Fintech Acquisitions and Market Reactions: The Role of Information Asymmetry and Pandemic Shocks

Ying Shi[a] and Takashi Hatakeda[b]

[a]Graduate School of Business Administration, Kobe University
Rokkodai 2-1, Nada, Kobe 657-8501, Japan
221b105b@stu.kobe-u.ac.jp

[b]Graduate School of Business Administration, Kobe University
Rokkodai 2-1, Nada, Kobe 657-8501, Japan
hatakeda@kobe-u.ac.jp

[a]Corresponding author: Ying Shi

Abstract

As financial technology (fintech) startups reshape the financial sector, traditional financial institutions are increasingly engaging in fintech acquisitions. This study investigates whether investor reactions to fintech acquisitions differ from those to non-fintech deals, especially during the COVID-19 pandemic. We focus on the role of information asymmetry, which arises from valuation challenges and uncertainties related to post-acquisition integration. Based on 398 acquisition deals by Japanese financial institutions, we find that fintech acquisitions trigger significantly more negative investor reactions. Causal mediation analysis shows that this effect is partly explained by information asymmetry. The negative response intensifies during the pandemic but returns to normal levels afterward. Robustness checks using alternative return measures, propensity score matching, and double machine learning with LASSO, Ridge, and SVM confirm these results. Further analysis shows that the negative impact is stronger when information asymmetry is likely to be higher, such as in acquisitions involving younger targets or larger deal sizes. We also find that negative reactions are more pronounced for non-bank acquirers and firms with higher financial leverage.

Keywords: Information asymmetry; Fintech acquisitions; Market reactions

1. Introduction

The financial industry has undergone substantial transformation in recent years, largely driven by the rise of financial technology (fintech) firms. As of 2024, over 29,000 active fintech firms are operating globally[1]. These firms offer innovative products, services, and new concepts that traditional financial institutions have historically not provided. Characterized by agility and innovation, fintech firms exert considerable pressure on traditional financial institutions, compelling them to accelerate their digital transformation efforts (Milian et al., 2019).

In response, many traditional financial institutions have intensified their innovation initiatives. However, internally developed digital solutions often lag behind those of fintech startups in terms of cost efficiency or user experience (Akhtar & Nosheen, 2022). Consequently, acquiring fintech startups has become an increasingly popular strategy for traditional financial institutions—both to gain access to external technological expertise and to reduce competitive threats (Akhtar & Nosheen, 2022; Collevecchio et al., 2024; Kueschnig & Schertler, 2024). The COVID-19 pandemic further intensified this trend by accelerating the demand for digital financial services, prompting institutions to pursue fintech acquisitions more aggressively.

However, fintech acquisitions pose a distinct challenge for market investors: information asymmetry—that is, the difficulty in accessing the same level of information as firm managers regarding the transaction. Reliable information is critical for market investors to accurately assess the potential risks and benefits of mergers and acquisitions (M&A). M&A announcements often trigger a surge in information asymmetry, which can negatively impact market reactions (Howe & Morillon, 2020). Managers typically have access to more detailed and first-hand information through the due diligence process and negotiation processes than investors. They also possess material knowledge derived from their involvement in their firms' daily operations, which allows them to evaluate potential synergies of the impending transaction more accurately than market investors (Hassan & Alhenawi, 2022). In response to such heightened information asymmetry, investors demand compensation for the information disadvantage. This is typically reflected in the discounting of the acquirer's stock price following the M&A announcement, as market investors adjust their valuation downward to reflect the uncertainty and information disadvantage they face (Malmendier & Tate, 2008; Song et al., 2021). Compared to conventional acquisitions, the

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[1] Data source: Statista. Number of fintechs worldwide from 2008~2024, by region. https://www.statista.com/statistics/893954/number-fintech-startups-by-region/

acquisitions of fintech firms tend to exacerbate information asymmetry between the acquirer and market investors. This is largely due to the challenges in valuing the intangible nature of fintech assets, and the integration risks—particularly whether a traditional financial institution can effectively absorb and utilize a technology-oriented target.

While a growing body of empirical research examines market reactions to fintech acquisitions, findings remain mixed—ranging from significantly positive to negative or statistically insignificant effects (Carlini et al., 2022; Kueschnig & Schertler, 2024; Zheng & Mao, 2024). Recent studies also highlight the role of macroeconomic conditions in shaping these reactions (Ochirova & Miriakov, 2025). A common limitation of this literature is its exclusive focus on fintech acquisitions, without comparison to non-fintech acquisitions (Kueschnig & Schertler, 2024). Consequently, it remains unclear whether investor responses to fintech acquisitions systematically differ from those to other deals—and if so, whether this difference persists over time or varies in response to external shocks such as the COVID-19 pandemic.

The COVID-19 pandemic offers a unique quasi-natural experiment to explore this question. While most industries suffered from economic uncertainty, the crisis accelerated digital adoption and widespread use of fintech services. This exposure made investors and consumers more familiar with fintech business models and revenue structures, potentially reducing information asymmetry between firms and capital markets. However, at the same time, the heightened uncertainty during the pandemic may have increased investors' sensitivity to information gaps, leading to greater demand for compensation for perceived risks—just as in other industries. These opposing forces make fintech acquisitions particularly relevant for analyzing heterogeneous investor reactions under varying macroeconomic conditions.

Using a sample of 398 acquisition deals by traditional financial institutions from 2015 to 2024, this study examines the role of information asymmetry in shaping market investor reactions to fintech acquisitions. We find that the announcements of fintech acquisitions trigger more negative market reactions than those of non-fintech acquisitions. A causal mediation analysis confirms that information asymmetry significantly contributes to this effect. We also investigate how this relationship evolved during the COVID-19 pandemic, finding that investor reactions became significantly more negative during the pandemic period. However, compared to the pre-pandemic period, investor reactions in the post-pandemic period do not show a significantly more postive or negative response.

To address potential selection bias, we employ a propensity score matching difference-in-differences (PSM-DID) approach. After matching the treatment and control groups and verifying the parallel trends assumption, our results remain robust. The findings also hold when alternative measures of market reaction are applied.

Furthermore, we incorporate a Double Machine Learning (DML) to validate the robustness of our findings. DML method is recognized as a breakthrough in causal inference (Yin et al., 2025). Compared to the traditional regression method, DML method allows for flexible estimation by addressing both nonlinearity and the high dimensionality of control variables (Chernozhukov et al., 2018). It also employs cross-fitting to mitigate overfitting and model misspecification. By leveraging machine learning techniques including LASSO, Ridge, and SVM, it enhances estimation accuracy and further supports the robustness of our results.

Fintech acquisitions receive a more negative market reaction due to the heightened information asymmetry which arises from the difficulty to valuation and the risk associated with post integration between two difference industry. To verify this possible mechanism, we test two channels that may amplify information asymmetry: target firm age and deal size. Younger targets often lack transparent financial histories, making their valuation more uncertain. Meanwhile, larger deals relative to the acquirer's size are typically have higher post integration risk. By examining these channels, we aim to clarify whether the negative investor reactions to fintech acquisitions are amplified under conditions that heighten information asymmetry.

Finally, we conduct three cross-sectional analyses to explore heterogeneity in investor reactions based on the acquirer's industry and financial structure. Specifically, we show that the negative market reaction to fintech acquisitions is more prominent for acquisitions of young targets and acquirers with higher leverage. Moreover, during the COVID-19 pandemic, this negative effect is particularly significant for non-bank acquirers and those with higher leverage ratios.

The contributions of this study are as follows. First, this study confirms that information asymmetry is a key mechanism driving negative investor reactions to fintech acquisition announcements. While prior studies have reported mixed market responses—ranging from negative to insignificant effects—these inconsistencies may stem from variations in sample periods and the omission of investor responses to information asymmetry. This gap is particularly relevant in the context of fintech, where the COVID-19 pandemic heightened both uncertainty and reliance on fintech solutions. These changes likely amplified the role of information asymmetry in shaping investor behavior. By considering this dynamic, our study helps reconcile the divergent findings in earlier literature.

Second, existing research on fintech M&A has predominantly focused on Western markets characterized by relatively transparent information environments. However, not all markets operate under such conditions. We select Japan as our research setting due to its higher degree of information frictions resulting from a less mature private equity market compared to the U.S. or U.K. This context enables us to explore how information asymmetry affects market reactions in less mature or less transparent capital markets, offering insights that may inform studies in other emerging or less transparent markets.

Third, existing research has shown that public health events, such as SARS and COVID-19, tend to affect financial markets in comparable ways (Ru et al., 2021). Our findings may serve as a reference for future external shocks of a similar nature. Specifically, understanding how pandemics exacerbate investor sensitivity to information asymmetry can help regulators and firms develop more effective communication and disclosure strategies during such crises.

2. Literature review

2.1 Impact of fintech acquisitions on financial institutions

Previous research has explored the impact of fintech acquisitions on financial institutions from various theoretical perspectives. According to synergy theory, fintech acquisitions are expected to generate greater value for both the acquiring and target firms than they would achieve independently, either through cost reduction or revenue enhancement (Ismail, 2011). Empirical studies have shown that, in the long term, fintech acquisitions can enhance the financial performance of acquiring firms, improve innovation output, and support strategic transformation (Akhtar & Nosheen, 2022; Y. Wang, 2024; Zheng & Mao, 2024). Similar to other types of M&A transactions, fintech acquisitions can create value through informational synergies (Zhang et al., 2024). Drawing on signaling theory, a firm's first fintech acquisition is often perceived by investors as a credible signal of commitment to a digital future, resulting in a stronger positive stock price reaction compared to subsequent fintech deals (Kueschnig & Schertler, 2024). However, market responses are not uniformly positive. Some studies suggest that the complexity of integrating divergent business models can lead to negative investor reactions, particularly in cases of full fintech acquisitions (Cappa et al., 2022). Furthermore, these responses can vary depending on macroeconomic conditions such as GDP growth or inflation rates (Ochirova & Miriakov, 2025).

Despite these contributions, the role of information asymmetry in fintech acquisitions remains underexplored. Information asymmetry plays a critical role in shaping market reactions, especially in M&A settings where investors must assess uncertain future synergies based on incomplete information. The accuracy of these assessments depends heavily on the availability and quality of data. This challenge is particularly pronounced in fintech acquisitions, where complex technologies and novel business models further widen the information gap between acquirers and investors. Therefore, addressing this gap is critical for a more nuanced understanding of the heterogeneous market responses to fintech-related M&A transactions.

2.2 Heightened information asymmetry in fintech acquisitions

Compared to other acquisition types, the acquisitions of fintech firms are characterized by higher levels of information asymmetry. This heightened asymmetry arises from two main sources. First, fintech firms, like other companies in technology-related industries, rely heavily on research and development (R&D) as a core driver of innovation and growth. However, R&D investment introduces significant information opacity because (1) R&D projects are often unique and firm-specific, limiting external comparability; (2) they lack observable market prices, making valuation inherently subjective; and (3) accounting standards restrict the transparent reporting of R&D productivity and future value (Aboody & Lev, 2000). Collectively, these factors hinder external investors' ability to accurately assess the intrinsic value of fintech acquisition targets.

Second, there is considerable uncertainty in evaluating post-merger integration outcomes. Fintech firms often differ significantly from traditional financial institutions in terms of organizational structure, technology, business models, and corporate culture. These differences complicate integration processes and increase the risk that anticipated synergies or performance improvements will not be realized (Buono et al., 1985; Oh & Johnston, 2020). Consequently, investors face greater difficulty in assessing post-merger risks and synergies, further exacerbating the degree of information asymmetry surrounding fintech-related M&A deals.

Based on these considerations, we propose the following hypothesis:

H1: Fintech acquisitions by financial institutions elicit more negative market reactions than non-fintech acquisitions, due to higher levels of information asymmetry.

2.3 COVID-19 and amplified information asymmetry

The negative impact of information asymmetry on market reactions is likely to be amplified during the COVID-19 pandemic. Existing studies indicate that in periods of heightened environmental uncertainty, market investors demand greater compensation for bearing risk. For instance, Pastor and Veronesi (2013) develop a general equilibrium model of government policy choice and show that the premium required for political uncertainty increases under weaker economic conditions. Similarly, Gortz and Yeromonahos (2022) employ various measures to demonstrate that overall risk premia rise sharply during recessions. One explanation for this phenomenon lies in investor sentiment. Events such as infectious disease outbreaks can trigger fear, leading to negative shifts in investor sentiment that significantly influence investment decisions and, in turn, stock market performance (H. Liu et al., 2020). In such environments, investors become more sensitive to incomplete or ambiguous information, thereby intensifying the negative market response to information asymmetry.

The COVID-19 pandemic has substantially heightened environmental uncertainty (S. Liu et al., 2023). The macroeconomic landscape and business operating conditions have changed dramatically, rendering much of the historical data less informative and reducing their predictive value. This makes it more challenging for investors to make accurate judgments based on available information. In such an environment, market investors are expected to request more compensation for bearing risks associated with information asymmetry in acquisition deals. Moreover, given the inherently opaque nature of fintech firms, as previously discussed, it is expected that M&A transactions involving fintech firms will trigger stronger negative market reactions during the pandemic.

Therefore, we propose the following hypothesis:

H2a: The negative market impact of information asymmetry in fintech acquisitions becomes more pronounced than in non-fintech acquisitions during the COVID-19 pandemic.

However, the pandemic has also created unique growth opportunities for the fintech sector. On the demand side, restrictions on in-person activities and the need for social distancing have accelerated the adoption of digital and contactless financial services (Fu & Mishra, 2022). A surge in financial app downloads following the COVID-19 outbreak reflects a widespread shift toward fintech solutions. On the supply side, traditional financial institutions have expanded their fintech offerings. Together, these developments have reinforced the growth prospects of the fintech industry, potentially distinguishing it from other industries that were more adversely affected during and after the pandemic.

As a result, despite heightened information asymmetry and risk perceptions during the pandemic, investors have become more familiar with fintech firms' business models, user bases, and growth potential. This increased familiarity has enhanced their ability to process relevant information, thereby reducing the negative market reactions typically associated with information asymmetry. Accordingly, we propose the following alternative hypothesis:

H2b: The negative market impact of information asymmetry in fintech acquisitions becomes less pronounced than in non-fintech acquisitions during the COVID-19 pandemic.

3. Data collection and descriptive statistics

3.1 Data collection

M&A transaction data are obtained from the Securities Data Company Platinum database based on the following selection criteria:

a. The sample period spans from 2015 to 2024. The year 2015 is commonly recognized as the "first year of fintech" in Japan, marking the point at which financial institutions and government agencies began implementing formal fintech-related initiatives.

b. Acquirers are limited to traditional financial institutions, including banks, brokerages, insurance companies, credit institutions, and other intermediaries such as miscellaneous intermediation, real estate credit providers, and offices of bank holding companies.

c. Financial M&A transactions that are primarily investment-driven, such as those involving venture capital or private equity firms, are excluded.

d. All acquirers are publicly listed firms at the time of the transaction.

e. To avoid bias from very small transactions, we restrict the sample to transactions with a disclosed value > JPY 150 million (approximately USD 1 million).

After excluding observations with missing data for key variables, our final sample comprises 398 observations.

3.2 Variable measurement

3.2.1 Independent variable

The first independent variable, *fintech*, is defined as a dummy variable that equals 1 if the transaction is identified as a fintech acquisition, and 0 otherwise. Following Wang(2024), a fintech acquisition is defined as a transaction in which the acquirer is a financial institution, and the target firm operates in the technology industry.

To account for the temporal effects of the COVID-19 pandemic, we construct a categorical variable, *COVID*, representing three distinct periods: “before” for the pre-pandemic period (2015.01–2019.12), “during” for the pandemic period (2020.01–2023.04), and “post” for the post-pandemic period (2023.05–2024.12). This classification reflects the key stages of the pandemic and the corresponding shifts in public health policy. The first confirmed COVID-19 case in Japan was reported on January 16, 2020, marking the onset of potential pandemic-related market disruptions. In May 2023, the World Health Organization declared the end of the global public health emergency. Subsequently, the Japanese government reclassified COVID-19 from Category II to Category V under the Infectious Disease Control Law, signaling the end of the pandemic period.

3.2.2 Dependent variable

To examine market reactions to the announcement of fintech acquisitions by financial institutions, we employ an event study methodology. Specifically, we calculate cumulated abnormal returns (CARs) over two event windows: [–1, 3] and [–1, 5], given time 0 as the date of the announcement. Abnormal returns are estimated using the Fama-French three-factor model over the estimation window of 270 to 21 trading days prior to the announcement event. *CAR* is computed as the sum of these abnormal returns, as specified in the following equation:

$$AR_{i,T} = R_{i,T} - [\alpha + \beta_1 * (Rm_T - Rf_T) + \beta_2 * SMB_T + \beta_3 * HML_T] \tag{1}$$

$$CAR[t_1, t_2]_{i,t} = \sum_{T=t_1}^{T=t_2} AR_{i,T} \tag{2}$$

3.2.3 Control variables

We also include several control variables to account or potential impact. First, we control for the transaction characteristics, including *dv_log*, as the natural logarithm of deal value; *pct_acq*, as the percentage of the acquisition; *cash*, a dummy variable that equals 1 if the payment is made by cash, 0 otherwise; *cross_border*, a dummy variable that equals 1 if the M&A transaction is a cross border deal, 0 otherwise; and *first_fintech*, a dummy variable that equals 1 if the fintech acquisition is the acquirer's first fintech acquisition. Second, we control for the target characteristic by including *t_public*, a dummy variable that equals 1 if the target is a public firm. Third, we also control for acquirers' characteristics, including *tobin_q*, as the ratio of acquirers' market value to book value; *bm*, as the ratio of book value to market value; *bl*, as the natural logarithm of the number of business line; and *assets*, as the natural logarithm of acquirers' total assets. We also include *topix*, as the natural logarithm of the TOPIX index to control the impact of the macro environment, and *ipo_deals*, as the number of new initial public offering (IPO) deals for each month. Appendix A presents a detailed description of the study's variables.

3.3 Descriptive statistics

Panels A and B in Table 1 show the annual and industry distributions of samples. Panel A presents the distribution of the number of samples by year. Out of a total of 398 transactions, 33 deals are identified as fintech acquisitions, while the remaining 365 deals are non-fintech acquisitions. We observe that the number of M&A transactions within our samples gradually increase over the sample period. Although the number of fintech transactions remains relatively low throughout the sample period, they show a modest upward trend in recent years, peaking at 9 cases in 2023.

Panel B presents the distribution of the number of samples by industry. Banks represent the largest share of M&A activity with 166 transactions, followed by brokerage (94 deals) and insurance firms (80 deals). Fintech acquisitions are most concentrated in the brokerage sector, accounting for approximately 42% of all fintech-related transactions in the sample. This is followed by the banking sector (27%) and the insurance sector (15%), suggesting that brokerages are comparatively more active in acquiring fintech firms than other traditional financial institutions.

Insert Table 1 Here

Table 2 reports the mean, standard deviation, and median for the full sample of 398 transactions, as well as for the fintech acquisitions (n = 33) and non-fintech acquisitions (n = 365) subsamples. Column 10 presents univariate comparisons of transaction characteristics between fintech and non-fintech acquisitions.

Insert Table 2 Here

For the main dependent variable, *CAR*, both CAR windows (CAR[–1, 3] and CAR[–1, 5]) exhibit positive mean values across the full sample. However, the medians are lower than the means, suggesting a right-skewed distribution with several large positive outliers. The relatively large standard deviations further indicate substantial variability across observations. Column 10 of Table 2 compares acquirers' CARs between fintech and non-fintech acquisitions. We find that fintech acquisition announcements are associated with significantly more negative market reactions. Specifically, the difference in CAR[–1, 3] is negative and statistically significant, supporting H1.

Regarding the main independent variable, *COVID*, approximately 41.4% of all deals occurred before the COVID-19 pandemic, 35.3% during the pandemic, and 23.3% after. The distribution is broadly similar between fintech and non-fintech acquisitions. A chi-square test of independence reveals no statistically significant association between the timing of the transaction (pre-, during-, or post-pandemic) and the likelihood of a transaction being a fintech acquisition ($\chi^2 = 1.82$, $p = 0.403$). This suggests that the distribution of fintech and non-fintech acquisitions across the pre-pandemic, pandemic, and post-pandemic periods does not statistically differ.

Regarding the transaction characteristics, the average deal value (*dv_log*) of fintech acquisitions is significantly lower than that of non-fintech acquisitions. Notably, 48% of fintech acquisitions in the sample represent the acquirer's first fintech transaction (*first_fintech*). No statistically significant differences are observed between fintech and non-fintech acquisitions in terms of ownership percentage acquired (*pct_acq*), payment method (*cash*), or cross-border status (*cross_border*).

Regarding the target characteristics, 62% of non-fintech acquisitions involve public targets (*t_public*), compared to 45% for fintech acquisitions. This 17% difference is statistically significant at the 10% level, suggesting that financial institutions are more likely to acquire public targets in non-fintech acquisitions.

Regarding acquirers' characteristics, the acquirers of non-fintech acquisitions have a significantly higher book value to market value (*bm*) at the 1% level, implying that they are more likely to be value-oriented firms, potentially reflecting more conservative investment strategies. The acquirers of fintech deals tend to operate across more business lines (*bl*). Other variables—including firm size (*assets*), market index (*topix*), and new IPO deals in the acquisition month (*ipo_deals*)—do not differ significantly between fintech and non-fintech acquisitions.

4. Empirical results

4.1 Impact of the announcement of fintech acquisitions and market investors' reactions

4.1.1 Non-parametric test

We begin our analysis by investigating whether announcements of fintech acquisitions by financial institutions arouse more negative market reactions compared to announcements of other types of acquisitions. For that purpose, we first conduct non-parametric tests to compare CARs between fintech and non-fintech deals. To further validate the findings and control for potential confounding factors, we estimate regression models with industry- and year-fixed effects.

For the non-parametric tests, we calculate cumulative average abnormal returns (CAARs) by averaging the CARs across all transactions (*N*) within a specified event window, as follows:

$$CAAR_{i,t} = \frac{1}{N} * \sum_{i,t} CAR_{i,t}$$

To test the CAAR's statistical significance, we employ the KP test proposed by Kolari and Pynnönen (2010), which improves upon the traditional event study t-test by accounting for clustering effects commonly observed in M&A deal waves. As a non-parametric alternative, we also apply the generalized rank (GRANK) test proposed by Kolari and Pynnönen (2011). This test enhances the robustness of our analysis by relaxing the assumption of normally distributed returns.

Table 3 presents the results. The CAARs for non-fintech acquisitions over the [–1, 3] and [–1, 5] event windows are significantly positive according to the KP and GRANK tests. By contrast, all CAARs for fintech acquisitions are negative but not statistically significant. These findings suggest that market reactions to fintech M&As are significantly more negative than those to non-fintech M&As, consistent with H1.

Insert Table 3 Here

4.1.2 Regression model

To further examine the differences in market reactions between fintech and non-fintech acquisitions, we estimate the following regression model:

$$CAR_{i,t} = \alpha + \beta_1 fintech_i + \beta_2 Controls_{i,t} + \lambda_j + \varphi_j + \varepsilon_{i,t} \quad (3)$$

where *i* and *t* denote the financial institution and year, respectively. λ_j and φ_j represent the industry- and year- dummy variables, $\varepsilon_{i,t}$ is the error term. The dependent variable is *CAR*, calculated over two event windows: CAR[–1, 3] and CAR[–1, 5]. The independent variable, $fintech_i$, is a binary indicator equal to 1 if the acquisition is classified as fintech-related, and 0 otherwise. Appendix A provides a detailed description of the controls.

Columns 1 and 3 in Table 4 present the regression results. Column 1 shows that the announcement returns for fintech acquisitions, measured by CAR[–1, 3], are 3.477% lower than those for non-fintech acquisitions, a statistically significant difference. Similarly, Column 2 indicates that when the event window is extended to 6 days (CAR[–1, 5]), the announcement returns are 4.287% lower and significant at the 5% level. These results support H1 that fintech acquisitions are associated with more negative market reactions upon announcement.

Insert Table 4 Here

4.2 Impact of COVID-19 on the announcement of fintech acquisitions

In this section, we examine the impact of COVID-19 on the announcement effect of fintech acquisitions using the following regression model:

$$CAR_{i,t} = \alpha + \beta_1 fintech_i + \beta_2 COVID_{i,t} + \beta_3 fintech_i * COVID_{i,t}$$
$$+\beta_4 Controls_{i,t} + \lambda_j + \varphi_j + \varepsilon_{i,t} \qquad (4)$$

where the primary variable of interest is the interaction term between $fintech_i * COVID_{i,t}$. All control variables, as well as industry- and year- dummy variables are consistent with those used in Eq (1).

Columns 2 and 4 in Table 4 present the regression results. The coefficients of the interaction term between *fintech* and *COVIDduring* are significantly negative in both columns, implying that announcements of fintech acquisitions are associated with more negative market reactions during the COVID-19 pandemic. This finding supports H2a, suggesting that although fintech firms received increased attention during the pandemic, market investors reacted more negatively due to heightened information asymmetry in a riskier environment. In other words, elevated expectations for fintech firms were insufficient to offset investors' amplified sensitivity to information asymmetry, leading to stronger negative market responses toward fintech-related acquisitions during this period. However, the interaction term between *fintech* and *COVIDpost* is statistically insignificant, suggesting that the negative market reactions did not persist beyond the pandemic. Instead, investor responses appear to have reverted to levels comparable to those observed prior to COVID-19.

4.3 Mediation mechanism test

To assess whether the higher level of information asymmetry in fintech acquisitions contributes to more negative investor reactions, we conduct a causal mediation mechanism analysis.

Previous studies suggest that elevated information asymmetry reduces investors' willingness to trade, thereby decreasing stock liquidity (Schoenfeld, 2017; F. Wang et al., 2022). Accordingly, we use stock liquidity as a proxy for information asymmetry. Following Amihud (2002), we measure changes in illiquidity within two event windows—[–1, 3] and [–1, 5]—as indicators of information asymmetry. The Amihud illiquidity measure (*ILLIQ*), a widely used proxy for stock illiquidity, is calculated as the daily ratio of the absolute stock return to its dollar trading volume, averaged over a specified period. To capture shifts in liquidity around acquisition announcements, we calculate the difference in *ILLIQ* between a pre-announcement window of [–90, –30] and a post-announcement window of either [–1, 3] or [–1, 5]. A significant mediation effect would suggest that fintech acquisitions lead to increased information asymmetry—manifested as reduced liquidity—which, in turn, contributes to more negative market reactions.

Table 5 presents the results of the mediation analysis based on 1,000 bootstrap simulations. Panel A shows that for CAR[–1, 3] (*ΔILLIQ[–1, 3]*), the average causal mediation effect (ACME) is –0.299 ($p = 0.046$), indicating a marginally significant indirect effect through stock liquidity. The average direct effect remains significantly negative at –3.179 ($p = 0.006$), with a total effect of –3.477 ($p < 0.001$). Approximately 8.6% of the total effect is mediated through the change in liquidity.

The results are consistent when using CAR[–1, 5] and (*ΔILLIQ[–1, 5]*) as outcome variables. The ACME is –0.575 ($p = 0.024$), the direct effect is –3.712 ($p < 0.001$), and the total effect is –4.287 ($p < 0.001$). The proportion mediated remains at 13.4%, reinforcing the role of stock liquidity as a partial channel through which fintech acquisitions influence market reaction.

Collectively, these findings suggest that the negative CARs associated with fintech acquisitions are partly driven by a decline in stock liquidity, a proxy for information asymmetry. This supports the notion that information asymmetry serves as a mediating mechanism in shaping investor reaction to fintech acquisition announcements.

Insert Table 5 Here

4.4 Robustness checks and endogeneity

4.4.1 Difference-in-difference with PSM

The main analysis indicates that market investors respond more negatively to announcements of fintech acquisitions than to those of non-fintech acquisitions. However, these findings may be subject to selection bias, as fintech acquisitions could systematically differ from non-fintech acquisitions in observable characteristics. Therefore, to further address this potential bias, we employ a PSM technique. Specifically, we implement a nearest-neighbor matching procedure using one-to-five matching with replacement. Matching is conducted based on transaction-level, target-level, acquirer-level, and macroeconomic variables, consistent with those employed in the main analysis (except *first_fintech*). This approach pairs fintech acquisition deals (treatment group) with comparable non-fintech acquisition deals (control group)[2]. To evaluate the quality of the matching, we examine the mean differences in covariates between the treatment and control groups. Panel A of Table 6 presents these results. None of the mean differences in these variables are statistically significant, indicating that the treatment and control groups are well balanced in terms of the transaction-level, acquirer-level, and macro-level characteristics.

Using the matched sample, we conduct a DID analysis to estimate the dynamic effects of fintech acquisition announcements, particularly in the context of the COVID-19 pandemic. We first test the parallel trends assumption. As Panel B of Table 6 shows, the coefficients on the interaction terms for the pre-COVID periods are statistically insignificant, suggesting no systematic differences in CAR trends between the treatment and control groups before the pandemic. This finding supports the validity of the parallel trends assumption underlying the DID methodology.

Panel C in Table 6 presents the results of the PSM-DID analysis. Columns 1 and 3 indicate that, even after controlling for selection bias, market investors continue to respond more negatively to fintech acquisition announcements compared to non-fintech ones. Columns 2 and 4 further reveal that this negative market reaction intensifies significantly during the COVID-19 period.

[2] The results remain robust when we use matching with replacement.

These findings remain consistent with the results of the main analysis.

Insert Table 6 Here

4.4.2 Double Machine Learning

As a robustness check, we adopt the Double Machine Learning (DML) framework. DML method is recognized as a breakthrough in causal inference, which offers advantages over traditional estimation methods such as Ordinary Least Squares (OLS) (Yin et al., 2025). Comparing to OLS, DML method improves the estimation process by (1) avoiding the need to specify functional forms for control variables in advance; (2) reducing estimation bias caused by high-dimensional control variables through regularization and machine learning techniques (Chernozhukov et al., 2018). We employ Lasso, Ridge, and Support Vector Machine (SVM) models within the DML framework.

The empirical implementation of Double Machine Learning proceeds in the following steps:

First, we begin the partially linear DML model as:

$$CAR_{i,t} = \beta_1 fintech_i + g(Controls_{i,t}) + \varepsilon_{i,t},\ E(\varepsilon | fintech_i, Controls) = 0 \tag{5}$$

where $CAR_{i,t}$ *is the outcome variable,* $fintech_i$ *is the treatment variable,* $Controls_{i,t}$ *is a set of control variables, which is the same as the regression in Eq(1). The specific functional form* $g\left(Controls_{i,t}\right)$ *is unknown and needs to be estimated through machine learning.*

Second, to control for endogeneity, we express the treatment variable as a function of the controls:

$$fintech_i = \gamma_1 m(Controls_{i,t}) + \nu_{i,t},\ E(\nu_i | Controls_{i,t}) = 0 \tag{6}$$

where ν_i represents the error term, with a conditional mean of 0. the specific functional form $m\left(Controls_{i,t}\right)$ is unknown and needs to be estimated through machine learning.

Third, we construct the reduced-form equation by substituting Eq(6) into Eq(5):

$$CAR_{i,t} = \eta_1 Controls_{i,t} + \mu_{i,t},\ E\left(\mu_{i,t} \middle| Controls_{i,t}\right) = 0 \tag{7}$$

where $\eta = \beta_1\gamma_1 + \beta_2$ and $\mu_{i,t} = \beta_1\nu_{i,t} + \varepsilon_{i,t}$.

Fourth, we employ machine learning techniques (LASSO, Ridge and SVM) to estimate the $g(Controls_{i,t})$ and $m(Controls_{i,t})$ from Eq(6) and Eq(7).

To ensure unbiased estimation in DML, we implement cross-fitting procedure. The dataset is randomly divided into K folds. For each fold K, the model is trained on the other K-1 folds to estimate $\hat{g}(Controls_{i,t})$ and $\widehat{m}(Controls_{i,t})$, and the residuals are computed on the held-out fold K ($\widehat{v_{\iota,t}}_K, \widehat{u_{\iota,t}}_K$).

Lastly, we stack the residuals $\widehat{v_{\iota,t}}_K$ and $\widehat{u_{\iota,t}}_K$ from the K fold to form $\widehat{v_{\iota,t}}$ and $\widehat{\mu_{\iota,t}}$ and then perform OLS estimation of $\widehat{\mu_{\iota,t}}$ on $\widehat{v_{\iota,t}}$ to compute the β_1.

$$\widehat{\beta_1} = \left(\sum_{k=1}^{K} \widehat{v_{\iota,t}}_k{}^T \widehat{v_{\iota,t}}_k\right)^{-1} \left(\sum_{k=1}^{K} \widehat{v_{\iota,t}}_k{}^T \widehat{u_{\iota,t}}_k\right)$$

Panel A, Panel B and Panel C in Table 7 present the DML estimation results using three different machine learning methods: LASSO, Ridge regression, and SVM. Across all model specifications, we consistently find that fintech acquisitions trigger more negative market reactions compared to non-fintech acquisitions. Moreover, this negative effect is more pronounced during the COVID-19 pandemic, but tends to disappear in the post-pandemic period. These findings are consistent with the conclusions drawn from our earlier analyses.

Insert Table 7 Here

4.4.3 Alternative measures of CARs

In the earlier analysis, we measured investor reactions using CARs estimated with the Fama-French three-factor model. To ensure the robustness of the findings, we re-estimate the CARs using the market index (*TOPIX*) as an alternative benchmark. Furthermore, following previous studies, we employ average abnormal return (AAR) as an alternative measure of market reaction. AAR is defined as the average daily abnormal return over the event window (Tunyi et al., 2024). We calculate the AAR using the Fama-French three-factor model. Panels A and B of Table 8 present the results. Regardless of the method used to measure market reactions, we find that fintech acquisitions receive more negative market reactions than non-fintech acquisitions. This negative effect is more pronounced during the COVID-19 pandemic and dissipates in the post-pandemic period. These findings are consistent with the conclusions drawn from our earlier analysis.

Insert Table 8 Here

4.5 Possible channel analyses

The baseline hypothesis suggests that market investors respond more negatively to fintech acquisitions due to heightened information asymmetry, which stems from valuation challenges and integration uncertainties. Accordingly, we expect that factors intensifying valuation difficulties or integration risks will impact the negative market reaction.

4.5.1 The impact of targets' age

Firstly, we examine whether the targets' age affects market investors reactions to the announcement of fintech acquisitions. Younger firms tend to have more limited operating histories and less transparent financial records, making them harder to value and thus subject to greater information asymmetry to market investors (Baker & Wurgler, 2006). The sample is divided into two subsamples based on the median age (t_age=25): young targets and old targets.Based on this context, we expect that market investors will react more negatively to fintech acquisition announcements of younger targets.

Panel A of Table 9 presents the results[3]. For young target group, the coefficient of fintech is nagative for CAR[-1,5]. The coefficient of the interaction term between fintech and COVIDduring is significantly negative, but only for young target group. The findings suggest that the market reacts more negatively to fintech acquisitions of young target firms,especially in the context of the COVID-19 pandemic, supporting the view that the market investors' reactions will be more negatively to fintech acquisitions when the targets has a larger level of information asymmetry.

4.5.2 The impact of deal size

Secondly, we examine whether the targets' size affects market investors reactions to the announcement of fintech acquisitions. A higher deal value to acquirer's total Assets ratio indicates a heavier burden relative to firm size, which may strengthen post-merger integration risks and thus increase market concerns, particularly in fintech acquisitions where information asymmetry is already high. In this subsection, the sample is divided into two subsamples based on the median *dv_a_assets* (dv_a_assets = 0.0012781): high *dv_a_assets* group and *low dv_a_assets* group. Based on this context, we expect that market investors will react more negatively to fintech

[3] One firm was excluded from the sample due to a missing founding date, resulting in a final sample of 397 firms.

acquisition announcements of acquirer's who have a higher *dv_a_assets*.

Panel B of Table 9 presents the results. For high *dv_a_assets* group, the coefficient of fintech is nagative for CAR[-1,5]. The coefficient of the interaction term between fintech and COVIDduring is significantly negative, but only for high *dv_a_assets* group. The findings suggest that the market reacts more negatively to fintech acquisitions undertaken by acquirers that bear a higher level of post-merge integration risk, particularly in the context of the COVID-19 pandemic. This supports the view that market investors respond more negatively to fintech acquisitions when the level of information asymmetry associated transactions is greater.

Insert Table 9 Here

4.6 Further analysis

In this section, we conduct a cross-sectional analysis to examine how the impact of fintech acquisitions on stock market reactions varies by acquirer's characteristic-industry and leverage level.

4.6.1 The impact of acquirers' industry

To examine whether the acquirer's industry affects market investors' reactions to the announcement of fintech acquisitions, we divide the sample into two subsamples: bank and non-bank acquirers. Unlike other financial institutions, banks are generally more risk-averse, less profit-driven, and subject to stricter regulatory oversight. In Japan, major banks, such as the "megabanks" (e.g., MUFG, SMFG, Mizuho), are considered systemically important financial institutions, with strong governmental and regulatory ties. Prior research has shown that these institutions are perceived to enjoy implicit safety net subsidies because they are "too systemically important to fail"(Molyneux et al., 2014). The perceived safety net enhances investor confidence, even in the face of potentially risky strategies such as acquisitions, by reducing the perceived likelihood of catastrophic failure. Based on this context, we expect that market investors will react more negatively to fintech acquisition announcements made by non-bank acquirers, particularly during the COVID-19 period, characterized by uncertainty and heightened risk perceptions.

Panel A of Table 10 presents the results. The coefficient of *fintech* on CAR[–1, 3] is significantly negative for non-bank acquirers. Similarly, the coefficient of the interaction term between fintech and COVIDduring is significantly negative, but only for non-bank acquirers.

These findings suggest that the market reacts more negatively to fintech acquisitions by non-bank acquirers, particularly in the context of the COVID-19 pandemic. In contrast, fintech acquisitions by banks appear to be received more favorably, likely due to investors' perception of a regulatory safety net that mitigates concerns about information asymmetry.

4.6.2 The impact of acquirers' leverage

Next, we examine whether the acquirer's financial structure influences market investors' reactions to fintech acquisition announcements. The sample is divided into two subsamples based on the mean leverage ratio (the ratio of debt to total assets): low-leverage acquirers and high-leverage acquirers. High-leverage acquirers face a greater risk of financial distress or bankruptcy, especially when undertaking uncertain or complex investments such as fintech acquisitions. As a result, when highly leveraged acquirers pursue fintech acquisitions—often characterized by high information asymmetry—market participants may react more negatively due to heightened bankruptcy concerns. Therefore, we hypothesize that the negative market reaction to fintech acquisitions is more pronounced among high-leverage acquirers.

Panel B of Table 9 presents the results. The coefficient of *fintech* on CAR[−1, 3] is significantly negative for high-leverage acquirers, indicating that overall, the market reacts more negatively to fintech acquisitions when acquirers carry higher financial risk. However, the interaction term between *fintech* and *COVIDduring* is only negatively significant for the subsample of low-leverage acquirers. One possible explanation is that low-leverage acquirers pursuing fintech acquisitions during a period of heightened uncertainty (e.g., the COVID-19 pandemic) were penalized more by the market, possibly because such investments deviated from their typically conservative financial behavior.

Insert Table 10 Here

5. Conclusion

This study examines the role of information asymmetry in shaping market investors' reaction to fintech acquisitions. Analyzing 398 M&A transactions between 2015 and 2024, we find that compared with non-fintech acquisitions, fintech acquisitions receive more negative reactions from market investors owing to the higher level of information asymmetry. We also find that the negative market response to fintech acquisitions becomes more pronounced during the COVID-19 pandemic, though this heightened sensitivity does not persist in the post-pandemic period. Collectively, our results underscore the critical role of information asymmetry in explaining investor behavior around fintech M&A announcements and underscore the importance of accounting for macroeconomic shocks in evaluating market responses, such as the COVID-19 pandemic.

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Table 1. Distribution of sample by year and industry

Panel A Distribution of sample by year

Year	Full sample	Non-fintech acquisition		Fintech acquisition	
		Number	Percentage (%)	Number	Percentage (%)
2015	35	32	8.77	3	9.09
2016	35	31	8.49	4	12.12
2017	37	36	9.86	1	3.03
2018	27	26	7.12	1	3.03
2019	31	30	8.22	1	3.03
2020	33	29	7.95	4	12.12
2021	45	44	12.05	1	3.03
2022	48	44	12.05	4	12.12
2023	52	43	11.78	9	27.27
2024	55	50	13.70	5	15.15
Overall	398	365	100	33	100

Panel B Distribution of sample by industry

Industry	Full sample	Non-fintech acquisition		Fintech acquisition	
		Number	Percentage (%)	Number	Percentage (%)
Banks	166	157	43.01	9	27.27
Brokerage	94	80	21.92	14	42.42
Credit Institutions	44	41	11.23	3	9.09
Insurance	79	74	20.27	5	15.15
Other Financials	15	13	3.56	2	6.06
Overall	398	365	100	33	100

Table 1 presents the distribution of the sample by announcement year and acquirer industry. The year refers to the calendar year in which the acquisition announcement was made. The industry classification is based on the mid-level industry category of the acquirer, as reported by the SDC Platinum database.

Table 2. Descriptive statistics

	Full sample			Non-fintech acquisition			Fintech acquisition			Mean Difference
	N=398			N=365			N=33			
	Mean	SD	Median	Mean	SD	Median	Mean	SD	Median	
Dependent Variable										
CAR[-1,3]	1.44	5.79	0.56	1.64	5.78	0.80	-0.75	5.56	-0.37	-2.38**
CAR[-1,5]	1.46	7.25	0.98	1.68	7.07	1.04	-0.91	8.75	-0.34	-2.59
Independent Variable										
COVID										
before=1	165.00	41.5%		155.00	42.5%		10.00	30.3%		
during=1	141.00	35.4%		127.00	34.8%		14.00	42.4%		
post=1	92.00	23.1%		83.00	22.7%		9.00	27.3%		
Control Variable										
dv_log	8.74	1.85	8.64	8.83	1.86	8.73	7.72	1.27	7.59	-1.11***
pct_acq	0.22	0.41	0.00	0.21	0.41	0.00	0.27	0.45	0.00	0.06
cash	0.84	0.36	1.00	0.84	0.37	1.00	0.88	0.33	1.00	0.04
cross_border	0.09	0.29	0.00	0.09	0.28	0.00	0.15	0.36	0.00	0.06
first_fintech	0.04	0.20	0.00	0.00	0.00	0.00	0.48	0.51	0.00	0.48***
t_public	0.61	0.49	1.00	0.62	0.48	1.00	0.45	0.51	0.00	-0.17*
tobin_q	0.15	0.32	0.05	0.14	0.29	0.05	0.25	0.50	0.10	0.11
bm	1.85	1.26	1.55	1.89	1.28	1.58	1.35	0.81	1.24	-0.55***
bl	1.42	0.71	1.61	1.38	0.69	1.61	1.86	0.74	2.20	0.48***
assets	15.28	2.37	15.57	15.30	2.36	15.56	15.06	2.57	15.79	-0.24
topix	7.52	0.20	7.52	7.52	0.20	7.51	7.55	0.22	7.58	0.03
ipo_deals	5.32	6.82	3.00	5.35	6.81	3.00	5.00	6.97	1.00	-0.35

Table 2 presents the mean, median, and standard deviation for the main variables of the full sample as well as the subsamples of fintech acquisitions and non-fintech acquisitions. All continuous variables are winsorized at 1% and 99% levels. All variables are defined in Appendix A. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 3. Nonparametric test (KP test & GRANK test)

	Method	All acquisitions	Fintech acquisitions	Non-fitnech acquisitions
CAAR[-1,3]	KP	4.97***	-0.77	5.43***
	GRANK	4.33***	-1.21	4.82***
CAAR[-1,5]	KP	4.02***	-0.60	4.53***
	GRANK	4.30***	-0.74	4.72***

Table 3 presents the results of non-parametric tests to compare the difference of CAARs between fintech and non-fintech acquisitions, using KP test and GRANK test. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4. The impact of fintech and COVID-19 pandemic

	CAR[-1,3]		CAR[-1,5]	
	(1)	(2)	(3)	(4)
fintech	-3.490**	2.111	-4.300**	1.134
	(1.492)	(2.980)	(1.806)	(3.609)
COVIDduring		3.607		9.275**
		(3.633)		(4.400)
COVIDpost		3.791		10.626**
		(3.849)		(4.662)
fintech*COVIDduring		-7.051**		-6.956*
		(3.115)		(3.772)
fintech*COVIDpost		-2.707		-1.631
		(2.821)		(3.417)
dv_log	0.352	0.374	0.513*	0.538*
	(0.230)	(0.230)	(0.278)	(0.278)
pct_acq	-1.568*	-1.459*	-0.881	-0.830
	(0.802)	(0.810)	(0.971)	(0.982)
cash	1.575*	1.864**	1.104	1.420
	(0.884)	(0.890)	(1.070)	(1.078)
cross_border	0.374	0.286	0.112	-0.027
	(1.068)	(1.066)	(1.293)	(1.291)
tobin_q	-4.917***	-5.197***	-4.595**	-4.937**
	(1.626)	(1.636)	(1.967)	(1.981)
first_fintech	3.176	-0.707	3.374	-0.640
	(2.040)	(2.622)	(2.469)	(3.175)
t_public	0.646	0.581	1.146	1.058
	(0.748)	(0.746)	(0.905)	(0.904)
bm	0.122	0.079	0.761**	0.720*
	(0.307)	(0.307)	(0.371)	(0.371)
bl	0.859*	0.889*	3.047***	3.085***
	(0.469)	(0.468)	(0.568)	(0.567)
assets	-1.031***	-1.065***	-1.209***	-1.242***
	(0.223)	(0.224)	(0.270)	(0.272)
topix	-5.726	-6.474	-12.273*	-14.942*
	(6.035)	(6.562)	(7.304)	(7.947)
ipo_deals	0.111**	0.105**	0.189***	0.185***
	(0.049)	(0.049)	(0.059)	(0.059)
Constant	54.869	60.490	98.268*	117.957**
	(44.350)	(48.120)	(53.671)	(58.276)
Year Dummies	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES
Observations	398	398	398	398

Table 4 presents the results showing the impact of fintech on market investor's reaction and how this impact changes by the COVID-19 pandemic. All variables were defined in Appendix A. Industry- and year dummy variables are included in all regressions. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 5. Test results of the mediating mechanism effect

Pannel A. CAR[-1,3]				
Effect	Estimate	CI.Lower	CI.Upper	P.Value
ACME	-0.299	-0.697	-0.002	0.046
ADE	-3.179	-5.017	-1.157	0.006
Total Effect	-3.477	-5.283	-1.490	<0.001
Proportion Mediated	0.086	0.0005	0.291	0.046

Pannel B. CAR[-1,5]				
Effect	Estimate	CI.Lower	CI.Upper	P.Value
ACME	-0.575	-1.257	-0.048	0.024
ADE	-3.712	-5.874	-1.356	<0.001
Total Effect	-4.287	-6.483	-2.013	<0.001
Proportion Mediated	0.134	0.011	0.379	0.024

Table 5 presents the mediation effect test of information asymmetry based on 1,000 bootstrap simulations. we use the change in illiquidity with a window of [-1,3] and [-1,5] **(**ΔILLIQ[-1,3]) and *ΔILLIQ[-1,5]*)**)** as the proxy of information asymmetry. Control variables used in the process of mediating mechanism test are consistent with those in Table 2 and defined in Appendix A.

Table 6. Difference-in-difference with PSM

Panel A. Differences in means of control variables between treatment and control group				
	Control group	Treatment group	Difference	P_Value
dv_log	8.05	7.72	-0.33	0.21
pct_acq	0.21	0.27	0.06	0.48
cash	0.87	0.88	0.01	0.85
cross_border	0.11	0.15	0.04	0.54
t_public	0.48	0.45	-0.03	0.75
tobin_q	0.20	0.25	0.05	0.56
bm	1.37	1.35	-0.02	0.88
bl	1.68	1.86	0.18	0.20
assets	15.04	15.06	0.02	0.97
topix	7.54	7.55	0.01	0.82
ipo_deals	5.15	5.00	-0.15	0.91

Panel B. Parallel trends test	
	Coefficient
fintech*2016	-6.000
fintech*2017	-9.752
fintech*2018	-5.165
fintech*2019	-6.092
fintech*2020	-9.044*
fintech*2021	-5.368
fintech*2022	-10.588**

fintech*2023	-11.909***
fintech*2024	-7.743*

Panel C. The results of DID with PSM (Nesrest neighbour matching, 1:5)				
	CAR[-1,3]		CAR[-1,5]	
	(1)	(2)	(3)	(4)
fintech	-1.961*	1.390	-3.244**	0.462
	(1.093)	(1.828)	(1.275)	(2.130)
COVIDduring		3.290		10.911*
		(4.790)		(5.582)
COVIDpost		3.300		12.792**
		(5.296)		(6.173)
fintech*COVIDduring		-6.901***		-7.449**
		(2.538)		(2.958)
fintech*COVIDpost		-2.374		-2.397
		(2.779)		(3.239)
dv_log	0.150	0.025	-0.071	-0.214
	(0.396)	(0.395)	(0.462)	(0.460)
pct_acq	-0.886	-0.790	0.645	0.725
	(1.089)	(1.093)	(1.271)	(1.274)
cash	1.124	1.235	-0.536	-0.381
	(1.311)	(1.291)	(1.530)	(1.505)
cross_border	0.204	0.088	0.117	-0.140
	(1.340)	(1.329)	(1.564)	(1.549)
tobin_q	-2.971	-3.121	-3.406	-3.358
	(2.446)	(2.470)	(2.854)	(2.878)
bl	0.982	1.381*	5.159***	5.589***
	(0.823)	(0.825)	(0.961)	(0.962)
t_public	-0.069	-0.031	-0.258	-0.200
	(1.065)	(1.050)	(1.243)	(1.224)
bm	0.345	0.415	0.812	0.918
	(0.782)	(0.771)	(0.913)	(0.898)
assets	-1.018***	-0.927***	-1.070***	-0.934**
	(0.348)	(0.352)	(0.406)	(0.410)
topix	-10.984	-12.529	-15.067	-20.377*
	(8.224)	(9.238)	(9.598)	(10.767)
ipo_deals	-0.050	-0.062	0.142	0.124
	(0.079)	(0.078)	(0.092)	(0.091)
Constant	98.245	107.939	120.262*	156.876**
	(60.418)	(67.555)	(70.516)	(78.732)
Year Dummies	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES
Observations	198	198	198	198

Table 6 presents the results of the PSM-DID approach. All control variables used in Table 2, except for first_fintech, are employed as matching covariates to construct a comparable control group for fintech acquisitions. Panel A reports the mean differences in variables between the treatment and control groups after matching, to assess the quality of the match. Panel B provides the results of the parallel trends test. Specifically, we examine the pre-treatment evolution of the outcome variable (CARs) between fintech and non-fintech acquisitions. Panel C presents the DID regression results based on the matched sample. Control variables are consistent with those in Table 2 and defined in Appendix A. All regressions include industry- and year- dummy variables. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Double machine learning

Panel A: DML(LASSO)				
	CAR[-1,3]		CAR[-1,5]	
Fintech	-3.676***	-2.085	-3.473***	-2.351
	(0.985)	(2.343)	(1.335)	(3.916)
Fintech*COVIDduring		-5.221**		-6.251*
		(2.289)		(3.542)
Fintech*COVIDpost		-2.348		-0.956
		(1.99)		(2.659)
Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
K Fold	5	5	5	5
Observations	398	398	398	398

Panel B: DML(Ridge)				
	CAR[-1,3]		CAR[-1,5]	
Fintech	-3.841***	-2.709	-3.793**	-1.681
	(0.987)	(2.487)	(1.487)	(3.637)
Fintech*COVIDduring		-6.792***		-8.097***
		(2.018)		(3.083)
Fintech*COVIDpost		-1.157		-2.266
		(2.028)		(2.515)
Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
K Fold	5	5	5	5
Observations	398	398	398	398

Panel C: DML(SVM)				
	CAR[-1,3]		CAR[-1,5]	
Fintech	-2.439**	-3.617	-2.889**	-4.558
	(1.096)	(3.204)	(1.447)	(4.016)
Fintech*COVIDduring		-3.389*		-6.015***
		(1.758)		(1.985)
Fintech*COVIDpost		-1.443		-0.536
		(2.022)		(2.108)
Controls	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Industry Dummies	Yes	Yes	Yes	Yes
K Fold	5	5	5	5
Observations	398	398	398	398

Table 7 presents the results of Double Machine Learning (DML) Method. The treatment variable is fintech, and the outcome variable is CAR. All control variables used in Table 2 are included in the high-dimensional control set. To address potential nonlinearity and high-dimensional confounding, we employ machine learning methods including LASSO (Panel A), Ridge (Panel B), and SVM (Panel C) to estimate the nuisance components. All estimations include industry- and year-dummy variables, and control variable definitions are provided in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Alternative measures of market reaction.

Panel A: Alternative measures of market reactions (CAR: Market model)				
	CAR[-1,3]		CAR[-1,5]	
	(1)	(2)	(3)	(4)
fintech	-3.415**	0.569	-3.819**	1.103
	(1.563)	(3.129)	(1.858)	(3.717)
COVIDduring		6.635*		12.155***
		(3.790)		(4.502)
COVIDpost		6.625*		12.827***
		(4.004)		(4.756)
fintech:COVIDduring		-5.475*		-6.556*
		(3.271)		(3.885)
fintech:COVIDpost		-0.516		-0.937
		(2.962)		(3.519)
Constant	89.153*	95.379*	127.732**	141.183**
	(46.042)	(49.984)	(54.708)	(59.373)
Controls	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES
Observations	398	398	398	398

Panel B: Alternative measures of market reactions (AAR:Fama-French three-factor model)				
	AAR_1_3		AAR_1_5	
	(1)	(2)	(3)	(4)
fintech	-0.782*	1.068	-0.640*	0.682
	(0.402)	(0.801)	(0.340)	(0.678)
COVIDduring		0.561		0.416
		(0.976)		(0.827)
COVIDpost		0.724		0.403
		(1.034)		(0.876)
fintech:COVIDduring		-2.242***		-1.622**
		(0.837)		(0.709)
fintech:COVIDpost		-1.118		-0.803
		(0.758)		(0.642)
Constant	4.842	7.084	3.641	3.959
	(11.953)	(12.930)	(10.090)	(10.952)
Controls	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES
Observations	398	398	398	398

Table 8 presents the results of the impact of fintech acquisitions on market reaction, using the alternative measures of market reaction. In Panel A, market reactions is measured by CAR[-1,3] and CAR[-1,5], which is estimated by the market model. In Panel B, market reactions is measured by AAR[-1,3] and AAR[-1,5], defined as the average daily abnormal return, calculated using the Fama-French three-factor model. Control variables are consistent with those in Table 2 and defined in Appendix A. All regressions include industry- and year- dummy variables. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Possible channel analysis

Panel A : The imapct of target's age

	Young target				Old target			
	CAR[-1,3]		CAR[-1,5]		CAR[-1,3]		CAR[-1,5]	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
fintech	-2.744	6.332*	-3.405*	4.402	-2.933	-7.280	-3.553	-5.387
	(1.812)	(3.552)	(2.044)	(4.052)	(3.243)	(7.424)	(4.095)	(9.386)
COVIDduring		-3.022		-3.966		8.662		22.042***
		(5.188)		(5.919)		(5.392)		(6.818)
COVIDpost		-2.579		-3.089		10.429*		25.996***
		(5.793)		(6.610)		(5.328)		(6.736)
fintech*COVIDduring		-9.840***		-8.513**		3.752		1.419
		(3.593)		(4.099)		(8.487)		(10.730)
fintech*COVIDpost		-9.400***		-7.706*		7.632		6.038
		(3.601)		(4.108)		(5.275)		(6.669)
Constant	-34.900	-37.772	-59.725	-54.596	133.809**	159.410**	273.949***	313.887***
	(65.351)	(72.584)	(73.719)	(82.810)	(62.371)	(65.992)	(78.759)	(83.433)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197	197	197	197	200	200	200	200

Pame B: The impact of deal size

	High dv_a_assets				Low dv_a_assets			
	CAR[-1,3]		CAR[-1,5]		CAR[-1,3]		CAR[-1,5]	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
fintech	-2.744	6.332*	-3.405*	4.402	-2.933	-7.28	-3.553	-5.387
	-1.812	-3.552	-2.044	-4.052	-3.243	-7.424	-4.095	-9.386
COVIDduring		-3.022		-3.966		8.662		22.042***
		-5.188		-5.919		-5.392		-6.818
COVIDpost		-2.579		-3.089		10.429*		25.996***
		-5.793		-6.61		-5.328		-6.736
fintech:COVIDduring		-9.840***		-8.513**		3.752		1.419
		-3.593		-4.099		-8.487		-10.73
fintech:COVIDpost		-9.400***		-7.706*		7.632		6.038
		-3.601		-4.108		-5.275		-6.669
Constant	-34.9	-37.772	-59.725	-54.596	133.809**	159.410**	273.949***	313.887***
	-65.351	-72.584	-73.719	-82.81	-62.371	-65.992	-78.759	-83.433
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	197	197	197	197	200	200	200	200

Table 9 presents the results of the possible channel analysis that examines whether the impact of fintech acquisitions on market reactions is moderated by factors that may intensify information asymmetry. In Panel A, we investigate the role of target firm age by dividing the sample into younger and older targets based on the median age (t_age = 25). In Panel B, we examine the role of deal size using the ratio of deal value to acquirer total assets (dv_a_assets). The sample is split into high and low dv_a_assets groups based on the median value. The dependent variables are CAR[–1, 3] and CAR[–1, 5]. Control variables are consistent with those in Table 2 and defined in Appendix A. All regressions include industry and year fixed effects. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Cross-section analysis

Panel A. The impact of acquirer's industry

	Bank				Non-bank			
	CAR[-1,3]		CAR[-1,5]		CAR[-1,3]		CAR[-1,5]	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
fintech	-3.209	-1.706	-1.895	-3.614	-2.979*	4.389	-2.364	7.044
	(4.601)	(5.757)	(6.277)	(7.877)	(1.777)	(4.205)	(2.018)	(4.759)
COVIDduring		10.741**		27.477***		-3.113		-4.555
		(4.802)		(6.570)		(5.201)		(5.888)
COVIDpost		8.455*		28.834***		-1.814		-2.700
		(5.077)		(6.946)		(5.654)		(6.399)
fintech*COVIDduring		2.150		3.239		-8.336*		-10.648**
		(5.502)		(7.527)		(4.433)		(5.017)
fintech*COVIDpost		-1.331		1.632		-5.307		-6.635
		(3.681)		(5.037)		(4.303)		(4.870)
Constant	115.160**	95.504	283.780***	299.665***	-19.695	0.318	-37.585	-9.273
	(56.716)	(61.685)	(77.367)	(84.401)	(64.890)	(72.398)	(73.692)	(81.947)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	166	166	166	166	232	232	232	232

Panel B. The impact of acquirer's leverage

	Low leverage firm				High leverage firm			
	CAR[-1,3]		CAR[-1,5]		CAR[-1,3]		CAR[-1,5]	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
fintech	-2.705	4.470	-1.315	7.270	-4.757*	-2.151	-6.436*	-3.273
	(1.945)	(4.285)	(2.132)	(4.681)	(2.648)	(4.692)	(3.388)	(5.997)
COVIDduring		-1.076		-3.924		9.184*		22.946***
		(5.322)		(5.813)		(5.112)		(6.533)
COVIDpost		-0.640		-3.060		8.718		24.148***
		(5.668)		(6.192)		(5.434)		(6.946)
fintech*COVIDduring		-7.838*		-9.303**		-4.977		-7.015
		(4.202)		(4.590)		(7.339)		(9.380)
fintech*COVIDpost		9.283		10.482		-2.161		-2.325
		(6.865)		(7.499)		(3.856)		(4.929)
Constant	-6.202	-7.975	-45.834	-44.965	148.102**	143.302**	279.901***	295.035***
	(66.034)	(71.508)	(72.383)	(78.118)	(62.236)	(68.054)	(79.623)	(86.982)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Year Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Industry Dummies	YES	YES	YES	YES	YES	YES	YES	YES
Observations	187	187	187	187	211	211	211	211

Table 10 presents the results of the cross-section analysis of whether the impact of fintech acquisitions on market reactions varies with the characteristic of acquirers. In Panel A, we explore the role of the acquirer's industry by splitting the sample into bank and non-bank acquirers. In Panel B, we examine the influence of the acquirer's leverage level, defined as the ratio of total debt to total assets. The sample is split into high- and low-leverage groups based on the mean leverage of the full sample. Control variables are consistent with those in Table 2 and defined in Appendix A. All regressions include industry- and year- dummy variables. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix A. The definition of variables

Panel A. Dependent Variable		
Variable	Definition	Source
CAR[-1,3]	The sum of abnormal returns from 1 day before to 3 days after the announcement date.	Nikkei NEEDS Financial Quest
CAR[-1,5]	The sum of abnormal returns from 1 day before to 5 days after the announcement date.	Nikkei NEEDS Financial Quest
Panel B. Independent Variable		
Variable	Definition	Source
fintech	A dummy variable equal to 1 if the acquirer is a financial institution and the target belongs to the technology industry.	SDC Platinum database
COVID	A categorical variable indicating whether the acquisition occurred before, during, or after the COVID-19 pandemic	Official government press releases and regulatory announcements
Panel C. Control Variables		
Variable	Definition	Source
dv_log	The natural logarithm of the deal value.	SDC Platinum database
pct_acq	A dummy equals to 1 if the percentage of shares acquired in the transaction exceeds 50%.	SDC Platinum database
cash	A dummy equals to 1 if the transaction is fully paied in cash.	SDC Platinum database
cross_border	A dummy equals 1 if the transaction is cross-border.	SDC Platinum database
tobin_q	Theratio of market value to total asset.	Nikkei NEEDS Financial Quest
first_fintech	A dummy variable equal to 1 if it is the acquirer's first fintech acquisition.	SDC Platinum database
t_public	A dummy eqauls 1 if the target is a public firm.	SDC Platinum database
bm	The ratio of book value to market value.	Nikkei NEEDS Financial Quest
bl	The natural logarithm of the number of business lines.	SDC Platinum database
assets	The natural logarithm of total assets	Nikkei NEEDS Financial Quest
topix	The natural logarithm of TOPIX index	Nikkei NEEDS Financial Quest
ipo_deals	The number of newly listed IPO firms each month.	IPO white paper

Appendix A contains definitions for all variables in this study.