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M&A between financial services firms or banks and fintech's

Fusiones y adquisiciones entre empresas de servicios financieros o bancos y fintechs

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Abstract

Objective: This paper investigates whether acquiring fintech firms enhances the financial performance of traditional financial service firms and banks, and how these effects vary across countries and sectors.
Methodology: We employ a panel-data difference-in-differences (DiD) approach with Mundlak correction to estimate the causal effects of fintech mergers and acquisitions (M&As). Our sample includes 6,460 M&A deals from 2014 to 2023.
Results: The subgroup analysis reveals that acquiring fintechs from Japan and Australia significantly improves ROE, while acquisitions from Spain, India, Germany, and Canada show heterogeneous and often negative performance outcomes.
Limitations: The analysis is limited by the availability of financial data and potential unobserved confounding factors. Findings are not generalizable beyond the studied period or sectors.
Originality: This study contributes new causal evidence on the financial outcomes of fintech acquisitions utilizing a novel subsample search algorithm.
Conclusions: Fintech M&A outcomes are highly context-dependent. Sectoral and geographic characteristics must be considered in strategic acquisition planning.

Keywords: Fintech acquisitions; financial performance; difference-in-differences; subgroup analysis; mergers and acquisitions.
JEL Classification: G34, G21, L86, C23, M10.

Resumen

Objetivo: Analizar si la adquisición de fintech mejora el desempeño financiero de firmas de servicios financieros tradicionales, y cómo varían estos efectos según el país y el sector del objetivo.
Metodología: Utilizamos un enfoque de diferencia en diferencias (DiD) con corrección de Mundlak sobre datos de panel para estimar efectos causales de adquisiciones fintech.
Resultados: El análisis por subgrupos revela que adquirir fintechs de Japón y Australia mejora significativamente el ROE, mientras que adquisiciones desde España, India, Alemania y Canadá muestran efectos heterogéneos y en muchos casos negativos.
Limitaciones: La disponibilidad de datos financieros y factores no observados, es una limitación. Los resultados no son generalizables fuera del periodo o sectores analizados.
Originalidad: Aporta nueva evidencia causal sobre el impacto financiero de adquisiciones fintech, utilizando un algoritmo iterativo para buscar efectos heterogéneos por subgrupo.
Conclusiones: Los efectos de adquisiciones fintech dependen del contexto. Las características sectoriales y geográficas deben considerarse en la planificación estratégica de M&A.

Palabras clave: Adquisiciones Fintech; desempeño financiero; diferencias en diferencias; análisis de subgrupos; fusiones y adquisiciones.
Clasificación JEL: G34, G21, L86, C23, M10.

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Introduction

Financial services have evolved in response to the digital and global economy, resulting in financial customers demanding innovative and efficient solutions. Therefore, banks have developed diverse digital innovations internally. However, their performance cannot compare to the digital facilities created by fintech firms in terms of cost, user-friendliness, and customer accessibility, forcing financial service firms to re-evaluate their corporate boundaries (Boot *et al.,* 2021; Kohtamäki *et al.,* 2019). On the other hand, the fintech phenomenon has shown that fintech can either substitute or complement traditional banking within specific product and client segments (Jagtiani & Lemieux, 2018; Tang, 2019). The latter has caused some traditional financial services firms to adopt fintech technology through mergers and acquisitions (M&A) (Mnohoghitnei *et al.,* 2019).

In this paper, we define fintech firms not merely as financial service providers but as organizations that incorporate technological capabilities aligned with the fintech ecosystem. Following Arner *et al.,* (2015) and Leong (2018), we employ a keyword-based classification method to identify fintech targets in M&A transactions systematically. This approach relies on business descriptions containing terms such as digital finance, neobank, insurtech, regtech, crowdfunding, peer-to-peer lending, and robo-advisors, among others. By adopting this replicable classification strategy, we ensure that fintech firms in our sample are consistently defined as technology-driven actors within the financial services sector, providing conceptual clarity and methodological rigor from the outset.

Some researchers have concluded that by acquiring fintech startups, banks aim to reduce costs, streamline business processes, and increase profitability by offering rapid and highquality services to a broader customer base, rather than investing in internal R&D (Chen *et al.,* 2021; Cui & Leung, 2020). In an M&A context, Akhtar and Nosheen's (2022) research employs a range of performance indicators to evaluate the outcomes for acquiring companies following mergers and acquisitions. Their findings reveal that acquirers' performance is often varied, with some companies demonstrating notable enhancements in financial measures while others experience reductions in profitability.

Despite growing interest in fintech M&A, the existing literature primarily examines the generic impacts of cross-sector or cross-border M&A. Research focusing specifically on M&A between fintech and financial service firms remains limited (Dranev *et al.,* 2019). Nevertheless, multiple studies suggest that post-acquisition outcomes depend heavily on both the sector and the geographic context of the target. Schiffbauer *et al.,* (2017) demonstrated that the performance effects of foreign acquisitions vary considerably across industries, particularly high-tech sectors. These findings highlight how industry-specific dynamics influence the realization of synergy.

The geographic dimension also introduces heterogeneity. Brózda-Wilamek (2023) highlights the diverse institutional and regulatory environments encountered by acquirers across different countries, drawing on a comprehensive study of global cross-border M&A networks. Similarly, Ings and Inoue (2012) show that cross-border deals can yield higher returns than domestic ones, particularly when advanced economy firms acquire targets in rapidly growing markets.

This research seeks to fill this void by investigating the financial performance outcomes of financial service firms and banks that acquire fintech companies. The central research question guiding this study is: Does acquiring a fintech firm improve the financial performance of financial service companies or banks? And how do these effects vary depending on the sector or country of the target?

Our empirical strategy is a panel data difference-in-difference (DiD) approach, along with a Mundlak correction. The methodology compares the effect of an event on groups (treated group) with those unaffected by the same event (control group) (Vig, 2013). In this research, the event is the completion of the deal; the treated and control groups consist of buyers in the financial sector who acquire fintech and non-fintech firms, respectively. We consider the buyer's financial performance one year before the completion date and one year after. The difference will impact on the financial performance of buyers who acquire fintech companies.

Our study makes three key contributions. First, we provide one of the first large-scale causal estimates of the impact of fintech acquisitions on firm performance –measured by ROA, ROE, and cash flow– offering robust evidence for informed regulatory debates on the role of M&A in fostering financial innovation. Second, we show that the performance effects vary significantly by geography and industry, highlighting the contextual nature of fintech synergies. Finally, we propose a transparent and replicable framework for identifying fintech targets and evaluating strategic acquisitions in the digital economy – one that can be used not only by researchers, but also by corporate strategists and policymakers to guide due diligence, design evidence-based competition policies, and assess whether M&A activity promotes innovation, enhances financial inclusion, and supports the stability of financial systems. This practical relevance strengthens the contribution of our study, making it a valuable reference point for regulators seeking to balance innovation incentives with consumer protection and systemic risk considerations.

Literature Review

Fintech innovations are widely recognized as key drivers of transformation in the financial services industry. Puschmann (2017) characterizes FinTech as a force of disruptive innovation, framing it as a driver of structural change in financial services through digital technologies such as blockchain, robo-advisory, and peer-to-peer platforms. In contrast, the Financial Stability Board defines FinTech more broadly as "technologically enabled financial innovation". This definition is intentionally inclusive and policy-oriented, encompassing both incremental and radical innovations. This broader framing allows regulators to monitor systemic risks while fostering innovation. Complementing these perspectives, Zavolokina *et al.*, (2016) emphasize the ecosystemic nature of FinTech, highlighting the interaction between incumbents, start-ups, consumers, and regulators as a defining feature of its evolution. Building on this conceptual diversity, Rupeika-Apoga and Thalassinos (2020) propose a detailed taxonomy of FinTech activities that captures the heterogeneity of business models and regulatory implications. Their classification includes: Payments and transfers (digital wallets, mobile payments, cross-border remittances), Deposits and loans (peer-to-peer lending, crowdfunding, digital banks), Insurance technologies (InsurTech) (usage-based insurance, automated claims), Investment and wealth management (robo-advisors, algorithmic trading), RegTech and compliance solutions (AML/KYC automation, risk analytics), and Market provisioning (data aggregators, credit scoring platforms).

These distinctions are not merely semantic—they have direct implications for post-M&A outcomes. Acquisitions targeting payment platforms may yield rapid revenue synergies through transaction volume scaling, whereas RegTech acquisitions may create longer-term value by reducing compliance costs and enhancing risk management. Similarly, lending-focused FinTech acquisitions may expose acquirers to credit risk heterogeneity and regulatory scrutiny, affecting the post-deal performance trajectory.

Our study builds on this rich definitional landscape by adopting the Financial Stability Board's (FSB) broad interpretation of FinTech, which frames it as "technologically enabled financial innovation" across the entire financial ecosystem. This choice allows us to construct a comprehensive and inclusive sample of FinTech firms, capturing activities that range from payments and lending to InsurTech, RegTech, and digital investment platforms. By doing so, we ensure that our identification strategy does not inadvertently exclude emerging business models that may be critical drivers of value creation. Moreover, this broader lens enhances the external validity of our findings, as it aligns with the taxonomy used by regulators and international policy bodies to monitor systemic risk and innovation trends. In the context of our M&A analysis, this approach enables us to disentangle how performance effects vary not only across geographies and industries but also across distinct FinTech verticals, shedding light on why certain acquisitions yield immediate synergies while others require longer integration horizons.

In the environment of mergers and acquisitions (M&A), FinTech adoption via acquisition represents a strategic move for financial service firms seeking competitive advantages through innovation. Kimetto (2019) and Septian & Dharmastuti (2019) point out that synergies—such as cost efficiencies, technological integration, and enhanced market reach— drive improvements in post-acquisition performance. These studies also affirm the importance of synergy realization in boosting key indicators such as ROA, thereby justifying the choice of these metrics in our empirical analysis.

From a theoretical perspective, this phenomenon can be interpreted through the dynamic capabilities framework (Teece, Pisano, & Shuen, 1997), which posits that firms must continuously integrate, build, and reconfigure internal and external competencies to address rapidly changing environments. Acquiring a FinTech firm can be seen as a reconfiguration mechanism, enabling incumbent financial institutions to access novel technological resources and customer-centric capabilities that would be difficult to develop organically.

Additionally, open innovation theory (Chesbrough, 2003) offers a complementary lens, emphasizing that firms are increasingly relying on external sources of innovation—such as start-ups and technology providers—to accelerate knowledge flows and reduce time-to-market. In this sense, M&A activity in the FinTech sector facilitates inbound open innovation by granting incumbents access to new digital infrastructures (*e.g.*, APIs, AI-driven credit scoring, blockchain solutions), which can be leveraged to co-create value and maintain competitiveness in the digital economy. Together, these theoretical perspectives reinforce the strategic rationale for FinTech acquisitions and help explain why post-M&A performance improvements are contingent upon a firm's ability to absorb and exploit acquired capabilities effectively.

Although Fintech acquisitions are rare -accounting for only 2.28% of our sample- such infrequency is not unusual in financial research. Many studies involving binary outcomes, such as loan defaults or M&A failures, also involve rare events. King and Zeng (2001) emphasize that valid inference can still be drawn without artificially rebalancing the data. Similarly, Calabrese and Osmetti (2013) proposed statistical methods tailored for binary outcomes in highly imbalanced settings. Empirical evidence further shows that even infrequent fintech transactions generate measurable market effects. For example, Dranev, *et. al.,* (2019) documented significant positive abnormal returns in the short term, followed by negative long-term performance, using an event study of fintech M&As. More recently, Ochirova and Miriakov (2025) confirmed that fintech

M&A announcements lead to positive short-term abnormal returns, with macroeconomic conditions amplifying or moderating these effects. Together, this evidence highlights that rare fintech acquisitions can still have significant implications for financial markets.

In terms of methodological design, our approach is grounded in established practices of panel data econometrics. The use of targeted subgroup analysis is supported by Angrist & Pischke (2009), Berman & Israeli (2022), and Schiffbauer *et al.*, (2017), who emphasized that treatment effects may be heterogeneous across sectors or countries. Akhtar & Nosheen (2022) provided empirical evidence that bank acquirers experience divergent performance outcomes when acquiring Fintechs. This motivates our iterative procedure to detect subgroups where effects are significant, even when the average effect is null. Moreover, our strategy parallels modern causal inference frameworks—such as causal trees and forests—advocated by Athey & Imbens (2016) and Wager & Athey (2018), which partition datasets to uncover treatment heterogeneity.

In summary, this literature supports the theoretical rationale, empirical approach, and analytical techniques employed in our study, offering a robust framework for understanding how Fintech M&A impacts post-acquisition performance.

Data and methodology

We identified M&A globally where the buyers' companies were in the financial sector from 2014 to June 2023. The M&A data is from S&P Capital IQ, which categorizes companies in this sector as those engaged in banking, financial services, and consumer finance, among other activities.

We implemented a customized Python-based text-mining algorithm designed to identify firms with technological capabilities related to fintech by analyzing their business descriptions. Specifically, the algorithm searches each target firm's description for the presence of 44 predefined keywords. To ensure consistency, we defined a set of representative terms for the fintech ecosystem, selecting only one version per concept to avoid typographic duplicates (*e.g.*, eliminating variants such as "fin tech," "fin-tech," and "fin_tech"). The selected terms include fintech, financial technology, financial tech, digital finance, neobank, insurtech, regtech, e-centralized finance, open banking, digital wallet, e-wallet, embedded finance, crowdfunding, crowdlending, peer-to-peer lending, digital lending, alternative finance, API-based finance, and robo advisor, among others. These terms and their synonyms are based on terminology used in Arner et al. (2015) and Leong & Sung (2018). The algorithm is case-insensitive and robust to formatting variations such as hyphens and underscores (*e.g.*, "financial technology," "financial-technology," and "financial_technology" are treated as equivalent).

We acknowledge that keyword-based classification has inherent limitations. Potential false positives (non-fintech firms flagged as fintech) and false negatives (fintech firms missed due to the absent keywords) may occur. Such errors are random rather than systematic and therefore would tend to weaken the estimated effects rather than artificially create significant results. To illustrate, firms flagged as fintechs in our sample include targets specializing in digital wallets, peer-to-peer lending platforms, and insurtech solutions, which align with established definitions of fintech. For each keyword, the function iterates through all firm observations in the dataset and flags entries where the term is present. In **Figure 1**, we present the Algorithm: Identification of Fintech Firms via Text Mining in Python.

Then, our fintech definition is not about being in the financial sector, but rather about possessing capabilities that align with the fintech definition. To minimize potential selection bias, all M&As

in which the target was not a fintech were also included (Agyei-Boapeah, 2019).

Following Ferris & Sainani, (2021), we limited our analysis to M&A fulfilling the following criteria: i) Completed or terminated transactions; ii) Transactions completed before 2023 because of the availability of the financial information one year after that date; iii) Transactions under change in control, acting on behalf of the acquirer, holdings less than 50% of the target before the announcement and obtainings at least 51% ownership of the target firm; iv) Buyer firms with available financial information. For data cleaning, we filtered for deal sizes greater than zero, buyers' firms with available financial information, and data with errors in the financial information register, such as negative total assets, no sector classification, or no business description. These criteria yield 12,183 deals.

Our empirical strategy employs a panel data difference-in-differences (DiD) approach with a random effects estimator, predicated on the assumption that individual-specific effects are random rather than fixed. We ruled out fixed effects primarily due to the substantial loss of degrees of freedom they entail, which is particularly concerning given our large overall sample and the relatively small number of treated units (Baltagi, 2021; Clark & Linzer, 2015). Additionally, our focus is on estimating the average effect of fintech acquisitions at the population level -not on capturing firm-specific heterogeneity- making fixed effects less relevant to our objectives (Croissant & Millo, 2019).

Crucially, the DiD design already controls unobserved time-invariant differences between the treated and control groups (Angrist & Pischke, 2009). To further buffer against omittedvariable bias, we implemented the Mundlak (1978) correction -also known as the correlated random effects model- by introducing firm-level means of time-varying covariates into the specification. This adjustment relaxes the strict exogeneity assumption of the standard random-effects model combining the efficiency advantages of random effects with the robustness typically associated with fixed effects (Mundlak, 1978; Bell & Jones, 2015; Greene, 2012).

While we did not conduct a Hausman test, recent literature advises caution in interpreting its results. Baltagi (2023) emphasized that rejection of the Hausman null is not an automatic indictment against random effects; rather, it indicates some correlation between regressors and unit effects not necessarily a significant or substantively important correlation. In fact, in large panels, even marginal correlations may be flagged due to the test's considerable power, potentially leading to overly conservative model selection (Croissant & Millo, 2019). Given that our Mundlak specification both diagnoses and corrects for this correlation, we determined that a separate Hausman pre-test was unnecessary.

Moreover, empirical evidence suggests that random-effects estimates remain robust even when their distributional assumptions are moderately violated (Bell & Jones, 2015). Considering our objective -to estimate the average population-level effect of fintech acquisitions- and the context of a few treated units, the Mundlak-corrected random-effects model offers an appropriate and efficient compromise. It allows us to retain the benefits of the DiD design, preserve degrees of freedom, and mitigate endogeneity concerns while adhering to best practices in panel econometrics (Samartsidis *et al.,* 2019).

Hence, our preferred specification is the DiD model with Mundlak-corrected random effects, which delivers population-relevant estimates, robust inference, and an efficient use of data in small-treatment settings. We propose the following model:

$$\begin{aligned} &FinPerform_{it} \\ &= \beta_0 + \beta_1 Post_{it} + \beta_2 (Fintech_i \cdot Post_{it}) \\ &+ \beta_3 Fintech_i + \gamma' X_{it} + \delta' X_i + c_i + u_{it} \end{aligned} \quad (1)$$

The $Fin\_perform_{it}$ represents financial performance and is measured using indicators such as return on assets (ROA, defined as net income divided by total assets), return on equity (ROE, net income divided by shareholders' equity), and cash flow from operating activities scaled by total assets (see Barth *et al.,* 2001). The subscript i refers to the firm involved in the M&A, and t denotes the time period. The term c_i captures unobserved heterogeneity specific to each M&A, while u_i is the idiosyncratic error term. The variable $Post_{it}$ is a posttreatment indicator that equals one if the observation corresponds to $t+1$, i.e., one year after the acquisition was completed. This variable controls changes in corporate performance before and after the acquisition (Agyei-Boapeah, 2019). Vector X_{it} contains control variables, including the natural logarithm of total assets (book value) to account for firm size, consistent with prior literature (*e.g.*, Titman & Wessels, 1988; Frank & Goyal, 2009), and the ratio of total debt (long-term plus short-term) to total assets to control leverage.

Additional controls include binary indicators for cross-border transactions, private targets, and stock-financed mergers. The cross-border variable equals one if the deal involves firms from different countries. The private target variable equals one if the target is a privately held company. The stock payment variable equals one if the deal was financed entirely with equity (common or preferred shares). Parameter γ' is the transposed vector of coefficients for the time-varying covariates X_{it}, capturing within-firm effects. Vector $\overline{X}_i$ includes the firm-level averages of these covariates (Mundlak correction terms), specifically Fintech, Post, firm size, and leverage. Parameter δ' is the transposed vector of coefficients for $\overline{X}_i$, capturing between-firm effects. Regarding the parameter β_1, a negative (positive) coefficient indicates a deterioration (improvement) in performance one year after the acquisition. The variable $Fintech_{it}$ equals one if the target company operates in the fintech sector. The parameter of primary interest in this study is β_2. A statistically significant negative (positive) coefficient on β_2 would support the hypothesis that acquiring fintech capabilities through M&A is associated with a decline (improvement) in the acquirer's post-acquisition performance. **Table 1** displays the summary statistics for the variables used in the analysis.

Table 1 shows that, with a dataset of 12,183 M&A transactions, some variables have fewer observations due to missing values. Additionally, the average for fintech of 0.0228 means that, on average, the target was a Fintech in 2.28% of the M&A transactions.

We acknowledge that the variable Fintech is highly imbalanced. However, this imbalance reflects the empirical reality of the sample. We chose to preserve the natural imbalance to maintain the representativeness of the data and avoid introducing bias through artificial rebalancing. Adjusting the class proportions (*e.g.*, oversampling treated cases) would imply sampling conditional on the outcome, which requires methodological corrections to produce unbiased estimates (Imbens, 1992). By keeping the actual frequency of rare events, we ensure that estimated coefficients reflect the effect of fintech acquisitions under realistic conditions. Previous research has shown that forcing balance in rare binary treatments can reduce variance but at the cost of distorting the model's sensitivity and specificity (Salas-Eljatib *et al.,* 2018). Indeed, rebalancing may improve classification metrics but undermines the capability to generalize the results to real-world distributions (Sun *et al.,* 2009). Therefore, we retained the original proportions to produce interpretable and unbiased estimates under empirically valid assumptions.

Results

We begin our empirical analysis by estimating

equation 1 on the full sample of M&A transactions. The results of this estimation are presented in **Table 2**.

The interaction term (Fintech × Post), our primary variable of interest, is positive across all three performance indicators (ROA, ROE, and Cash Flow), yet it lacks statistical significance. This result is not unexpected in panel-data applications involving treatment heterogeneity, where aggregate effects often mask significant subgroup differences (Abrahamowicz *et al.,* 2013).

Previous literature in the M&A domain supports this view. Studies such as those by Schiffbauer *et al.*, (2017) and Akhtar and Nosheen (2022) demonstrate that firm-level responses to acquisitions can vary significantly across sectors and geographies. Therefore, our null result for the full sample warrants further investigation through targeted subsample analyses.

To explore heterogeneous effects, we implemented an automated algorithm that iteratively re-estimates the model on subsamples defined by acquirer country, target country, and target sector. The algorithm identifies subgroups where the Fintech × Post interaction term is statistically significant. The process follows best practices in empirical panel-data research and is consistent with recommendations by Berman and Israeli (2022). We show the Algorithm in **Figure 2**.

Subgroup analysis reveals significant heterogeneity in post-acquisition performance. **Table 3** provides the interaction effects by sector.

Table 3 presents findings for targets based in Japan and Australia, where the acquisition of fintech firms is associated with significant improvements in ROE. This is likely attributable to the strong technological infrastructure and innovation ecosystems in these countries, which facilitate better integration and synergy realization. Regulatory support and mature digital markets further enhance performance outcomes in these regions (Suzuki, 2025). Conversely, **Table 4** displays results for country-level heterogeneity.

In **Table 4**, we show that fintech acquisitions in Spain and India are associated with adverse effects. In Spain, all performance metrics decline post-acquisition, which may reflect integration challenges and competitive pressures from incumbent banks (Moro-Visconti *et. al.*, 2020). Indian acquirers experience a significant drop in ROE, consistent with evidence from the Indian beverage sector. Mahamuni *et al.*, (2023) found that post-merger profitability often declines due to managerial control-loss problems and the complexity of post-merger integration processes, which can erode operational efficiency and strategic focus. Further heterogeneity is observed in Germany and Canada (**Table 5** summarizes post-acquisition performance by acquirer country).

In Germany, fintech acquisitions have a negative impact on ROE and cash flow, potentially due to high integration costs (SPER Market Research, 2024). In Canada, the decline in cash flow suggests that acquisitions are part of long-term strategic transformations that may not yield immediate returns (Nishant & Saini, 2024). The role of acquirer characteristics is underscored in **Table 6**, which shows heterogeneity effects by target sector.

Acquirers from Switzerland and Japan exhibit significantly positive outcomes across ROA, ROE, and cash flow. These results align with prior findings indicating strong digital readiness and strategic execution in these countries (Arvanitis & Stucki, 2015; Ings & Inoue, 2012). In Switzerland, for instance, fintech M&A have enabled firms to reduce costs and improve operational liquidity (PwC, 2023). Finally, **Table 7** focuses on sector-specific effects.

Acquisitions in the consumer finance sector exhibit mixed outcomes. While some indicators improve, the Fintech × Post interaction term for ROE and cash flow is negative, suggesting that fintech integration challenges may be particularly pronounced in this segment. This could be attributed to consumer protection regulations, legacy IT constraints, or competitive dynamics in consumer markets.

Overall, our findings confirm that the financial impact of fintech acquisitions is highly contingent on both the geographic and sectoral context. Rather than a uniform effect, performance outcomes are shaped by a complex interplay of institutional environments, technological compatibility, and integration capability.

We acknowledge that the Fintech variable is highly imbalanced. However, this imbalance reflects the empirical reality of the sample, and we chose to preserve it to maintain representativeness. Artificial rebalancing (*e.g.*, oversampling treated cases) would condition on the outcome and require corrections to avoid bias (Imbens, 1992). Prior research indicates that forcing balance can reduce variance, but at the expense of distorting sensitivity and generalizability (Salas-Eljatib *et al.,* 2018; Sun *et al.,* 2009). By keeping the actual frequency of rare events, we ensure that estimated coefficients reflect the effect of fintech acquisitions under realistic conditions.

Discussion

This article examines whether mergers and acquisitions (M&A) involving fintech targets lead to improved financial performance for acquiring banks. Leveraging a panel dataset of global M&A transactions over the past decade, we apply a difference-in-differences (DiD) framework with a correlated random effects (Mundlak) specification to isolate the impact of fintech acquisitions. While these deals are relatively rare, our findings reveal significant heterogeneity in outcomes, driven by factors such as deal structure, acquirer characteristics, and regional context. This variation highlights the limitations of relying solely on average treatment effects and underscores the importance of identifying the specific conditions under which fintech M&A generates value.

Under conditions of variable imbalance, interpretation must be cautious but remains valid. Our coefficients capture the average effect of acquiring a fintech on firm performance outcomes. While the estimates are based on a relatively small subset of treated observations, their statistical significance suggests that the effect is strong enough to be detected despite the increased variance. Finding significance in a rare-treatment setting underscores robustness rather than fragility. Furthermore, because the primary objective of this study is causal inference rather than prediction, we employed robust standard errors to mitigate concerns about inflated confidence intervals."

Our results contribute to the literature on technological integration in financial markets by demonstrating that fintech acquisitions do not universally yield performance gains. Innovation-based theories posit that acquiring tech-driven firms should enhance operational efficiency and market competitiveness. However, our findings indicate that such synergies are not automatic. Instead, the success of fintech M&A depends on contextual factors such as acquirer size, pre-deal profitability, and geographic location. These insights support a contingent theoretical perspective on post-merger value creation and extend prior research by incorporating the digital finance domain into strategic M&A frameworks.

These divergent outcomes across indicators reflect the multidimensional nature of postmerger performance. For example, ROA and ROE may improve due to efficiency gains and better asset utilization, while cash flow can simultaneously decline as integration costs and restructuring expenditures materialize in the short term. Such patterns are consistent with prior research, which shows that synergies are realized unevenly across performance dimensions (Mahamuni *et* *al.,* 2023; Moro-Visconti *et. al.*, 2020).

From a managerial standpoint, the study offers a cautionary message: fintech acquisitions should not be treated as routine growth strategies. Given their infrequency and complexity, these deals require targeted strategic alignment, robust due diligence, and strong post-merger integration capabilities. Managers must assess not only the technological fit but also the organizational readiness to absorb and deploy fintech innovations. Our findings suggest that successful integration is more the exception than the rule, reinforcing the need for deliberate planning and execution.

This study is not without limitations. First, our analysis is confined to short- to medium term financial outcomes and does not capture long term innovation spillovers or market share effects. Second, unobserved factors such as management quality, cultural fit, or internal governance structures may influence post-merger performance but are not captured in our model. Third, we analyze only completed M&A transactions, excluding failed deals that could offer insights into selection dynamics. Future research should extend the analysis to longer time horizons, explore unsuccessful deals, and consider qualitative evidence on integration challenges and organizational frictions.

Recent empirical studies lend additional weight to our findings. De Boyrie and Pavlova (2025) document a positive association between fintech M&A activity and improved ROA and ROE among acquiring banks, suggesting that these deals, when successful, can outperform alternative innovation investments such as AI. Similarly, research on the Indian banking sector by Kumar and Verma (2024) and Rizvi and Khan (2024) shows that mergers -particularly those involving public sector banks- lead to tangible improvements in ROA and ROE, primarily due to better asset utilization and cost efficiencies. These studies also highlight the role of cash flow from operating activities as a key post-merger performance metric, reflecting enhanced financial discipline and process optimization.

Methodologically, we estimate our DiD model using a correlated random effects (Mundlak) specification (Mundlak, 1978; Wooldridge, 2021), which allows us to retain efficiency while accounting for potential correlation between regressors and unobserved heterogeneity. This approach incorporates firm-level averages of time-varying covariates to address possible systematic differences between treated and control units. While this specification improves upon standard random effects, it may still be inadequate when the number of treated units is small. Future research should therefore consider inference methods tailored to rare-treatment settings, such as randomization inference, synthetic control, or placebo-based testing, and aim to increase the sample of fintech-related acquisitions.

Our model does not incorporate sector fixed effects or macroeconomic variables such as GDP growth or fintech regulation indices. This decision is grounded in both methodological and practical considerations. The primary focus of our study is on firm-level variation, and we include year fixed effects to absorb standard macroeconomic shocks. Introducing additional sector or macro-level controls in a dataset with few treated observations risks overcontrolling and multicollinearity. This modeling choice is consistent with the existing literature, which relies on firm-level dynamics to capture M&A outcomes (*e.g.*, Andrade & Stafford, 2004; Bhagwat *et al.,* 2016). Future research with broader samples may benefit from integrating contextual economic variables to further refine the understanding of fintech M&A performance.

In sum, this study underscores the contingent and context-dependent nature of fintech acquisitions. While they offer strategic promise, their success hinges on careful deal selection, strategic fit, and disciplined post-merger execution. By highlighting both the potential and pitfalls of fintech M&A, we contribute to a more nuanced understanding of digital transformation strategies in the financial sector.

Conclusion

This paper investigates whether the acquisition of fintech firms by banks and financial service companies leads to improved post-merger financial performance. Using a panel differencein-differences (DiD) approach with Mundlak corrections, we assess the causal effect of fintech acquisitions on three core performance indicators: Return on Assets (ROA), Return on Equity (ROE), and operating Cash Flow. Our analysis draws on a comprehensive global dataset of M&A transactions between 2014 and 2023.

Our findings suggest that acquiring a fintech firm does not significantly improve performance when evaluating the full sample. However, further subgroup analysis reveals substantial heterogeneity in outcomes based on the country of the target, the acquiring country, and the sector involved. For instance, acquiring a fintech firm in Japan or Australia is associated with significant improvements in ROE. At the same time, acquisitions in countries such as Spain and India have shown adverse effects on multiple performance dimensions. These results underscore the significance of geographic and sectoral context in influencing the success of fintech-related M&A transactions.

Theoretically, our findings contribute to the existing literature on technological integration and strategic alignment in the financial services sector. They support the argument that value creation through M&A is not uniform, but instead contingent upon institutional settings, technological complementarities, and the characteristics of both acquirers and targets. This aligns with existing literature suggesting that M&A outcomes are shaped by interaction effects across economic, regulatory, and organizational dimensions (Schiffbauer *et al.,* 2017; Ings & Inoue, 2012).

From a managerial perspective, our results underscore the importance of due diligence and strategic fit when evaluating fintech acquisition opportunities. Managers should consider not only the technological capabilities of target firms but also their geographic and sectoral positioning. Our results suggest that deals involving targets in emerging economies or consumer-focused sectors pose integration challenges that undermine financial performance. Conversely, acquirers operating in technologically advanced markets with mature regulatory environments may find greater success through fintech M&A.

Finally, while our study provides robust empirical evidence, it also has limitations. The analysis focuses on short-term post-merger effects and does not capture longer-term synergies or delayed integration outcomes. Future research could extend this work by evaluating the persistence of performance changes over more extended periods or by incorporating qualitative factors, such as innovation adoption or cultural integration.

In conclusion, fintech acquisitions can enhance financial performance, but the value added depends critically on where and what kind of fintech is acquired. These insights offer valuable guidance for academics, policymakers, and practitioners navigating the evolving landscape of financial technology integration.

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Table 1

Descriptive statistics

	Count	mean	std	min	max
Fintech	12183	0.0228	0.1493	0.0000	1.0000
				-	
Firm size	10776	8.3815	3.1073	12.326	15.161
Leverage	10776	8.2771	829.03	0.0000	86060
cross_border	12183	0.2036	0.4027	0.0000	1.0000
private_target	12183	0.1134	0.3170	0.0000	1.0000
Stock payment	12183	0.0635	0.2439	0.0000	1.0000
				-	
ROA	10776	-0.2373	12.626	921.17	689.7842
				-	
ROE	10939	0.0081	8.9990	583.32	380.0134
				-	
Cash_flow	10776	-0.1606	11.8861	917.13	689.7842
pos	12183	0.5037	0.5000	0.0000	1.0000
deal_size	12183	278586	1732981	0.0000	47000000

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Table 2

Full sample analysis

	ROA	Cash_flow	ROE
Fintech	-4.4007	-2.9542	-0.0286
Post	-0.0013	0.0449	-0.0221
Fintech x post	3.3869	2.5383	0.1093
Deal size	0.0000 *	0.0000	0.0000
Firm size	0.3615 *	0.2617	0.1238
Leverage	0.0001***	0.0001	0.0000
Cross border	-0.6968	-0.5824	0.2144
Private target	0.0657	-0.1109	0.2552
Stock payment	0.705	1.0185	-0.1078
Constant	-3.104	-2.2627	-1.2054
r squared	0.0073	0.0048	0.0018
r squared_overall	0.0084	0.0054	0.0018
r squared_between	0.0159	0.012	0.0025
r squared_within	0.0002	-0.0008	0.0009
Number of obs.	10767	10767	10767
Period (years)	10	10	10
Number of M&A	5384	5384	5384

This table shows the results of the random effect method. *, *** is significance at 1% and 10%, respectively

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Table 3
Target Countries: Japan and Australia

	Japan			Australia		
	ROA	**Cash_flow**	**ROE**	**ROA**	**Cash_flow**	**ROE**
Fintech	-0.041	-0.0306	0.029	4.0752	3.6616	-0.4762 *
	-		-			
Post	0.0032	-0.0001	-0.0251	-2.6189	-2.4515	-0.0707
Fintech x post	0.0189	0.0148	0.1749 ***	-2.5387	-3.2691	0.1731 *
Deal size	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Firm size	0.0077	0.0078	0.0298	-1.3864	-1.5602	0.0122
	-					
Leverage	0.3996 ***	-0.3776 ***	0.5479 **	-9.995	-7.46	0.9019 **
Cross border	0.0804 ***	0.0771 ***	0.0938	1.9666	2.9575	-0.036
Private target	0.037	0.0395	-0.001	-5.7202	-5.96	-0.1047
	-		-			
Stock payment	0.1415 ***	-0.1435 ***	-0.2239	10.5501	11.1177	-0.3577 *
			-			
Constant	0.0564	0.0523	0.3309	13.1928	13.6149	-0.1441
r squared	0.5238	0.5063	0.2141	0.0396	0.0428	0.097
			-			
r squared_overall	0.185	0.1646	0.0861	0.0403	0.0441	0.0703
			-			
r squared_between	0.0373	0.02	0.6211	0.0398	0.045	0.0718
r squared_within	0.6993	0.6856	0.4395	0.035	0.0364	0.1301
Number of obs.	301	301	301	524	524	524
Period (years)	10	10	10	10	10	10
Number of M&A's	150	150	150	262	262	262

This table shows the results of the random effect method. *, **, *** is significance at 1%, 5% and 10%, respectively.

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Table 4
Target Countries: Spain and India

	Spain			India		
	ROA	Cash_flow	ROE	ROA	Cash_flow	ROE
Fintech	0.0389	0.0411 ***	-0.0179	0.0129	0.0000	-0.0434
Post	0.0587 **	0.0217 ***	0.0647 *	-0.0067	-0.0091	0.0428
Fintech x post	-0.1767 ***	-0.1288 ***	-0.1872 ***	-0.0201	0.0057	-0.1664 *
Deal size	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Firm size	0.0325 ***	0.0181 ***	0.0448 ***	0.0118	0.0112	-0.016
Leverage	0.2474 ***	0.1887 ***	0.3105 ***	-0.1097 ***	-0.1355 ***	-0.1332
Cross border	-0.0815 **	-0.0425 **	-0.0818 *	-0.0668	-0.0527	0.2964
Private target	-0.001	-0.0467	0.0098	-0.2218	-0.2247	0.8472
Stock payment	-0.2269	0.0111	-0.3862 *	0.0568	0.0537	-0.2582
Constant	-0.3675 ***	-0.1894 ***	-0.4553 ***	0.0026	0.0094	0.1831 *
r squared	0.2449	0.3222	0.2596	0.142	0.1699	0.1597
r squared_overall	0.2604	0.2469	0.2813	0.0719	0.0473	0.169
r squared_between	0.2729	0.1408	0.3089	0.1804	0.1628	0.2273
r squared_within	0.2034	0.3904	0.1988	0.0941	0.1938	0.0304
Number of obs.	215	215	215	238	238	238
Period (years)	10	10	10	10	10	10
Number of M&A	108	108	108	119	119	119

This table shows the results of the random effect method. *, **, *** is significance at 1%, 5% and 10%, respectively.

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Table 5
Target Countries: Germany and Canada

	Germany			Canada		
	ROA	Cash_flow	ROE	ROA	Cash_flow	ROE
			-			
Fintech	-0.031	-0.0353	0.0083	-37.776	-23.7906	2.0845
Post	0.030 **	0.0277 ***	0.0712 **	-0.3626 *	-0.1833 **	-0.402
			-			
Fintech x post	-0.1354	-0.1277 *	0.6328 *	-0.4353	-2.5418 *	-2.5826
Deal size	0.0000	0.0000	0.0000	0.0000 *	0.0000	0.0000
Firm size	0.0157 **	0.011 **	0.0374 ***	1.1207 **	0.3614 **	0.8352
Leverage	0.0853	0.0703	0.0364	0.0003 ***	0.0001 ***	0.0001
			-			
Cross border	-0.0501	-0.0323	0.0864	1.8774	1.515	2.5092
Private target	0.0137	0.0153	0.0657	4.7753	1.8753	4.255
			-			
Stock Payment	-0.1122	-0.0476	1.2882	9.9878	5.2361	4.8072
Constant	-0.1187 *	-0.0696	-0.238 **	-9.3682 **	-3.6745 *	-8.7682
r squared	0.118	0.0988	0.2113	0.1598	0.1572	0.0211
r squared_overall	0.1176	0.0968	0.1988	0.0758	0.058	0.0057
r squared_between	0.1441	0.1071	0.3271	0.1524	0.1265	0.0111
r squared_within	0.108	0.1005	0.1362	0.1725	0.2184	0.0313
Number of obs.	346	346	346	438	438	438
Period (years)	10	10	10	10	10	10
Number of M&A's	173	173	173	219	219	219

This table shows the results of the random effect method. *, **, *** is significance at 1%, 5% and 10%, respectively.

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Table 6

Actual Acquirer Countries: Switzerland and Japan

	Switzerland			Japan		
	ROA	**Cash_flow**	**ROE**	**ROA**	**Cash_flow**	**ROE**
				-		
Fintech	0.1598 ***	0.1606 ***	0.2239 **	0.0201	-0.01	-0.071
				-		-
Post	0.0161 **	0.0151 **	0.0726 **	0.0079 *	-0.0049	0.0018
Fintech x post	0.0229 **	0.0232 ***	0.0101	0.037 ***	0.0325 ***	0.1473 ***
Deal size	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	-					
Firm size	0.0037	-0.0055	0.0049	0.0061	0.006	0.0138 **
	-		-			
Leverage	0.0495	-0.0405	0.0773	0.0228	0.0389 *	0.0823 ***
						-
Cross border	0.043	0.0408	0.0398	-0.026 *	-0.022	0.0602 **
	-		-			
Private target	0.0745	-0.0872	0.1508	0.0079	0.0141	0.0084
	-			-		-
Stock payment	0.6283 ***	-0.4808 **	-3.664 ***	0.0098	-0.0132 *	0.0724 **
				-		-
Constant	0.0954	0.1139	0.0712	0.0499	-0.0508	0.0721
r squared	0.0801	0.0608	0.4323	0.0463	0.0503	0.1062
r squared_overall	0.1217	0.1108	0.4392	0.0553	0.0702	0.127
r squared_between	0.2149	0.1765	0.6972	0.0356	0.0472	0.1117
	-					
r squared_within	0.0191	-0.0262	0.0386	0.0518	0.0449	0.0876
Number of obs.	219	219	219	329	329	329
Period (years)	10	10	10	10	10	10
Number of M&A	110	110	110	164	164	164

This table shows the results of the random effect method. *, **, *** is significance at 1%, 5% and 10%, respectively.

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Table 7
Target sector, Consumer

	ROA	Cash_flow	ROE
Fintech	0.392 **	-0.4159	0.1116
Post	0.11	0.0119	0.1562
Fintech x post	-2.3113	-1.0757 *	-2.8948
Deal size	0.0000	0.0000	0.0000
Firm size	0.1159 ***	0.0721 **	0.0283
Leverage	-0.5334 ***	-0.5362 ***	0.0112
Cross border	-0.0405	-0.0607	0.1258 *
Private target	-0.2792	-0.087	0.1033
Stock payment	-2.5313	-0.0487	-3.1352
Constant	-0.8886 **	-0.4539 *	-0.2355
r squared	0.5623	0.8842	0.0603
r squared_overall	0.5623	0.8925	0.0603
r squared_between	0.8099	0.9566	0.1071
r squared_within	0.0387	0.1848	0.004
Number of obs.	709	709	709
Period (years)	10	10	10
Number of M&A	354	354	354

This table shows the results of the random effect method. *, **, *** is significance at 1%, 5% and 10%, respectively.

Figure 1

Algorithm: Identification of fintech firms via text mining in python

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REQUIRE: Dataset $\mathcal{D} = \{D_1, D_2, ..., D_n\}$ with firm descriptions; list of keywords $K = \{k_1, k_2, ..., k_m\}$

ENSURE: Binary indicator FintechFlag[i] $\in \{0,1\}$ for each firm i

```
for i in range(len(D)):
   FintechFlag[i] = 0
   D[i] = D[i].lower()  # convert to lowercase
   for k in K:
      k_pattern = re.sub(r' ', r'[_\- ]*', k)  # normalize pattern
      If re.search(k_pattern, D[i]):
         FintechFlag[i] = 1
         break

return FintechFlag
```

Figure 2

Algorithm: Subsample-specific estimation of fintech acquisition effects

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```
Input:
   D: Full dataset with panel structure
   G: Set of grouping variables (e.g., AcquirerCountry, TargetCountry, Sector)
   T: Outcome variable (e.g., ROA, ROE, Cash Flow)
   X: Set of covariates (including Fintech, Post, Fintech × Post, controls)

Procedure:
   Initialize empty result_list

   For each g in G:
      For each category c in unique(g):
         Subset Dc ← D where g == c

         Estimate Mundlak-corrected DiD model on Dc:
            T_it = α + β₁·Post_it + β₂·Fintech_it + β₃·(Fintech × Post)_it +
                 γ'·X_it + δ'·X̄_i + u_i + ε_it

         If coefficient β₃ is statistically significant:
            Append (group = g, category = c, β₃, p-value, direction) to result_list

Output:
   Table of subsample-specific estimates where Fintech × Post is significant
```

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