	Prepackaged Software
		7373	Computer Integrated Systems Design
		7374	Computer Processing, Data Preparation, Processing Services
NAIC	Finance	52	Finance and Insurance
	Technology	511210	Software Publisher
		518210	Data Processing, Hosting, Related Services
		541511	Custom Computer Programming Services
		541519	Other Computer Related Services

In addition, the screening for FinTech targets is expanded manually using CBInsights, Crunchbase, the Nasdaq Fintech Index and, if necessary, firm-specific websites. This also enables the assignment of targets into one of the six considered FinTech classifications. The detailed inspection of each deal in the general M&A data set ultimately yields a sample of 203 FinTech targets.

Next, the corresponding deal-specific variables are also obtained from the Thomson One database, including the merger announcement date, the method of payment (cash vs stock), the transaction value as well as the acquisition premium paid for public targets. Further, acquirer and target related control variables such as the acquirer's market capitalization, the acquirer's book value of assets, the acquirer's market and book value of equity, and the status of the target (private or public) are also extracted from Thomson One. As not all variables are available for each identified FinTech acquisition, the sample is further reduced to 146 observations.

To evaluate the announcement effect on shareholder returns, the acquirers' stock prices prior to and around the announcement date are extracted from Eikon Datastream. To mitigate the effect of other irrelevant events and to approximate the stock returns by a normal distribution, an estimation window of 180 days before the event window is considered (Dranev et al., 2019). Then, the cumulative abnormal returns are calculated using the Datastream Event Study Tool.

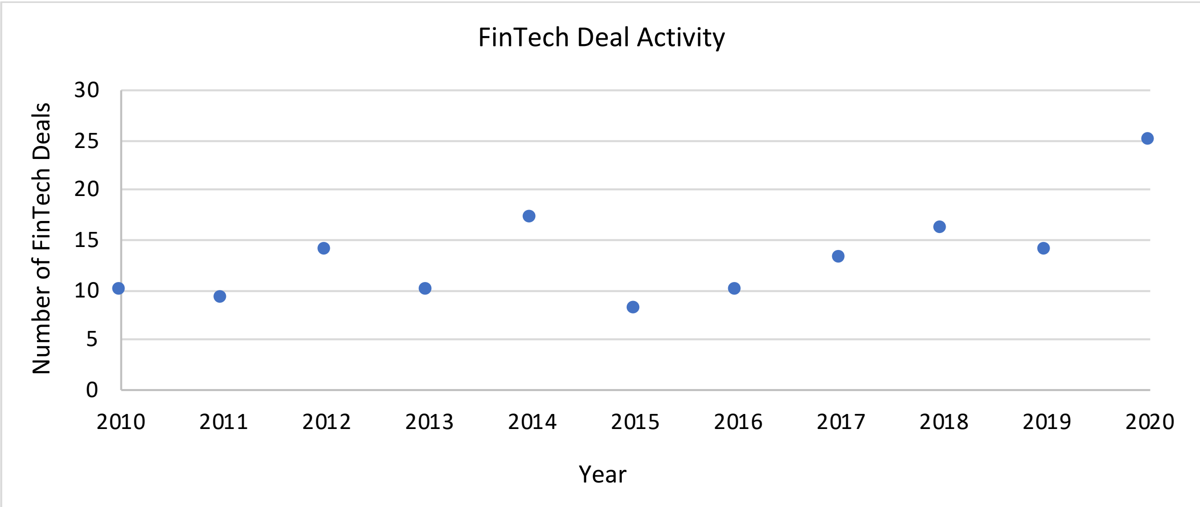
As a benchmark for FinTech acquirer returns, a control sample of 976 deals is used. This sample is based on the same seven conditions mentioned above. Further, it contains targets that are identified by the financial and tech-related SIC and NAIC codes (see table 3); however they do not classify as FinTechs. By comparing the FinTech sample of interest with M&A deals in related sectors – while specifically excluding all FinTech targets – more precise conclusions can be drawn concerning FinTech acquisition returns relative to other finance or tech-related acquisition returns.

4.2. Dataset Composition and Descriptive Statistics

The final sample of interest comprises of 146 relevant FinTech acquisitions between 2010-2020. These deals are distributed across the considered time frame as follows:

Graph 1. FinTech M&A activity in the final sample of interest.

Notes: The graph visualizes the evolvement of FinTech M&A activity along the considered time dimension 2010-2020. The horizontal axis represents the specific year, while the vertical axis counts the number of deals each year in the sample of in total 146 deals.



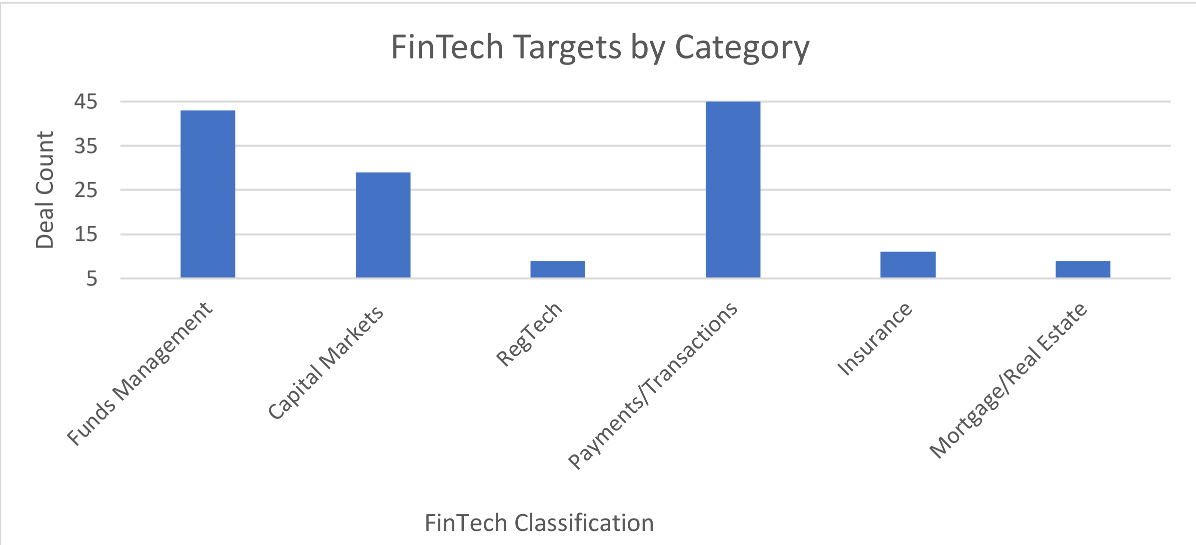
As highlighted by the Ropes and Gray (2019) report, FinTech M&A activity has accelerated substantially in the last few years. Similarly, the deal count in the sample underlying this research has been steadily increasing since 2015 – with the exception being the year 2019. Nevertheless, the number of FinTech deals increased by 250% within the eleven-year time span: 25 deals in 2020 compared to only ten acquisitions in 2010. Given the rising attractiveness of FinTechs over the last years, one may assume that also deal competition and acquisition premia have increased (Ropes & Gray, 2019; Deloitte, 2020)

Further, each target is manually classified into either of the FinTech classifications as defined by CBInsights (see chapter 2). The distribution across the considered categories within the sample is represented in graph 2 below.

Graph 2. Classification of FinTech targets into CBInsights FinTech categories.

Notes: The classification of the sample targets was based on the eight FinTech categories defined by CBInsights (see chapter 2 above). However, many FinTechs have overlapping activities and the distinction between the different categories appears difficult in some cases. For this reason, the Funds Management and the Personal Finance categories were merged as well as the Capital Markets and Blockchain/Crypto classifications. In the end, this research distinguishes between six FinTech subsectors.

The chart depicts the number of sample targets according to their specific FinTech category: Funds Management (43 observations), Capital Markets (29 observations), RegTech (9 observations), Payments/Transactions (45 observations), Insurance (11 observations), Mortgage/Real Estate (9 observations). This leads to a total of 146 targets in the sample.



The graph reveals that a majority - namely 30% - of the acquired FinTechs operate in the payments and transaction execution sector (to be precise: 45 out of 146 targets). Again, this corresponds with the Ropes & Gray (2019) report highlighting that the most prominent FinTech sector is related to mobile/online payment services. Moreover, the categories ‘Funds Management’ and ‘Capital Markets’ are prevalent and comprise 29% and 20% of the total sample respectively.

To gain a better understanding of the underlying sample and the corresponding data set, the following table highlights additional descriptive statistics.

Table 4. Descriptive statistics of the regression variables.

Notes: This table provides descriptive statistics for the dependent variables (CARs), the independent variables of interest (the complement dummy, the bank dummy, and the acquisition premium) as well as for the considered control variables. For a description of the variable abbreviations see section 3.2 table 1 (Cash Payment Dummy, Relative Deal Size=Transaction Value/Acquirer Market Cap, Deal Size=Transaction Value in million USD, M/B=Acquirer Market-to-Book Ratio, Assets=Acquirer Total Assets Book Value in million USD, Tobin's Q=Acquirer Market Value of Equity/Acquirer Book Value of Equity, Public=Public Target Dummy). The full sample consists of 146 deals. However, for hypothesis two only a subsample of the public targets is used. Hence, the number of observations for the acquisition premium variable is reduced to 30.

Relevance	**Variable**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Dependent variables						
	CAR(-10,+10)	146	.0220	.1300	-.1824	1.1034
	CAR(-5,+5)	146	.0183	.0760	-.1801	.3386
	CAR(-3,+3)	146	.0137	.0666	-.1763	.3146
	CAR(-2,+2)	146	.0101	.0634	-.1858	.2844
	CAR(-1,+1)	146	.0063	.0628	-.3365	.2136
	CAR(-1,+2)	146	.0095	.0586	-.1670	.2242
	CAR(-1,+3)	146	.0114	.0593	-.1583	.2455
Variables of interest						
H2	Premium	30	44.0333	36.7870	0.2400	197.0600
H3	Complement	146	.5274	.5010	0	1
H4	Bank	146	.0685	.2535	0	1
Control variables						
Deal characteristics	CashPayment	146	.6027	.4910	0	1
	Relative Deal Size	146	.2816	.6425	.0033	5.6435
	Deal Size	146	1,864.01	4,767.72	8.45	35,031.87

Acquirer characteristics	M/B	146	2.1321	2.6650	.0012	16.9171
	Assets	146	45,828.68	153,015.0	13.5	955,940.0
	Tobin's Q	146	4.9379	13.0828	-78.5135	72.8085
Target characteristics	Public	146	.2055	.4104	0	1

Dependent variables

To evaluate the effect of FinTech acquisitions on short-run acquirer returns, CARs of different event windows are considered. The average CARs of the sample (CAARs) are positive for each of the seven event windows, suggesting that FinTech M&A might have a positive effect on short-term returns. This, however, needs to be statistically tested (see chapter 5.1. below). The smallest CAAR of 0.0063 was measured in the three-day event window, and the largest CAAR of .022 stems from the 21-day event window.

Hypothesis 2

The sample of 146 FinTech acquisitions includes 30 public targets, representing a share of approximately 21%. This subsample is used to evaluate the relationship between deal premia, i.e., the offer price in excess of the target closing stock price four weeks prior to the announcement date. Accordingly, the average acquisition premium amounts to 44%, with values ranging from 0.24% up to 197%. According to Bloomberg data, the majority of M&A deals have a premium between 0% and 25%, while only 5% of the targets obtain a premium above 50%. Hence, the higher-than-average sample premium supports the idea that the highest acquisition premia are paid for technology-intensive targets (such as FinTechs) and that an increase in buy-side deal competition may have increased FinTech acquisition prices (Kohers & Kohers, 2001; Ropes & Gray, 2019).

Hypothesis 3

Next, looking at the complement dummy reveals that approximately 53% of the acquirer-target pairs complement each other. Buying complementary skills, resources and technologies is an often-cited rationale for acquisitions. However, when inspecting the individual acquirer-target pairs, it becomes obvious that many deals are characterized by a supplementary fit: enhancing the existing skills and technologies of the acquirer instead of adding new resources. Hence, the corresponding share of 47% deals may not benefit from complementarities.

Hypothesis 4

Inspecting the mean value of the bank dummy reveals that only approximately 7% of the acquirers in the sample are banks. The relatively low proportion of traditional financial institutions among FinTech acquirers may suggest that there remains some skepticism regarding the reliability and sustainability of the FinTech business models: cybersecurity and data privacy issues as well as regulatory and legal uncertainty (Ryu, 2018).

Control variables

First, the mean of the cash payment dummy implies that approximately 60% of the FinTech acquisitions were fully financed with cash, while 40% of the deals were equity financed (either a mixture of cash and stock or a 100% stock).

Next, the relative deal size – as measured by the transaction value over the acquirer's market capitalization prior to the announcement – range from 0.0033 to 5.6435. On average, however, the transaction value represents 28% of the acquirer's market capitalization. On the one hand, the variation of relative deal size may be explained by variation in the absolute deal size – as measured by the transaction value. The largest deal in the sample is the acquisition of Worldpay (an American payment processing company) by Fidelity National Information Services (an American Fortune 500 company that offers a wide range of financial products and services) in 2019. The transaction value amounted to 35,199.01 million USD. On average, though, acquirers paid 1,864.01 million USD for FinTech targets.

Further, the acquirers' market-to-book ratio and total book value of assets amount to 2.13 and 45,828.68 million USD, respectively, on average. The standard deviations of these measures of acquirer size are rather large because the spectrum of the considered acquirers is broad – ranging from Morgan Stanley with assets of 955,940 million USD to smaller FinTech firms such as Calpian Inc., an Indian mobile payment platform with only 13.5 million USD assets.

When comparing the M/B to Tobin's Q (which is used for robustness checks), the average Tobin's Q of 4.9373 is slightly larger and has a much greater standard deviation of 13.0828. Two acquirers can explain the negative Tobin's Q values with their negative book values of equity.

Finally, the distribution of each relevant variable was carefully analyzed. As Relative Deal Size, Deal Size, M/B, Assets and Tobin’s Q have large positive outliers, the natural logarithm of these variables is used for later analyses. This not only reduces the effect of outliers but also leads to an approximated normal distribution of the control variables, making it easier to draw statistical conclusions in the results chapter.

5. Results

5.1. Results Hypothesis 1

To test whether the acquisition of a FinTech has a significant positive short-run effect on the cumulative abnormal returns of the acquirer, one-sided t-tests are performed using the CAARs of several event windows. Further, the FinTech merger announcement returns are benchmarked against the non-FinTech control sample using two-sample mean comparison tests. Based on variance ratio tests (F-tests), unequal variances in the FinTech and the control sample must be assumed. Table 5 below summarizes the results of the performed t-tests.

Table 5. Results of one-sided t-tests on acquirer abnormal returns.

Notes: This table summarizes the results of the one-sided t-tests for the FinTech sample (column 2) and the control sample (column 3). The FinTech sample is based on 146 observations, while the control sample consist of 976 non-FinTech deals. Below, market-model CAARs and the associated standard errors (in brackets) are reported. The corresponding null hypothesis assumes that CAAR=0 while the alternative hypothesis states CAAR>0. Using a 5% significance level, the null hypothesis may be rejected if the p-value is smaller than 0.05.

Further, column 4 reports results regarding the differences in means across the FinTech and the control sample. The corresponding null hypothesis assumes that CAAR Fintech - CAAR control sample = 0, while the alternative tests whether CAAR FinTech – CAAR control sample >0. For this purpose, a two-sample mean comparison test is applied. Given the results of corresponding F-tests, unequal variances are assumed.

, **, and * indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively*

Event window	CAAR FinTech	CAAR Control Sample	CAAR FinTech – CAAR Control Sample
(-10,+10)	.0220**	.0065**	.0155*
	(.0107)	(.0038)	(.0114)
(-5,+5)	.0183***	.0094***	.0088
	(.0063)	(.0034)	(.0071)
(-3,+3)	.0137***	.0084***	.0053
	(.0055)	(.0030)	(.0063)
(-2,+2)	.0101**	.0088***	.0013
	(.0052)	(.0028)	(.0059)
(-1,+1)	.0063	.0087***	-.0025
	(.0052)	(.0028)	(.0059)
(-1,+2)	.0095**	.0093***	.0002
	(.0049)	(.0028)	(.0056)
(-1,+3)	.0114**	.0087***	.0027
	(.0049)	(.0029)	(.0057)

FinTech Sample (column 2)

The performed t-tests indicate that FinTech M&A has a positive effect on short-term acquirer returns. The CAARs of the 11-day and 7-day event window are highly significant at 1%. Accordingly, FinTech acquirers experience, on average, returns that are .0183 and .0137 higher than those predicted by the market model over the (-5,+5) and (-3,+3) event window, respectively. Further, all other CAARs (i.e., those of the 21-, 5-, 4-day event windows) are significant at 5%, with the exception being the 3-day event window. Thus, the corresponding null hypotheses that CAAR=0 can be rejected in favor of the alternative, namely CAAR>0.

These findings, which are based on market-model CARs, are robust to another type of abnormal returns, namely mean-adjusted CARs (see appendix, table 1, column 2). Accordingly, FinTech M&A creates value in the short run, as represented by significant mean-adjusted abnormal returns over all considered event windows.

The observed positive FinTech merger announcement returns are in line with previous literature: Kohers & Kohers (2000), for example, find that acquirers of high-tech firms experience a significant positive cumulative abnormal return of 1.26% over a 2-day event period, on average. Similarly, the research by Dranev et al. (2019) reveals a significant positive abnormal return for FinTech acquirers of 1.25%, .87% and .84% over the 21-, 7-, and 3-day event windows, respectively. Hence, both the sign and magnitude of the observed FinTech acquisition returns match those of previous empirical analyses.

Given that this paper's results are a) unanimous, b) robust to several event windows, c) consistent when using mean-adjusted CARs and d) in accordance with existing literature, the first hypothesis - stating that "FinTech M&As have a significant positive effect on the cumulative abnormal returns of the acquiring firm in the short run" – cannot be rejected.

Control Sample (column 3)

Similar results are, however, found in the non-FinTech control sample. Announcement returns are positive and significant at 1% for each of the considered event windows, with the exception being the 21-day event window, where the positive CAAR is significant at 5%. To be precise, acquirers of finance or tech-related targets – excluding FinTechs - experience returns in excess of what the market model would predict by .0065-.0094. The significant, positive announcement effect in the control sample is robust when using mean-adjusted CAR instead of market-model based CAR (see appendix, table 1, column 3).

However, these results do not coincide with findings of traditional M&A literature, stipulating that announcement returns for acquirers, in general, are zero or even negative (Adnan & Hosssain, 2016; Georgen & Renneboog, 2004; Moeller, Schlingemann & Stulz, 2005). This could possibly be explained by an overrepresentation of tech targets in the control sample. According to Kohers & Kohers (2000), acquirers of high-tech firms do experience significant positive cumulative abnormal return of 1.26% over a 2-day event period, on average.

Difference CAAR FinTech and CAAR Control Sample (column 4)

To understand the impact of FinTech M&A relative to the acquisition performance of similar targets, the CAARs of the two samples are compared and evaluated. In general, the greater the event window, the larger the difference between the CAARs. However, this difference is significant only for the 21-day event window at 10%. Over this time frame, acquirers of FinTechs experience abnormal returns that are .0155 larger than abnormal returns for non-FinTech acquirers. These findings are, however, not robust to different event windows. Similarly, when using mean-adjusted CARs, the difference between FinTech and non-FinTech announcement returns is insignificant (see appendix, table 1, column 4). Hence, one cannot conclude that FinTech M&A is more profitable than M&A in the broader tech- and finance-related sectors. These findings may be explained by the riskiness and difficulties of integrating a FinTech into traditional corporate structures.

5.2. Results Hypothesis 2

The following regression results are analyzed to assess whether short-run CARs and the acquisition premium paid for a public target have a negative association. Therefore, the coefficient of “ln(premium)” represents the measure of interest.

Table 6. Regression results hypothesis 2.

*Notes: This table summarizes the regression results for hypothesis 2, with the dependent variable being market model-based CARs. The coefficient of interest refers to ln(premium), which quantifies the natural logarithm of the acquisition premium paid for the target (measured using the target’s stock price 4 weeks prior to the deal announcement). Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses standard errors clustered at firm level (accordingly, 23 clusters are created). *, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Moreover, as this hypothesis focusses on the subsample of public FinTech targets, the sample size is reduced to 30 deals and the public dummy becomes redundant. Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Further, the insurance dummy is omitted due to a limited number of observations in the subsample. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	**(-5,+5)**	**(-3,+3)**	**(-2,+2)**	**(-1,+1)**	**(-1,+2)**	**(-1,+3)**
Constant	-.0106	.0097	.1384	.1024	.2760*	.1137	.1395
	(.2911)	(.1993)	(.1341)	(.1139)	(.1555)	(.0876)	(.0983)
Ln(Premium)	**-.0243**	**-.0259**	**-.0260**	**-.0260****	**-.0411***	**-.0252****	**-.0260*****
	(.0220)	**(.0208)**	**(.0157)**	**(.0116)**	**(.0221)**	**(.0101)**	**(.0122)**
CashPayment	.0634	.0556	.0683	.0718	.0759	.0759**	.0707**
	(.0880)	(.0549)	(.0447)	(.0424)	(.0689)	(.0328)	(.0346)
Ln(RelativeDealSize)	-.0275	-.0115	-.0078	-.0015	.0125	-.0020	-.0064
	(.0256)	(.0203)	(.0145)	(.0120)	(.0160)	(.0099)	(.0108)
Ln(Assets)	-.0094	-.0020	-.0106	-.0048	-.0086	-.0065	-.0104
	(.0307)	(.0210)	(.0135)	(.0116)	(.0114)	(.0086)	(.0093)
Ln(MB)	-.0017	-.0022	-.0105	-.0033	-.0017	-.0012	-.0057
	(.0291)	(.0188)	(.0131)	(.0116)	(.0134)	(.0088)	(.0096)
Funds	.0589	.0662	.0551	.0572	-.0194	.0465	.0356
	(.0748)	(.0656)	(.0522)	(.0427)	(.0767)	(.0352)	(.0400)

Capital	-.0279	-.0181	.0058	.0128	-.0098	-.0073	-.0175
	(.0545)	(.0443)	(.0362)	(.0296)	(.0423)	(.0203)	(.0230)
RealEstate	.1052	.2005**	.2170***	.2245***	.0477	.0461	.0420
	(.1107)	(.0858)	(.0674)	(.0572)	(.0838)	(.0351)	(.0361)
RegTech	-.1198	-.0450	.0268	.0059	.0347	-.0087	.0013
	(.1153)	(.0778)	(.0626)	(.0565)	(.0925)	(.0425)	(.0466)
Obs.	30	30	30	30	30	30	30
$\boldsymbol{R^2}$	.5515	.6461	.7114	.7538	.6522	.7419	.7377
Adj. $\boldsymbol{R^2}$	.2254	.3887	.5015	.5748	.3992	.5542	.5470
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Based on the regression results, one may conclude that acquisition premia and short-run FinTech acquirer returns are negatively associated. The coefficients of the deal premium variable are negative for each of the considered CARs, however significant only for the (-2,+2), (-1,+1), (-1,+2), and (-1,+3) event windows and insignificant for the (-10,+10), (-5,+5) and (-3,+3) periods.

To be more precise, the greatest negative correlation is observed with respect to the 3-day event window. A 1% increase in the acquisition premium is associated with a .0411 decrease in cumulate abnormal returns the two days around the announcement date, on average. This coefficient is significant at 10%. On the other hand, the smallest, significant correlation is found concerning the (-1,+2) event window. Accordingly, a 1% increase in the acquisition premium is associated with a decline in acquirer CARs by .0252 on average over the period starting the day prior to the announcement and lasting until two days after. This coefficient is significant at 5%. The most significant negative coefficient is observed with respect to the (-1,+3) event window and is significant at 1%.

The observed negative relationship between acquisition premia and merger announcement returns passes several robustness checks. When using mean-adjusted CARs, the coefficient of the deal premium remains negative for all event windows, however significant only for the (-2,+2), (-1,+1) and (-1,+2) time frames (see appendix, table 2). Similarly, when considering the 1-day and the 1-week acquisition premium – as opposed to the 4-week premium in the base specification – the negative association with CARs persists and is significant over multiple event windows (see appendix, table 3 and 4). Finally, these findings are robust to an alternative set of control variables, replacing the M/B ratio with Tobin's Q and the relative deal size with the transaction value (see appendix, table 5).

Given that the negative acquisition premium coefficients are significant and robust to several alternative model specifications, the second hypothesis - stating that "*Short-run cumulative abnormal returns (CAR) of FinTech acquirers and the acquisition premium paid have a negative association* "- cannot be rejected.

These findings are in line with previous literature: Alexandridis et al. (2013) show that a 1% increase in the offer premium corresponds to a 0.36 basis point reduction in bidder announcement returns. Similarly, Díaz et al. (2009) obtain empirical evidence for a significant negative influence of acquisition premia on abnormal returns. Accordingly, acquirers paying double the target's market valuation (i.e., a 100% premium) - as opposed to paying only the target's market valuation - experience .0969 lower announcement returns. Even though the negative influence of acquisition premia appears small, it is statistically significant and robust across different empirical analyses.

Finally, it is crucial to highlight that the constant term remains positive even after controlling for deal, acquirer and target characteristics and is significant with respect to the (-1,+1) event window. This further strengthens the empirical evidence of a positive announcement effect for FinTech acquirers (hypothesis 1).

5.3. Results Hypothesis 3

To assess whether complementarities between bidder and FinTech target positively influence announcement returns, the sign and significance of the complement dummy in the following regressions (see table 7) are examined.

Table 7. Regression results hypothesis 3.

Notes: This table summarizes the regression results for hypothesis 3, with the dependent variable being market model-based CARs. The coefficient of interest refers to the complement dummy, which indicates whether the bidder and the target have complementary skills, technologies, or product/service offerings. Further, the control variables' coefficients are listed, with the corresponding standard error in brackets below. The multivariate regression uses clustered standard errors at firm level (accordingly, 98 clustered are created)., **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	(-5,+5)	(-3,+3)	(-2,+2)	(-1,+1)	(-1,+2)	(-1,+3)
Constant	.0959	.0386	.0160	.0251	.0230	.0416*	.0419
	(.0699)	(.0380)	(.0312)	(.0277)	(.0252)	(.0252)	(.0282)
Complement	**.0427***	**.0253***	**.0146**	**.0128**	**.0076**	**.0172**	**.0152**
	(.0235)	**(.0138)**	**(.0122)**	**(.0117)**	**(.0124)**	**(.0108)**	**(.0113)**
CashPayment	.0074	-.0054	.0014	-.0038	-.0049	.0013	-.0002
	(.0302)	(.0139)	(.0112)	(.0109)	(.0105)	(.0107)	(.0106)
Ln(RelativeDeal Size)	-.0016	.0003	.0021	.0027	.0041	.0008	.0003
	(.0079)	(.0054)	(.0046)	(.0043)	(.0041)	(.0039)	(.0041)
Ln(Assets)	-.0132	-.0062	-.0032	-.0028	.0010	-.0058	-.0056
	(.0113)	(.0045)	(.0041)	(.0036)	(.0037)	(.0033)	(.0035)
Ln(MB)	-.0060	-.0003	.0004	.0023	.0032	-.0019	-.0025
	(.0113)	(.0058)	(.0051)	(.0047)	(.0040)	(.0041)	(.0042)
Public	-.0041	.0200	.0216	.0109	-.0090	.0046	.0106
	(.0238)	(.0180)	(.0150)	(.0146)	(.0185)	(.0130)	(.0127)

Funds	-.0244	-.0067	-.0070	-.0167	-.0220	-.0184	-.0140
	(.0222)	(.0171)	(.0145)	(.0147)	(.0158)	(.0138)	(.0136)
Capital	.0025	-.0049	.0009	-.0092	-.0079	-.0110	-.0018
	(.0267)	(.0171)	(.0153)	(.0151)	(.0140)	(.0129)	(.0137)
RealEstate	.1149	.0534	.0458	.0298	.0129	.0237	.0317
	(.1099)	(.0412)	(.0415)	(.0366)	(.0260)	(.0301)	(.0273)
RegTech	-.0367	.0034	-.0149	-.0072	-.0125	-.0077	-.0006
	(.0352)	(.0226)	(.0201)	(.0197)	(.0187)	(.0183)	(.0200)
Insurance	-.0416	-.0132	-.0019	-.0210	-.0280*	-.0197	-.0054
	(.0357)	(.0229)	(.0203)	(.0168)	(.0164)	(.0185)	(.0207)
Obs.	146	146	146	146	146	146	146
$\boldsymbol{R^2}$	.2073	.2258	.2093	.2178	.2071	.2340	.2129
Adj. $\boldsymbol{R^2}$	.0357	.0581	.0382	.0485	.0354	.0681	.0425
F-stat	1.47	1.80	1.56	1.63	1.77	1.69	1.60
Prob>F	.1066	.0289	.0770	.0587	.0332	.0445	.0647
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

In general, the coefficient of the complement dummy is positive for all considered event windows, however only significant with respect to the (-10,+10) and (-5,+5) event windows. The positive association between the complement dummy and bidder CARs is largest for the 21-day event window and significant at 10%. To be precise, acquirers of FinTech targets with complementarities experience on average abnormal returns that are .0427 higher than the abnormal returns from acquirers lacking such complementarities. Over the shorter 11-day event window, this positive correlation of complementarities and CARs decreases to .0253, however it remains significant at 10%.

To assess the robustness of the observed positive association between complementarities and merger announcement returns, mean-adjusted CARs and alternative control variables are consulted. Accordingly, the positive coefficient of the complement dummy is significant over the (-5,+5) event window when using mean-adjusted CARs (see appendix, table 6) and over the (-10,+10), (-5,+5) time spans when incorporating the Tobin's Q and the absolute deal size (see appendix, table 7).

Consequently, the third hypothesis – stating that "*Complementarity between the acquirer and the FinTech target (in terms of knowledge, skills, product and service offerings) are positively related to short-run cumulative abnormal returns."* – cannot be rejected.

These findings support the theory behind complementary mergers: complementary tangible and intangible assets of acquirer and FinTechs allow the former to expand its portfolio without having to invent applications or services internally (Hornuf, et al., 2018). Even further, complementary scientific and technological knowledge significantly enhance the innovative capabilities of acquirers after the merger (Makri, Hitt & Lane, 2007). Ultimately, such complementarities have proven to induce significant post-merger synergies in previous literature already (Hornuf et al., 2018) and are quantified in terms of positive stock price reactions for the first time in this study.

Finally, the constant term is positive throughout all regression models and significant at 10% for the (-1,+2) event window. This further strengthens the empirical evidence of a positive announcement effect for FinTech acquirers (hypothesis 1).

5.4. Results Hypothesis 4

Finally, to evaluate whether banks experience a significantly larger announcement return as opposed to other types of acquirers, the following regression analyses are conducted – with the focus lying on the coefficients of the bank dummy. Again, multiple event windows are considered.

Table 8. Regression results hypothesis 4.

*Notes: This table summarizes the regression results for hypothesis 4, with the dependent variable being market model-based CAR. The coefficient of interest refers to the bank dummy, which indicates whether the acquiring firm was a traditional bank. Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses clustered standard errors at firm level (accordingly, 98 clustered are created). *, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Finally, the regression controls for time-fixed effects (by using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	(-5,+5)	(-3,+3)	(-2,+2)	(-1,+1)	(-1,+2)	(-1,+3)
Constant	.1027	.0427	.0182	.0268	.0237	.0440*	.0440
	(.0721)	(.0397)	(.0310)	(.0274)	(.0248)	(.0261)	(.0291)
Bank	**-.0355**	**-.0128**	**-.0208**	**-.0296**	**-.0371***	**-.0309***	**-.0311**
	(.0324)	**(.0228)**	**(.0243)**	**(.0207)**	**(.0209)**	**(.0181)**	**(.0194)**
CashPayment	.0088	-.0044	.0017	-.0039	-.0055	.0015	-.0002
	(.0309)	(.0138)	(.0108)	(.0104)	(.0100)	(.0105)	(.0104)
Ln(RelativeDealSize)	-.0041	-.0009	.0010	.0015	.0029	-.0006	-.0011
	(.0081)	(.0055)	(.0046)	(.0042)	(.0040)	(.0039)	(.0040)
Ln(Assets)	-.0112	-.0050	-.0026	-.0023	.0013	-.0051	-.0049
	(.0108)	(.0044)	(.0039)	(.0033)	(.0034)	(.0032)	(.0033)
Ln(MB)	-.0103	-.0022	-.0017	-.0005	-.0001	-.0049	-.0055
	(.0121)	(.0065)	(.0056)	(.0049)	(.0039)	(.0042)	(.0044)
Public	-.0060	.0187	.0212	.0107	-.0088	.0041	.0102
	(.0241)	(.0181)	(.0148)	(.0144)	(.0179)	(.0129)	(.0125)

Funds	-.0110	.0002	-.0013	-.0102	-.0155	-.0108	-.0068
	(.0230)	(.0193)	(.0159)	(.0161)	(.0171)	(.0150)	(0147)
Capital	.0124	.0004	.0048	-.0050	-.0042	-.0059	.0030
	(.0286)	(.0189)	(.0167)	(.0160)	(.0144)	(.0135)	(.0144)
RealEstate	.1265	.0603	.0497	.0333	.0149	.0283	.0358
	(.1150)	(.0438)	(.0437)	(.0387)	(.0277)	(.0325)	(.0297)
RegTech	-.0359	.0039	-.0147	-.0070	-.0125	-.0074	-.0004
	(.0368)	(.0246)	(.0205)	(.0199)	(.0190)	(.0196)	(.0215)
Insurance	-.0318	-.0072	.0013	-.0185	-.0268*	-.0161	-.0022
	(.0357)	(.0229)	(.0201)	(.0168)	(.0164)	(.0185)	(.0205)
Obs.	146	146	146	146	146	146	146
$\boldsymbol{R^2}$	.1900	.2058	.2047	.2203	.2207	.2306	.2132
Adj. $\boldsymbol{R^2}$	.0146	.2058	.0325	.0515	.0520	.0640	.0429
F-stat	1.54	1.89	1.65	1.76	1.87	1.82	1.69
Prob>F	.0825	.0196	.0536	.0343	.0218	.0267	.0445
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The regressions suggest that banks should, on average, experience lower announcement returns as compared to other acquirers. The coefficient of the bank dummy remains negative for all regressions. However, the negative association between acquirer CARs and the bank dummy is significant only for the (-1,+1) and the (-1,+2) event windows. To be precise, traditional banks experience abnormal returns that are .0371 and .0309 lower as compared to abnormal returns of other types of FinTech acquirers over the 3- and 4-day event window, respectively. These findings are significant at 10%.

Again, to evaluate the robustness of these results, mean-adjusted CARs and alternative control variables are used. The negative association between the bank dummy and the mean-adjusted CARs is significant over the (-1,+2) and the (-1,+3) event windows (see appendix, table 8). Similarly, this negative relationship remains significant over multiple event windows when incorporating Tobin's Q and the deal size into the model (see appendix, table 9).

Given the results in table 8 above as well as their robustness to mean-adjusted CARs and alternative control variables, the fourth hypothesis – stipulating that "*FinTech M&As have a larger effect on the cumulative abnormal returns of the acquiring firm in the short run if the acquirer is a traditional bank.*" – has to be rejected. Instead, empirical results suggest less wealth creation from FinTech M&A for traditional banks as compared to other types of acquirers.

This negative association between the bank dummy and abnormal acquirer returns is not in line with the suggested complementarity arising from bank-tech mergers in general (see chapter 2). McKinsey & Company highlights the opportunities that FinTechs may convey adjacent banks, and the 2019 Ropes & Gray report identifies FinTechs as a possibility for established banks to advance and modernize their capabilities. Accordingly, market reactions to bank-FinTech mergers have, in general, been positive in the last year (McKinsey & Company, 2019). Nevertheless, research has also revealed drawbacks that arise mainly from cybersecurity and data privacy issues, ultimately restraining the expected positive perception of bank-FinTech mergers (Ryu, 2018). An overemphasis of FinTech related risks by investors might overshadow the opportunities stemming from new technologies and thereby explain the encountered lower announcement returns for banks.

Finally, it is crucial to highlight that the constant term remains positive even after controlling for deal, acquirer and target characteristics and is significant with respect to the (-1,+2) event window. This further strengthens the empirical evidence of a positive announcement effect for FinTech acquirers (hypothesis 1).

6. Discussion and Conclusion

Due to the increasing relevance of technological innovation, the financial industry has been experiencing a paradigm shift towards alternative providers and digitized services (KPMG, 2017). New players, namely FinTechs, have entered the market sphere and disrupted the competitive environment. Ultimately, this sector-wide reorientation induced a substantial acceleration of FinTech M&A activity over the last decade (Ropes & Gray, 2019). Hence, this research investigates the following: "*What is the impact of FinTech M&A on shareholder return for U.S. acquirers between 2010-2020*?" Ultimately, empirical evidence reveals that FinTech M&A creates shareholder value but depends on factors such as the acquisition premium paid, potential complementarities between acquirer and target, as well as the type of acquirer.

In general, FinTech M&A has proven to create shareholder value in the short run, with significant abnormal returns for acquirers over multiple-day event windows. This contrasts the traditional academic consensus stating that acquirers experience negative or at most zero abnormal returns around the announcement date (Adnan & Hosssain, 2016; Georgen & Renneboog, 2004; Moeller, Schlingemann & Stulz, 2005). The positive market perception of FinTech acquisitions may, however, be explained by the potential they convey to acquirers: alternative, digitized service offerings; lower operating expenses; enhanced business processes; and solutions to complex IT problems (Dranev et al., 2019). Hence, when looking at specific, Fintech-related M&A literature, a similar positive merger announcement return for bidders is observed (Dranev et al., 2019; Kohers & Kohers, 2020; Tanjung, 2020). Nevertheless, there is no evidence that FinTech M&A creates significantly more value as compared to acquisitions of pure tech- or finance-focused targets (the control sample). This, in return, highlights that risks related to technology and cybersecurity are high, and the integration of FinTech targets may be cumbersome, ultimately limiting the positive perception of FinTech acquisitions (Buckley, Arner, Zetzsche & Selga, 2019).

However, the observed positive abnormal returns stemming from FinTech M&A are negatively associated with the acquisition premium paid. This is in line with traditional M&A literature that finds a significant, robust negative relationship between acquisition premia and short-term bidder returns (Alexandridis et al., 2013; Bruner, 2004; Díaz et al., 2019). According to theory, greater deal premia increase the likelihood of overpaying for potential future synergies that might never fully materialize (Sirower, 1994). Given that the highest acquisition premia have traditionally been paid to technology-intensive targets, the risk of overpayment is substantial for FinTech acquirers (Kohers & Kohers, 2001).

On the other hand, the empirical evidence of this research suggests that acquirer abnormal returns may be enhanced when merging with a complementary FinTech target. This is in accordance with the underlying theory: Digital technology advancements, improved, novel product offerings for consumers as well as fewer regulatory restrictions may allow the acquirer to expand its range of activities without having to invent applications or services internally (Navaretti, Calzolari & Pozzolo, 2018). Further, adding complementary skills and resources through a FinTech acquisition may enhance operating efficiency and thereby boost post-merger synergies, ultimately leading to more value creation (Bruner, 2004).

Even though one might expect especially strong complementarities between traditional financial institutions and FinTechs, banks, on average, experience lower FinTech merger announcement returns as compared to other types of acquirers. These findings suggest that investors downgrade the opportunity for established banks to expand into adjacent areas and advance their digital capabilities by acquiring a FinTech. Instead, the risks associated with FinTechs appear to outweigh gains from potential future synergies. Huge amounts of money are at stake, while the reliability and sustainability of the FinTech business models have yet to be proven (Zeranski & Sancak, 2020). Further, cybersecurity and data privacy concerns, as well as regulatory and legal uncertainties remain, ultimately holding back potential merger announcement returns for banks (Ryu, 2018).

Although the findings of this research are unambiguous, significant, and robust to different settings, the analysis comes with certain limitations. First, the sample size is small, consisting of 146 FinTech acquisitions between 2010-2020. The results regarding the acquisition premium are less reliable because the corresponding sub-sample of public targets contains 30 observations only. Moreover, the sample is restricted to U.S. domestic mergers. However, expanding the data set to cross border acquisitions may provide additional insights into the determinants of FinTech merger returns. Further, previous literature offers suggestions for additional merger-related control variables which were not included due to a lack of data and the limited scope of this paper. Finally, the control sample used to evaluate FinTech M&A returns against is not paired to the actual sample of interest. By pairing the firms based on age, year of the merger, and specific operating activities, for example, more reliable results regarding the value-creating potential of FinTech M&A – as opposed to M&A in the field of finance or technology only – could be obtained.

Given that the emergence of FinTechs is relatively recent, the potential for future research is vast. As discussed in this paper multiple times, risks associated with FinTechs are substantial. Hence, instead of evaluating CARs, it would be interesting to study the effect of FinTech merger announcements on acquirers' stock price volatility. Does the incorporation of novel FinTech business models increase a firm's risk – as perceived by stockholders? Second, complementarities have proven to help determine FinTech merger returns. However, a more precise analysis on the origin and type of complementarities (e.g., complementarities in human resources, complementarities in technologies, complementarities in product and service offerings, etc.) would enable a deeper understanding of where post-merger synergies with FinTechs stem from. Finally, most FinTech M&A literature focuses on short-term abnormal returns. Hence, analyzing the full integration process of FinTechs as well as the amount of shareholder wealth generated over longer time horizons would provide additional valuable insights for incumbent managers and investors.

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8. Appendix A: Robustness checks

8.1. Robustness Checks Hypothesis 1

Table 1. Results of one-sided t-tests on acquirer abnormal returns (**mean-adjusted returns**).

Notes: This table summarizes the results of the one-sided t-tests for the FinTech sample (column 2) and the control sample (column 3). The FinTech sample is based on 146 observations, while the control sample consist of 976 non-FinTech deals. Below, mean-adjusted CAARs and the associated standard errors (in brackets) are reported. The corresponding null hypothesis assumes that CAAR=0 while the alternative hypothesis states CAAR>0. Using a 5% significance level, the null hypothesis may be rejected if the p-value is smaller than 0.05.

Further, column 4 reports results regarding the differences in means across the FinTech and the control sample. The corresponding null hypothesis assumes that CAAR Fintech - CAAR control sample = 0, while the alternative tests whether CAAR FinTech – CAAR control sample >0. For this purpose, a two-sample mean comparison test is applied. Given the results of corresponding F-tests, unequal variances are assumed.

, **, and * indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively*

Event window	**CAAR FinTech**	**CAAR Control Sample**	**CAAR FinTech – CAAR Control Sample**
(-10,+10)	.0218**	.0072**	.0147
	(.0122)	(.0042)	(.0130)
(-5,+5)	.0169***	.0097***	.0073
	(.0068)	(.0036)	(.0077)
(-3,+3)	.0130**	.0082***	.0049
	(.0057)	(.0031)	(.0065)
(-2,+2)	.0109**	.0087***	.0021
	(.0054)	(.0029)	(.0061)
(-1,+1)	.0085**	.0084***	.0000
	(.0047)	(.0028)	(.0055)
(-1,+2)	.0108**	.0090***	.0018
	(.0050)	(.0029)	(.0058)
(-1,+3)	.0114**	.0081***	.0032
	(.0051)	(.0030)	(.0059)

8.2. Robustness Checks Hypothesis 2

Table 2. Regression results hypothesis 2 (**mean-adjusted CAR**).

*Notes: This table summarizes the regression results for hypothesis 2, with the dependent variable being **mean-adjusted CAR**. The coefficient of interest refers to ln(premium), which quantifies the natural logarithm of the acquisition premium paid for the target (measured using the target's stock price 4 weeks prior to the deal announcement). Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses standard errors clustered at firm level (accordingly, 23 clusters are created). *, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Moreover, as this hypothesis focusses on the subsample of public FinTech targets, the sample size is reduced to 30 deals and the public dummy becomes redundant. Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Further, the insurance dummy is omitted due to a limited number of observations in the subsample. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	**(-5,+5)**	**(-3,+3)**	**(-2,+2)**	**(-1,+1)**	**(-1,+2)**	**(-1,+3)**
Constant	-.0876	.0167	.0615	.0568	.1432	.0737	.0584
	(.4728)	(.1825)	(.1194)	(.1083)	(.1092)	(.0834)	(.0792)
Ln(Premium)	**-.0240**	**-.0200**	**-.0167**	**-.0248****	**-.0163***	**-.0200****	**-.0107**
	(.0358)	**(.0188)**	**(.0130)**	**(.0096)**	**(.0092)**	**(.0080)**	**(.0076)**
CashPayment	-.0065	.0198	.0416	.0328	.0188	.0365	.0647
	(.1610)	(.0417)	(.0367)	(.0325)	(.0364)	(.0297)	(.0190)
Ln(RelativeDealSize)	-.0203	-.0221	-.0131	.0091	.0118	.0076	-.0199
	(.0420)	(.0209)	(.0125)	(.0179)	(.0179)	(.0193)	(.0142)
Ln(Assets)	.0078	-.0052	-.0053	.0055	-.0014	.0016	-.0115
	(.0473)	(.0197)	(.0118)	(.0134)	(.0119)	(.0120)	(.0094)
Ln(MB)	.0103	-.0051	-.0084	.0022	.0015	.0027	-.0094
	(.0474)	(.0182)	(.0123)	(.0143)	(.0148)	(.0129)	(.0096)
Funds	.1920	.1849***	.1617***	.0958**	.0381	.0712	.1423
	(.1204)	(.0482)	(.0359)	(.0492)	(.0388)	(.0490)	(.0249)
Capital	-.0433	-.0100	.0209	.0130	-.0011	-.0108	.0094
	(.0837)	(.0321)	(.0248)	(.0299)	(.0261)	(.0261)	(.0134)
RealEstate	-.0164	.1439**	.1703***	.1797***	.0260	.0062	.0387

	(.1760)	(.0592)	(.0439)	(.0539)	(.0419)	(.0539)	(.0235)
RegTech	-.1226	-.0307	.0129	.0302	.0611	.0224	-.0066
	(.2178)	(.0660)	(.0556)	(.0457)	(.0536)	(.0366)	(.0332)
Obs.	30	30	30	30	30	30	30
$\boldsymbol{R^2}$	.5244	.7745	.8033	.7405	.5489	.6157	.8335
Adj. $\boldsymbol{R^2}$	.1785	.6105	.6603	.5518	.2209	.3362	.7124
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3. Regression results hypothesis 2 (**1-day acquisition premium**).

Notes: This table summarizes the regression results for hypothesis 2, with the dependent variable being ***market-model based CAR****. The coefficient of interest refers to ln(premium), which quantifies the natural logarithm of the acquisition premium paid for the target (measured using the* ***target's stock price 1 day prior*** *to the deal announcement). Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses standard errors clustered at firm level (accordingly, 23 clusters are created). *, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Moreover, as this hypothesis focusses on the subsample of public FinTech targets, the sample size is reduced to 30 deals and the public dummy becomes redundant. Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Further, the insurance dummy is omitted due to a limited number of observations in the subsample. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	**(-5,+5)**	**(-3,+3)**	**(-2,+2)**	**(-1,+1)**	**(-1,+2)**	**(-1,+3)**
Constant	-.0106	.0097	.1384	.1024	.2760*	.1137	.1395
	(.2911)	(.1993)	(.1341)	(.1139)	(.1555)	(.0876)	(.0983)
Ln(Premium)	**-.0243**	**-.0259**	**-.0260**	**-.0260****	**-.0411***	**-.0252****	**-.0260****
	(.0220)	**(.0208)**	**(.0157)**	**(.0116)**	**(.0221)**	**(.0101)**	**(.0122)**
CashPayment	.0634	.0556	.0683	.0718*	.0759	.0759**	.0707*
	(.0880)	(.0549)	(.0447)	(.0423)	(.0689)	(.0328)	(.0346)
Ln(RelativeDealSize)	-.0275	-.0115	-.0078	-.0015	.0125	-.0020	-.0064
	(.0256)	(.0203)	(.0145)	(.0120)	(.0160)	(.0099)	(.0108)
Ln(Assets)	-.0094	-.0020	-.0106	-.0048	-.0086	-.0065	-.0104
	(.0307)	(.0210)	(.0135)	(.0116)	(.0114)	(.0086)	(.0093)
Ln(MB)	-.0017	-.0022	-.0105	-.0033	-.0017	-.0012	-.0057
	(.0291)	(.0188)	(.0131)	(.0116)	(.0134)	(.0088)	(.0096)
Funds	.0589	.0662	.0551	.0572	-.0194	.0465	.0356
	(.0748)	(.0656)	(.0522)	(.0427)	(.0767)	(.0352)	(.0400)
Capital	-.0279	-.0181	.0058	.0128	-.0098	-.0073	-.0175
	(.0545)	(.0443)	(.0362)	(.0300)	(.0424)	(.0203)	(.0230)
RealEstate	.1052	.2005**	.2170***	.2245***	.0477	.0461	.0420

	(.1107)	(.0858)	(.0674)	(.0572)	(.0838)	(.0351)	(.0361)
RegTech	-.1198	-.0450	.0268	.0059	.0347	-.0087	.0013
	(.1153)	(.0778)	(.0626)	(.0565)	(.0925)	(.0425)	(.0466)
Obs.	30	30	30	30	30	30	30
$\boldsymbol{R^2}$	.5515	.6461	.7114	.7538	.6522	.7419	.7377
Adj. $\boldsymbol{R^2}$	.2254	.3887	.5015	.5748	.3992	.5542	.5470
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4. Regression results hypothesis 2 (**1-week acquisition premium**).

*Notes: This table summarizes the regression results for hypothesis 2, with the dependent variable being **market-model based CAR**. The coefficient of interest refers to ln(premium), which quantifies the natural logarithm of the acquisition premium paid for the target (measured using the **target's stock price 1 week prior** to the deal announcement). Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses standard errors clustered at firm level (accordingly, 23 clusters are created). *, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Moreover, as this hypothesis focusses on the subsample of public FinTech targets, the sample size is reduced to 30 deals and the public dummy becomes redundant. Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Further, the insurance dummy is omitted due to a limited number of observations in the subsample. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	**(-5,+5)**	**(-3,+3)**	**(-2,+2)**	**(-1,+1)**	**(-1,+2)**	**(-1,+3)**
Constant	-.1067	-.0925	.0356	.0031	.1097	.0174	.0370
	(.2561)	(.1776)	(.1276)	(.1172)	(.1637)	(.0984)	(.1045)
Ln(Premium)	**-.0117**	**-.0125**	**-.0124**	**-.0134***	**-.0186**	**-.0130***	**-.0125**
	(.0153)	**(.0137)**	**(.0100)**	**(.0076)**	**(.0144)**	**(.0072)**	**(.0084)**
CashPayment	.0729	.0657	.0784	.0821*	.0917	.0860**	.0808*
	(.0897)	(.0593)	(.0503)	(.0477)	(.0803)	(.0390)	(.0415)
Ln(RelativeDealSize)	-.0205	-.0040	-.0003	.0063	.0239	.0056	.0011
	(.0253)	(.0208)	(.0164)	(.0139)	(.0230)	(.0132)	(.0150)
Ln(Assets)	-.0027	.0051	-.0035	.0025	.0026	.0006	-.0032
	(.0292)	(.0208)	(.0145)	(.0128)	(.0169)	(.0103)	(.0112)
Ln(MB)	.0056	.0056	-.0028	.0047	.0102	.0065	.0020
	(.0288)	(.0192)	(.0149)	(.0138)	(.0200)	(.0116)	(.0122)
Funds	.0659	.0736	.0626	.0640	-.0068	.0531	.0431
	(.0779)	(.0693)	(.0571)	(.0473)	(.0837)	(.0396)	(.0452)
Capital	-.0309	-.0212	.0027	.0093	-.0143	-.0108	-.0206
	(.0566)	(.0483)	(.0408)	(.0333)	(.0478)	(.0231)	(.0266)
RealEstate	.1217	.2181**	.2348***	.2411***	.0772	.0621	.0597
	(.1141)	(.0877)	(.0700)	(.0590)	(.0859)	(.0375)	(.0407)

RegTech	-.1273	-.0530	.0187	-.0019	.0218	-.0163	-.0067
	(.1149)	(.0850)	(.0732)	(.0654)	(.1048)	(.0517)	(.0578)
Obs.	30	30	30	30	30	30	30
$\boldsymbol{R^2}$	.5342	.6240	.6786	.7219	.5859	.6916	.6847
Adj. $\boldsymbol{R^2}$	.1955	.3505	.4449	.5196	.2847	.4673	.4554
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5. Regression results hypothesis 2 (**alternative control variables: Tobin's Q and absolute deal size**.

Notes: This table summarizes the regression results for hypothesis 2, with the dependent variable being ***market-model based CAR****. The coefficient of interest refers to ln(premium), which quantifies the natural logarithm of the acquisition premium paid for the target (measured using the* ***target's stock price 4 week prior*** *to the deal announcement). Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses standard errors clustered at firm level (accordingly, 23 clusters are created). *, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Moreover, as this hypothesis focusses on the subsample of public FinTech targets, the sample size is reduced to 30 deals and the public dummy becomes redundant. Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Further, the insurance dummy is omitted due to a limited number of observations in the subsample. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	**(-5,+5)**	**(-3,+3)**	**(-2,+2)**	**(-1,+1)**	**(-1,+2)**	**(-1,+3)**
Constant	-.0407	.0004	.1041	.0610	.1423	.0752	.0846
	(.3163)	(.2045)	(.1334)	(.1194)	(.1111)	(.0849)	(.0814)
Ln(Premium)	**-.0205**	**-.0234**	**-.0207**	**-.0196***	**-.0150**	**-.0195****	**-.0122***
	(.0211)	**(.0201)**	**(.0153)**	**(.0117)**	**(.0096)**	**(.0078)**	**(.0064)**
CashPayment	.0689	.0533	.0671	.0716	.0155	.0344	.0616**
	(.1025)	(.0620)	(.0492)	(.0473)	(.0389)	(.0337)	(.0248)
Ln(DealSize)	-.0081	.0033	.0002	.0065	.0077	.0059	-.0132
	(.0248)	(.0169)	(.0133)	(.0124)	(.0163)	(.0169)	(.0112)
Ln(Assets)	.0043	-.0005	-.0061	-.0064	-.0097	-.0046	.0016
	(.0174)	(.0141)	(.0102)	(.0085)	(.0084)	(.0084)	(.0060)
Ln(Tobin's Q)	.0118	-.0032	-.0077	-.0064	-.0077	-.0041	.0020
	(.0202)	(.0165)	(.0115)	(.0097)	(.0080)	(.0095)	(.0087)
Funds	.0661	.0670	.0566	.0598	.0360	.0700	.1412***
	(.0719)	(.0638)	(.0535)	(.0449)	(.0410)	(.0515)	(.0277)
Capital	-.0298	-.0142	.0097	.0164	.0018	-.0091	.0110
	(.0571)	(.0515)	(.0433)	(.0350)	(.0280)	(.0280)	(.0194)
RealEstate	.1417	.2173**	.2271***	.2369***	.0163	.0012	.0436

	(.1160)	(.0846)	(.0662)	(.0572)	(.0500)	(.0624)	(.0258)
RegTech	-.0789	.0006	.0476	.0244	.0568	.0224	.0237
	(.1544)	(.1174)	(.0848)	(.0710)	(.0528)	(.0454)	(.0490)
Obs.	30	30	30	30	30	30	30
$\boldsymbol{R^2}$	.5110	.6401	.7088	.7441	.5391	.6149	.8178
Adj. $\boldsymbol{R^2}$	.1553	.3784	.4970	.5580	.2039	.3348	.6853
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

8.3. Robustness Checks Hypothesis 3

Table 6. Regression results hypothesis 3 (**mean-adjusted CAR**).

Notes: This table summarizes the regression results for hypothesis 3, with the dependent variable being ***mean-adjusted CAR****. The coefficient of interest refers to the complement dummy, which indicates whether the bidder and the target have complementary skills, technologies, or product/service offerings. Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses clustered standard errors at firm level (accordingly, 98 clustered are created).*, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	Acquisition Performance CAR(-t,+t)						
	(-10,+10)	(-5,+5)	(-3,+3)	(-2,+2)	(-1,+1)	(-1,+2)	(-1,+3)
Constant	.0970	.0295	.0145	.0217	.0276	.0442*	.0441
	(.0768)	(.0353)	(.0344)	(.0299)	(.0248)	(.0260)	(.0284)
Complement	**.0394**	**.0263***	**.0116**	**.0096**	**.0106**	**.0158**	**.0163**
	(.0259)	**(.0144)**	**(.0126)**	**(.0119)**	**(.0102)**	**(.0105)**	**(.0111)**
CashPayment	.0184	-.0065	.0026	-.0061	-.0093	-.0002	.0045
	(.0370)	(.0159)	(.0124)	(.0122)	(.0104)	(.0118)	(.0119)
Ln(RelativeDeal Size)	-.0040	-.0021	-.0001	.0021	.0027	-.0000	-.0019
	(.0084)	(.0057)	(.0049)	(.0045)	(.0039)	(.0041)	(.0041)
Ln(Assets)	-.0153	-.0077	-.0045	-.0025	.0005	-.0061	-.0076
	(.0132)	(.0053)	(.0048)	(.0041)	(.0035)	(.0038)	(.0040)
Ln(MB)	-.0072	.0004	-.0015	.0001	.0012	-.0047	-.0065
	(.0159)	(.0075)	(.0064)	(.0055)	(.0047)	(.0051)	(.0057)
Public	-.0096	.0173	.0184	.0155	.0047	.0123	.0122
	(.0301)	(.0171)	(.0132)	(.0132)	(.0113)	(.0117)	(.0113)
Funds	-.0289	-.0011	-.0015	-.0138	-.0147	-.0168	-.0096
	(.0255)	(.0184)	(.0163)	(.0143)	(.0138)	(.0129)	(.0145)
Capital	-.0111	-.0144	-.0072	-.0188	-.0183	-.0209	-.0094
	(.0330)	(.0203)	(.0179)	(.0160)	(.0131)	(.0133)	(.0159)

RealEstate	.1199	.0553	.0422	.0294	.0105	.0215	.0226
	(.1249)	(.0358)	(.0341)	(.0338)	(.0237)	(.0313)	(.0276)
RegTech	-.0327	.0049	-.0140	-.0052	-.0148	-.0086	-.0026
	(.0402)	(.0275)	(.0252)	(.0237)	(.0171)	(.0190)	(.0190)
Insurance	-.0231	-.0045	.0042	-.0205	-.0256	-.0164	.0018
	(.0336)	(.0254)	(.0215)	(.0184)	(.0181)	(.0196)	(.0212)
Obs.	146	146	146	146	146	146	146
R^2	.1521	.1870	.1473	.1880	.2216	.2147	.1753
Adj. R^2	-.0315	.0110	-.0372	.0122	.0531	.0447	.0615
F-stat	1.30	1.89	1.29	1.72	1.97	2.00	1.61
Prob>F	.1953	.0194	.1987	.0399	.0144	.0122	-0.0032
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Regression results hypothesis 3 (**alternative control variables: Tobin's Q and absolute Deal Size)**.

Notes: This table summarizes the regression results for hypothesis 3, with the dependent variable being market model-based CAR. The coefficient of interest refers to the complement dummy, which indicates whether the bidder and the target have complementary skills, technologies, or product/service offerings. Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses clustered standard errors at firm level (accordingly, 98 clustered are created)., **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	(-5,+5)	(-3,+3)	(-2,+2)	(-1,+1)	(-1,+2)	(-1,+3)
Constant	.0958	.0423	.0224	.0316	.0267	.0429*	.0440
	(.0658)	(0370)	(.0310)	(.0280)	(.0252)	(.0252)	(.0278)
Complement	**.0412***	**.0247***	**.0141**	**.0120**	**.0069**	**.0164**	**.0142**
	(.0232)	**(.0141)**	**(.0124)**	**(.0120)**	**(.0127)**	**(.0110)**	**(.0114)**
CashPayment	.0049	-.0054	.0019	-.0035	-.0051	.0003	-.0012
	(.0277)	(.0138)	(.0112)	(.0109)	(.0108)	(.0110)	(.0110)
Ln(DealSize)	-.0030	.0008	.0031	.0035	.0044	.0005	.0000
	(.0083)	(.0055)	(.0047)	(.0043)	(.0040)	(.0040)	(.0042)
Ln(Assets)	-.0097	-.0068	-.0060	-.0063	-.0033	-.0059	-.0052
	(.0087)	(.0048)	(.0042)	(.0041)	(.0037)	(.0037)	(.0037)
Ln(Tobin's Q)	-.0032	-.0027	-.0057	-.0040	-.0028	-.0031	-.0036
	(.0082)	(.0060)	(.0051)	(.0050)	(.0042)	(.0044)	(.0044)
Public	-.0028	.0195	.0213	.0103	-.0093	.0049	.0106
	(.0244)	(.0175)	(.0142)	(.0141)	(.0182)	(.0128)	(.0124)
Funds	-.0267	-.0077	-.0080	-.0174	-.0230	-.0202	-.0164
	(.0236)	(.0177)	(.0149)	(.0151)	(.0162)	(.0141)	(.0139)
Capital	.0008	-.0055	.0006	-.0097	-.0086	-.0121	-.0032
	(.0265)	(.0172)	(.0155)	(.0154)	(.0141)	(.0130)	(.0138)

RealEstate	.1128	.0522	.0447	.0290	.0119	.0217	.0291
	(.1094)	(.0420)	(.0425)	(.0375)	(.0264)	(.0302)	(.0275)
RegTech	-.0397	.0047	-.0109	-.0041	-.0113	-.0085	-.0016
	(.0374)	(.0236)	(.0208)	(.0205)	(.0190)	(.0188)	(.0202)
Insurance	-.0470	-.0132	-.0014	-.0220	-.0289*	-.0209	-.0062
	(.0390)	(.0245)	(.0221)	(.0179)	(.0174)	(.0197)	(.0222)
Obs.	146	146	146	146	146	146	146
$\boldsymbol{R^2}$	.2081	.2274	.2153	.2216	.2090	.2376	.2187
Adj. $\boldsymbol{R^2}$	.0330	.0566	0.0418	.0496	.0342	.0690	.0460
F-stat	1.43	1.78	1.56	1.61	1.79	1.73	1.67
Prob>F	.1252	.0314	.0773	.0630	.0304	.0384	.0489
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

8.4. Robustness Checks Hypothesis 4

Table 8. Regression results hypothesis 4 (**mean-adjusted CAR**).

*Notes: This table summarizes the regression results for hypothesis 4, with the dependent variable being **mean-adjusted CAR**. The coefficient of interest refers to the bank dummy, which indicates whether the acquiring firm was a traditional bank. Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses clustered standard errors at firm level (accordingly, 98 clustered are created). *, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	(-5,+5)	(-3,+3)	(-2,+2)	(-1,+1)	(-1,+2)	(-1,+3)
Constant	.1029	.0336	.0160	.0227	.0289	.0463*	.0462
	(.0791)	(.0360)	(.0337)	(.0293)	(.0243)	(.0266)	(.0290)
Bank	**-.0551**	**-.0281**	**-.0329**	**-.0384**	**-.0352**	**-.0391***	**-.0441***
	(.0418)	**(.0330)**	**(.0270)**	**(.0239)**	**(.0223)**	**(.0211)**	**(.0228)**
CashPayment	.0191	-.0058	.0024	-.0066	-.0096	-.0003	.0043
	(.0375)	(.0157)	(.0119)	(.0116)	(.0100)	(.0114)	(.0113)
Ln(RelativeDealSize)	-.0068	-.0038	-.0013	.0008	.0014	-.0016	-.0036
	(.0086)	(.0057)	(.0049)	(.0045)	(.0038)	(.0041)	(.0041)
Ln(Assets)	-.0135	-.0065	-.0040	-.0021	.0010	-.0053	-.0069*
	(.0125)	(.0052)	(.0045)	(.0038)	(.0034)	(.0036)	(.0038)
Ln(MB)	-.0130	-.0028	-.0045	-.0033	-.0020	-.0084	-.0106*
	(.0179)	(.0086)	(.0071)	(.0060)	(.0047)	(.0055)	(.0061)
Public	-.0109	.0162	.0182	.0155	.0047	.0121	.0120
	(.0300)	(.0173)	(.0132)	(.0131)	(.0111)	(.0119)	(.0114)
Funds	-.0136	.0080	.0052	-.0068	-.0079	-.0084	-.0004
	(.0262)	(.0208)	(.0178)	(.0153)	(.0142)	(.0135)	(.0157)
Capital	-.0005	-.0080	-.0030	-.0146	-.0141	-.0155	-.0036

	(.0349)	(.0219)	(.0194)	(.0170)	(.0141)	(.0140)	(.0167)
RealEstate	.1305	.0624	.0453	.0319	.0133	.0257	.0270
	(.1296)	(.0390)	(.0363)	(.0357)	(.0251)	(.0333)	(.0295)
RegTech	-.0321	.0054	-.0139	-.0051	-.0147	-.0084	-.0024
	(.0411)	(.0276)	(.0245)	(.0230)	(.0171)	(.0194)	(.0197)
Insurance	-.0144	.0014	.0064	-.0188	-.0237	-.0133	.0049
	(.0335)	(.0253)	(.0211)	(.0181)	(.0179)	(.0196)	(.0210)
Obs.	146	146	146	146	146	146	146
R^2	.1451	.1729	.1526	.2003	.2331	.2212	.1861
Adj. R^2	-.0381	-.0044	-.0290	.0289	.0688	.0544	.0117
F-stat	1.39	1.70	1.30	1.78	2.06	1.74	1.46
Prob>F	.1439	.0435	.1939	.0312	.0096	.0375	.1115
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 9. Regression results hypothesis 4 (**alternative control variables: Tobin's Q and absolute Deal Size)**.

*Notes: This table summarizes the regression results for hypothesis 4, with the dependent variable being market-model based CAR. The coefficient of interest refers to the bank dummy, which indicates whether the acquiring firm was a traditional bank. Further, the control variables' coefficients are listed with the corresponding standard error in brackets below. The multivariate regression uses clustered standard errors at firm level (accordingly, 97 clustered are created). *, **, and *** indicate the statistical significance at the 0.1, 0.05, and 0.01 levels, respectively.*

Regarding the FinTech classification dummies: the payments/transaction dummy is used as the reference category. Further, given the logarithmic transformation of the Tobin's Q variable, two observations with negative observations drop out. Hence, the sample size is reduced to 144. Finally, the regression controls for time-fixed effects (incorporated using dummy variables for the year of the acquisition announcement).

Variables	**Acquisition Performance CAR(-t,+t)**						
	(-10,+10)	(-5,+5)	(-3,+3)	(-2,+2)	(-1,+1)	(-1,+2)	(-1,+3)
Constant	.1032	.0471	.0244	.0326	.0262	.0450*	.0456
	(.0688)	(.0385)	(.0311)	(.0279)	(.0249)	(.0259)	(.0287)
Bank	**-.0350**	**-.0143**	**-.0225**	**-.0315**	**-.0375***	**-.0304***	**-.0307**
	(.0319)	**(.0214)**	**(.0232)**	**(.0202)**	**(.0207)**	**(.0179)**	**(.0190)**
CashPayment	.0048	-.0051	.0013	-.0046	-.0067	-.0005	-.0021
	(.0285)	(.0138)	(.0108)	(.0105)	(.0105)	(.0109)	(.0107)
Ln(DealSize)	-.0059	-.0008	.0017	.0018	.0027	-.0014	-.0017
	(.0086)	(.0054)	(.0047)	(.0043)	(.0039)	(.0039)	(.0041)
Ln(Assets)	-.0047	-.0041	-.0038	-.0039	-.0010	-.0032	-.0026
	(.0080)	(.0043)	(.0038)	(.0037)	(.0031)	(.0033)	(.0032)
Ln(Tobin's Q)	-.0050	-.0035	-.0066	-.0052	-.0042	-.0043	-.0048
	(.0082)	(.0061)	(.0052)	(.0048)	(.0041)	(.0041)	(.0043)
Public	-.0040	.0185	.0213	.0108	-.0082	.0051	.0110
	(.0244)	(.0177)	(.0140)	(.0140)	(.0177)	(.0129)	(.0124)
Funds	-.0150	-.0015	-.0027	-.0115	-.0172	-.0136	-.0102
	(.0242)	(.0196)	(.0161)	(.0164)	(.0174)	(.0152)	(.0149)
Capital	.0092	-.0008	.0041	-.0060	-.0053	-.0078	.0008

	(.0278)	(.0191)	(.0172)	(.0168)	(.0152)	(.0141)	(.0149)
RealEstate	.1227	.0583	.0479	.0316	.0132	.0255	.0323
	(.1141)	(.0448)	(.0447)	(.0396)	(.0282)	(.0327)	(.0299)
RegTech	-.0402	.0046	-.0114	-.0048	-.0123	-.0092	-.0023
	(.0388)	(.0250)	(.0208)	(.0203)	(.0190)	(.0198)	(.0213)
Insurance	-.0416	-.0096	-.0002	-.0216	-.0298*	-.0197	-.0054
	(.0388)	(.0244)	(.0219)	(.0179)	(.0176)	(.0199)	(.0222)
Obs.	144	144	144	144	144	144	144
$\boldsymbol{R^2}$	.1925	.2091	.2124	.2267	.2240	.2358	.2207
Adj. $\boldsymbol{R^2}$	.0159	.0360	.0401	.0576	.0542	.0687	.0503
F-stat	1.54	1.89	1.69	1.76	1.82	1.83	1.75
Prob>F	.0837	.0200	.0450	.0347	.0265	.0258	.0352
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes