FACTORS INFLUENCING THE FINTECH FIRM PERFORMANCE IN EAST ASIA

LING KWEI EN

BACHELOR OF FINANCE (HONOURS) FINANCIAL TECHNOLOGY

UNIVERSITY TUNKU ABDUL RAHMAN

FACULTY OF ACCOUNTANCY AND MANAGEMENT DEPARTMENT OF FINANCE

DECEMBER 2025

Copyright @ 2025

ALL RIGHTS RESERVED. No part of this paper may be reproduced, stored in a retrieval system, or transmitted in any form or by any means, graphic, electronic, mechanical, photocopying, recording, scanning, or otherwise, without the prior consent of the authors.

DECLARATION

We hereby declare that:

(1) This undergraduate research project is the end result of my own work and that due acknowledgement has been given in the references to ALL sources of information be they printed, electronic, or personal.
(2) No portion of this research project has been submitted in support of any application for any other degree or qualification of this or any other university, or other institutes of learning.
(3) The word count of this research report is 25,568.

Name of Student:	Student ID:	Signature:
Ling Kwei En	22UKB06940	

Date: 16 December 2025

Table of Contents

LIST OF TABLES

CHAPTER 3: METHODOLOGY

CHAPTER 4: DATA ANALYSIS

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

CHAPTER 2: LITERATURE REVIEW

CHAPTER 3: METHODOLOGY

LIST OF APPENDICES

ABSTRACT

This study investigates the factors that influence business performance among East Asian FinTech enterprises, with an emphasis on the functions of liquidity, working capital management, and leverage, as well as the moderating effect of COVID-19. Using panel data from 200 FinTech firms in China, Japan, and South Korea from 2016 to 2019 and 2021 to 2024, the study employs Fixed Effects regression models with robust standard errors to account for unobserved firm-specific heterogeneity. The empirical findings reveal that working capital management and leverage are important predictors of company performance, as assessed by Return on Assets, with working capital to total assets and debt to equity having negative and statistically significant effects. In contrast, liquidity, as measured by the Current Ratio, was found to have no substantial direct impact on profitability. Further research, including COVID-19 as a moderating variable, demonstrates that the pandemic only slightly decreased the association between liquidity and business performance, while the effects of working capital management and leverage remained constant. Overall, the findings show that firm-specific financial management practices have a greater impact on FinTech firm performance than external shocks, particularly in technologically advanced and resilient markets like China, Japan, and South Korea, and the study has important implications for policymakers, practitioners, and investors looking to improve financial resilience and long-term growth in the FinTech sector.

CHAPTER 1: INTRODUCTION

1.0 Introduction

This chapter lays the groundwork for the study by explaining the background and motivation for the investigation. It starts with a review of the overall financial landscape, followed by an overview of the FinTech business and its growing importance in East Asia. The chapter also discusses the research problem, formulates research objectives and questions, and creates study hypotheses. It also discusses the importance of research for academic, practical, and policy concerns. The chapter finishes with a summary of the thesis framework, providing a clear path for the following chapters.

1.1 Background of Study

The global financial system has undergone profound changes since the 2007–2009 Global Financial Crisis (GFC), which exposed the vulnerabilities of traditional financial institutions and raised critical concerns over risk management, funding structures, and capital adequacy (Vazquez & Federico, 2012). In response, sweeping reforms were introduced, most notably the Basel III framework, which strengthened liquidity requirements, leverage ratios, and capital buffers to enhance systemic resilience (Vazquez & Federico, 2012). Under this heightened regulatory environment, policymakers, regulators, and scholars increasingly turned their focus toward understanding the performance of financial firms (Athanasoglou, Delis, & Staikouras, 2006).

Traditionally, financial performance has been assessed through profitability measures such as Return on Assets (ROA), which reflect both internal and external drivers (Ercegovac & Ivica Klinac, 2020; Athanasoglou, Delis, & Staikouras, 2006). Internal determinants include capital adequacy, credit risk management, operational efficiency, liquidity, leverage, and firm size (Vazquez & Federico, 2012; Ercegovac & Ivica Klinac, 2020; Athanasoglou, Delis, & Staikouras, 2006; Aldboush, Almasria, & Ferdous, 2023). External factors such as macroeconomic growth, inflation, and market concentration also play a significant role in shaping profitability and stability within the financial sector (Ercegovac & Ivica Klinac, 2020; Vazquez & Federico, 2012; Athanasoglou, Delis, & Staikouras, 2006). These determinants became particularly critical during the GFC, when banks with weak liquidity positions and excessive leverage were disproportionately vulnerable to collapse (Vazquez & Federico, 2012).

Amid this shifting financial landscape, Financial Technology (FinTech) has emerged as a disruptive force, leveraging technological innovations to deliver financial services more efficiently and inclusively (Fan, Bae, & Liu, 2024; Phan, Narayanb, Rahman, & Hutabarat, 2020; Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). Over the past decade, FinTech firms have rapidly expanded by deploying big data, artificial intelligence, and blockchain to reduce information asymmetries, broaden access to finance, and lower transaction costs (Fan, Bae, & Liu, 2024). Their disruptive role has given rise to what scholars term the "substitution effect," whereby FinTech providers increasingly capture services once dominated by traditional banks, reshaping competitive dynamics in financial markets (Phan, Narayanb, Rahman, & Hutabarat, 2020; Fan, Bae, & Liu, 2024).

The COVID-19 outbreak marked a turning point for the FinTech industry in East Asia, accelerating digital adoption across China, Japan, and South Korea. Although China's FinTech sector was already expanding rapidly before 2020, the pandemic intensified the demand for contactless and technology-driven financial services. According to the SCMP (2020), investor confidence strengthened following several major FinTech IPOs, while consumers increasingly relied on digital channels to minimise face-to-face interactions. As mobile payments and online financial services grew sharply, Chinese FinTech firms experienced rapid expansion supported by enhanced innovation activities, as reflected in the rise in patent applications. As reported by KPMG (2021), a big growing fintech patent in China as ***Figure 1.1***. These trends indicate that Chinese FinTech firms did more than benefit from heightened demand—they actively strengthened their technological capabilities throughout the pandemic.

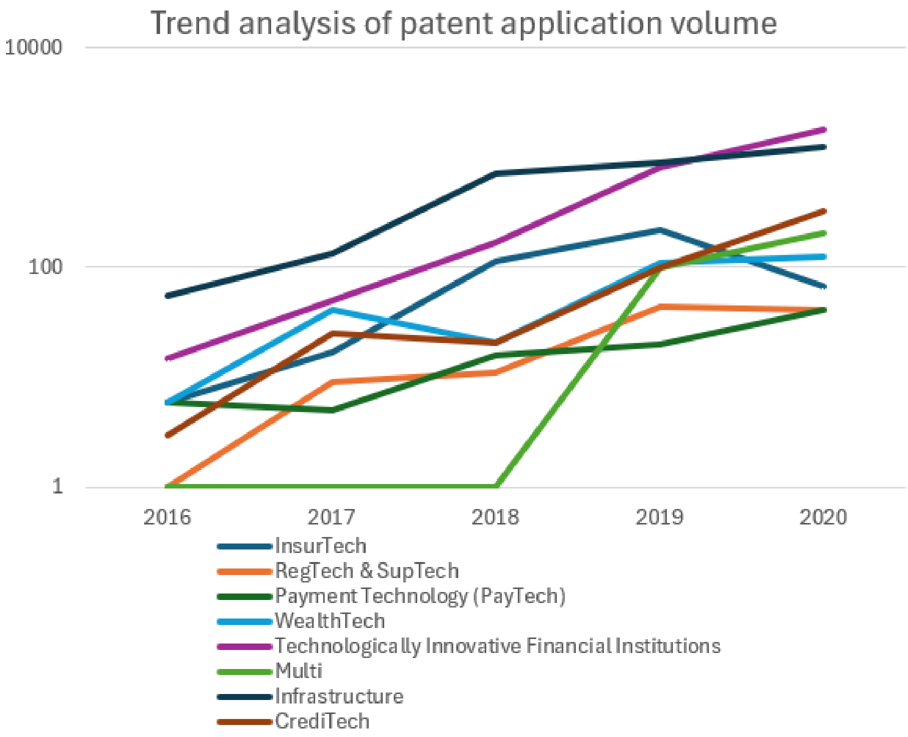


Figure 1. 1: China Fintech Trend Analysis (2016 – 2020)

Japan experienced a similar surge, although its growth was particularly concentrated in the asset-management segment. The FinCity Tokyo (2021) report projects that the discretionary robo-advisor market will expand by 137%, from 1.1 million to 2.6 million accounts ***(Refer to Appendices: Figure 1.2)***. This significant increase illustrates how social-distancing measures and reduced access to in-person financial services pushed Japanese consumers toward online investment tools and digital asset-management platforms. Consequently, the pandemic accelerated Japan's shift from traditional financial services to digital wealth management, creating favourable momentum for FinTech development.

In South Korea, the pandemic also fast-tracked FinTech adoption, supported by the country's strong digital infrastructure and high internet penetration. Data from Tenity (2024) shows a steady rise in the number of active FinTech companies during this period. As physical banking services became less accessible, Korean consumers increasingly embraced online banking, digital payments, and virtual financial platforms. This transformation was further supported by Fintech Center Korea (2024) measures promoting digital financial innovation, enabling FinTech firms to scale quickly and respond effectively to changing consumer needs

(Refer to Appendices: Figure 1.3).

Given these distinct but converging growth patterns, studying FinTech performance in East Asia has become particularly important. The region is one of the most dynamic and technologically advanced FinTech hubs in the world, characterised by large populations, high digital readiness, and supportive regulatory frameworks. Moreover, China, Japan, and South Korea differ significantly in their FinTech market structures—China being payment-driven, Japan investment-focused, and South Korea diversified—offering a unique opportunity to examine how financial determinants influence firm performance across varying environments. This diversity allows researchers to assess whether factors such as liquidity, working capital, and leverage exert similar effects across different types of FinTech markets.

Despite the rapid rise of FinTech in East Asia, substantial research gaps remain. Much of the existing literature centres on FinTech development, adoption patterns, or consumer behaviour, while relatively few studies evaluate the financial performance of FinTech firms using objective measures such as Return on Assets (ROA). In addition, prior research often focuses on Western markets or global samples, which may not accurately capture the unique regulatory structures and growth dynamics of East Asian FinTech ecosystems. Limited empirical work has examined how the pandemic-driven surge in digital financial activity affected the financial stability and profitability of FinTech firms in this region. Furthermore, cross-country comparative studies remain scarce, even though countries within East Asia differ significantly in technological maturity and FinTech models.

Therefore, this study addresses the lack of empirical evidence on the financial determinants influencing the performance of FinTech firms in East Asia, especially in the context of the sector's accelerated growth following the pandemic. As FinTech becomes increasingly integrated into the financial systems of China, Japan, and South Korea, understanding the drivers of firm performance is crucial for investors, regulators, policymakers, and industry practitioners. By focusing on ROA as the primary performance indicator and examining key determinants such as liquidity, working capital, and leverage, this study aims to bridge existing research gaps and provide deeper insights into FinTech profitability within a rapidly evolving regional landscape.

1.2 Development of the Fintech Industry

The development of fintech can be traced through distinct stages. In its earliest form, fintech was primarily confined to internal banking operations, where technology served to improve efficiency in record keeping, account administration, and transaction processing (Flinders & Smalley, 2024). During this stage, fintech functioned predominantly as a support mechanism for financial institutions rather than as a tool for individual consumers.

As digitalization advanced and the adoption of smartphones became widespread, fintech entered a new phase of expansion characterized by consumer-oriented services (Kagan, 2025). These services now include mobile banking, digital wallets, budgeting applications, peer-to-peer payment systems, and online trading platforms. This period also witnessed the rise of fintech startups that disrupted the dominance of traditional financial institutions by offering faster, more cost-effective, and more inclusive solutions. Such innovations were instrumental in promoting financial inclusion and extending access to services for underserved and marginalized groups.

The latest stage of fintech development is marked by the integration of advanced technologies such as artificial intelligence, machine learning, blockchain, and big data analytics. These innovations have enabled the delivery of personalized financial services, improved fraud detection, Robo-advisory solutions, and decentralized finance models built on cryptocurrency (Kagan, 2025). Evidence from the World Economic Forum (2025) indicates that approximately 80% of fintech firms report enhanced customer experiences through the adoption of artificial intelligence, while nearly three-quarters observe gains in profitability and cost efficiency (World Economic Forum, 2025).

The emergence of fintech has reshaped the financial landscape by disrupting conventional banking models and introducing a new era of digital financial services. This transformation requires more than advanced technological infrastructure; it also demands strategic foresight and comprehensive industry expertise. Over the past few years, fintech has expanded rapidly, positioning itself as a key driver of global economic change. Projections from Statista suggest that the digital assets market alone is expected to grow by 17.38% in 2025, underscoring the sector's accelerating momentum (Malyshev, 2025). As industry continues to advance, firms increasingly recognize the necessity of adopting digital solutions to deliver innovative financial products and services for both consumers and businesses. At the same time, this evolution creates substantial opportunities for entrepreneurs, particularly in the establishment of fintech-based institutions, which, despite their complexity and challenges, hold considerable potential for sustainable long-term growth.

The global financial services sector is undergoing profound transformation, with several disruptive forces driving the rapid expansion of the fintech industry (Malyshev, 2025). One of the most notable developments is the widespread adoption of digital banking. Both consumers and businesses increasingly favor accessing financial services through digital platforms such as smartphones and computers, which provide greater convenience, accessibility, and efficiency compared to traditional brick-and-mortar institutions. What was once considered an additional service has now become an integral part of modern finance, reflecting a broader shift toward fully digital financial ecosystems.

Another major catalyst for fintech growth is the accelerated rise of mobile payments. The demand for secure, seamless, and contactless transactions grew substantially during the COVID-19 pandemic, when health and safety concerns reshaped consumer preferences. Mobile wallets, QR code transactions, and peer-to-peer payment platforms have since become firmly embedded in everyday financial behavior, leading to a cultural shift in how individuals and businesses conduct routine financial activities. These innovations have expanded access for small enterprises and microbusinesses by offering cost-effective payment systems, thereby enhancing financial inclusion on a global scale.

Equally significant is the increasing acceptance and integration of cryptocurrencies. As digital currencies gain traction among both retail users and institutional investors, fintech firms are introducing platforms and services to facilitate their trading, storage, and broader applications (Malyshev, 2025). This expansion not only diversifies financial products but also fuels the growth of decentralized finance (DeFi), which challenges traditional financial intermediaries. Such developments are reshaping the global financial landscape and compelling regulators and central banks to re-evaluate existing policies and oversight mechanisms.

Crucially, these transformative trends are reshaping the competitive dynamics of the industry. While start-ups harness technological innovation to deliver agile and customer-centric solutions, established financial institutions are being compelled to adapt by integrating fintech-driven technologies such as blockchain applications, artificial intelligence-powered customer support, and advanced digital payment systems. The interplay between innovation and adaptation underscores the highly dynamic nature of fintech, reinforcing its role as both a driver of market growth and a catalyst for structural change within the global financial sector.

Another notable development in the sector is the shift from rapid customer acquisition to more sustainable and resilient growth. Earlier phases of fintech were characterized by exceptionally high expansion rates, with customer acquisition reaching nearly 50% annually. Recent figures, however, show that growth has moderated to around 37%. Despite this slowdown, revenues and profitability remain strong at about 40%, suggesting that the sector is entering a phase of stabilization while continuing to strengthen its financial performance (World Economic Forum, 2025).

Fintech has also emerged as a significant driver of financial inclusion. Data from the World Economic Forum (2025) reveal that micro, small, and medium-sized enterprises account for more than half of fintech users, with women and low-income groups also representing a substantial share of the customer base. This inclusive orientation is particularly important in emerging markets such as the Middle East and North Africa, where fintech firms often design their business models to address persistent barriers to financial access.

Collaboration between fintech companies and traditional financial institutions has likewise become a defining trend in recent years. The majority of fintech firms report partnerships with banks, most commonly through application programming interface integrations. Such collaborations enable fintech to expand more efficiently, enhance their credibility, and leverage the infrastructure of established institutions, while simultaneously introducing innovative approaches to customer engagement and service delivery (World Economic Forum, 2025).

In parallel, fintech continues to attract strong investment on a global scale. Market research highlights East Asia as one of the fastest-growing regions for venture capital investment in fintech. Between 2020 and 2023, the value of venture capital funding in East Asia and North Africa more than tripled, with an average annual growth rate of around 33%, positioning the region among the world's leading hubs for fintech expansion (World Economic Forum, 2025).

The fintech sector has experienced rapid expansion and has significantly reshaped the global financial landscape, yet it continues to face challenges that limit its full potential. Key concerns include regulatory fragmentation, funding constraints, and vulnerability to external shocks. These weaknesses became particularly evident during the COVID-19 pandemic, when heightened financial market volatility exposed the fragility of business models that depended heavily on investor confidence and steady liquidity flows. Such challenges highlight the reality that while innovation remains a vital driver of growth, resilience and adaptability are equally essential for ensuring long-term sustainability.

Financial variables have a significant impact on the performance of fintech firms. Kayani et al. (2025) highlight the importance of liquidity, as assessed by metrics such as the Current Ratio (CR), working capital efficiency (WC/TA), and leverage (D/E). These variables have a direct impact on profitability results, such as Return on Assets (ROA), which are important indications of efficiency and financial health. The findings indicate that fintech companies' success is driven not only by technological innovation but also by the soundness of their financial management procedures, which serve as a foundation for stability during times of rapid change or crisis.

1.3 Firm Performance

Firm performance is an important term in finance and business research because it represents how well a company uses its resources to generate value and sustain growth. Financial performance is frequently used as a wide indicator of a company's overall health, including profitability, liquidity, efficiency, and stability (Kenton, 2025). Profitability is the most direct indicator of a company's capacity to generate value for shareholders and ensure long-term survival in competitive marketplaces, hence it is the focus of this study.

Profitability is particularly important because it demonstrates the extent to which a firm's earnings exceed its costs, thereby offering a clear signal of managerial efficiency and operational success. Among the various measures available, this study employs Return on Assets (ROA) as a proxy for profitability. Both are well established in academic literature and professional practice, and when used together, they provide complementary insights into firm performance (Brealey, Myers, Allen, & Edmans, 2025).

ROA, calculated as the ratio of net income to total assets, captures how efficiently a company uses its resources to generate profits. Its strength lies in normalizing earnings relative to the asset base, enabling meaningful comparisons between firms of different sizes. A higher ROA reflects stronger managerial effectiveness in allocating resources, making it a reliable measure of operational efficiency. Nevertheless, ROA can be influenced by variations in capital structure and accounting practices, which calls for caution, especially when comparing firms across industries with different levels of asset intensity.

By employing both ROA, this study offers a more comprehensive view of firm performance. ROA emphasizes efficiency in the use of total resources. ROA measures capture distinct yet complementary aspects of financial success, ensuring that the evaluation of profitability is not only operationally sound but also aligned with shareholder interests.

1.4 Problem Statement

The rapid global expansion of the FinTech industry has brought both opportunities and challenges to the financial sector. On one hand, FinTech has the potential to enhance financial inclusion, improve service efficiency, and foster economic development through innovative technologies such as crowdfunding, peer-to-peer lending, mobile applications, blockchain, and big data analytics (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). On the other hand, these advancements also carry risks, including heightened financial fragility and the danger of households or businesses falling into debt traps as credit becomes increasingly accessible (Yue, Korkmaz, Yin, & Zhou, 2022). While extensive research has explored the determinants of performance in traditional financial institutions, focusing on aspects such as capital adequacy, risk management, liquidity, and market concentration (Osborne, Fuertes, & Milne, 2012; Ercegovac & Ivica Klinac, 2020; Athanasoglou, Delis, & Staikouras, 2006)—far less is understood about the factors driving the performance of FinTech firms, particularly in developing economies. This gap is especially evident in East Asia, where FinTech adoption is accelerating but empirical studies remain scarce.

A key issue lies in the fact that FinTech business models differ fundamentally from those of traditional financial institutions. Whereas banks typically depend on deposit-taking and interest-based lending, FinTech firms often operate through digital platforms, alternative funding models, and a customer base that frequently includes underserved or previously excluded communities. This raises the critical question of whether traditional profitability drivers apply equally to FinTech enterprises. For instance, while larger firm size is typically associated with greater profitability in banks due to economies of scale and broader resources (Aldboush, Almasria, & Ferdous, 2023; Modjo, Loekman, & Limijaya, 2022), FinTech companies often thrive on agility, leaner structures, and lower operating costs, potentially reshaping the size-profitability relationship. Similarly, liquidity and leverage—core performance measures for banks—may function differently in FinTech firms, given their distinct funding structures and the absence of traditional deposit-taking activities (Nanda & Panda, 2017; Akinlo & Asaolu, 2012). These differences underscore the need to study FinTech as a unique type of financial intermediary.

The urgency of this research has been amplified by recent global shocks, particularly the COVID-19 pandemic. During the crisis, FinTech firms played a vital role in providing loans and delivering digital financial solutions at a time when many traditional institutions were constrained. Yet, the pandemic also exposed vulnerabilities: delinquency rates on FinTech loans surged far more sharply than those on bank loans, revealing the sector's potential fragility under economic stress (Bao & Huang, 2020). These developments highlight the importance of understanding the profitability drivers of FinTech firms, not only for their business success but also for safeguarding overall financial system stability. Despite steady progress before 2020, the COVID-19 pandemic triggered a sharp jump in fintech startups and funding across East Asian countries, with the number of firms more than doubling and investment surging by over 180% in 2021. This rapid growth highlights a lack of understanding of the sustainability and long-term performance of these newly established fintech firms.

This study is motivated by three interrelated factors. First, there is a lack of empirical research on the determinants of FinTech profitability. While studies in North America and Europe have begun to examine financial ratios and performance drivers (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025), evidence from emerging regions such as the East Asia remains extremely limited. This study therefore aims to fill this gap by focusing on FinTech enterprises operating in a strategically important but underexplored market.

Second, the expansion of FinTech raises concerns for financial stability. As these firms grow in importance across credit, payments, and investments, their resilience—or lack thereof—can have systemic consequences. If FinTech companies are highly vulnerable to shocks, their instability could spill over to consumers, investors, and even the broader banking sector. This makes it essential to investigate how firm-level characteristics such as liquidity management, working capital, and leverage shape the resilience of FinTech firms during different phases of the economic cycle (Nanda & Panda, 2017; Akinlo & Asaolu, 2012; Kayani, Dsouza, Husain, Nawza, & Hasan, 2025).

Finally, the findings of this study hold practical value for decision-making. Insights into the financial drivers of FinTech profitability can guide managers and investors in strategy development, risk management, and capital allocation (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025; Kabuye, Kato, Akugizibwe, & Bugambiro, 2019). For policymakers and regulators, the results can support the design of policies that balance innovation with financial stability (Yue, Korkmaz, Yin, & Zhou, 2022). In East Asia in particular, effective regulation will be crucial to ensuring that digital finance develops sustainably while minimizing systemic risks.

In summary, this study directly addresses the limited empirical evidence on what drives the financial performance of FinTech firms in East Asia—an industry that experienced rapid acceleration during the pandemic but continues to face significant challenges in maintaining profitability. Although FinTech growth in China, Japan, and South Korea has been widely documented, far less is known about how firm-level financial factors such as liquidity, working capital, and leverage influence actual profitability outcomes, especially when measured through objective indicators like ROA. This gap is particularly important because East Asia's FinTech ecosystem operates within diverse market structures and regulatory environments, which may cause these financial determinants to behave differently across countries and business models.

By examining these determinants within the context of both normal economic conditions and periods of disruption such as COVID-19, this study aims to generate empirical insights that are relevant to scholars, industry practitioners, and policymakers. Understanding how internal financial management shapes profitability is crucial not only for improving firm resilience but also for strengthening the long-term sustainability of the region's rapidly expanding digital finance sector. Following this problem statement, the next section presents the study's research objectives, research questions, and hypotheses. Together, they provide a clear analytical framework for investigating how liquidity, working capital, and leverage affect the ROA of FinTech firms across East Asia, and how these relationships evolve in times of economic uncertainty.

1.5 Research Questions

1. How are liquidity, working capital, and leverage related to the profitability (ROA) of Fintech firms in East Asia?
2. Does COVID-19 has a moderating effect on how liquidity, working capital, and leverage affect the profitability of FinTech firms in East Asia?

1.6 Research Objectives

1. To examine how liquidity, working capital, and leverage relate to the profitability (ROA) of FinTech firms in East Asia.

2. To investigate the moderating effect of COVID-19 on the relationship between liquidity, working capital, leverage, and the profitability (ROA) of FinTech firms in East Asia.

1.7 Hypotheses of the Study

H1: *There is a significant relationship between liquidity and ROA.*

H2: *There is a significant relationship between working capital and ROA.*

H3: *There is a significant relationship between leverage and ROA.*

H4: *There is a significant moderating effect of COVID-19 on the relationship between liquidity and ROA.*

H5: *There is a significant moderating effect of COVID-19 on the relationship between working capital and ROA.*

H6: *There is a significant moderating effect of COVID-19 on the relationship between leverage and ROA.*

1.8 Significance of the Study

This study is crucial both academically and professionally since it fills critical gaps in existing literature while also providing valuable insights for stakeholders in East Asia's fast-evolving FinTech sector. From an academic standpoint, the study advances current knowledge by examining the financial performance of FinTech firms using empirical evidence—an area that remains underexplored despite the industry's global rise. While past research has focused heavily on digital finance technologies such as blockchain, big data analytics, and online platforms, there is limited investigation into how internal financial indicators influence the profitability of FinTech firms themselves. By analyzing liquidity, working capital, and leverage in relation to Return on Assets (ROA), this study provides a clearer understanding of the financial determinants that shape firm performance.

A major theoretical contribution lies in its regional focus. Although FinTech is a global phenomenon, determinants of success vary widely across regions due to differences in regulation, market structure, and technological maturity. East Asia—specifically China, Japan, and South Korea—represents one of the most dynamic yet understudied FinTech markets in academic literature. While Western economies dominate existing research, East Asia presents a unique ecosystem characterized by innovation-driven growth, strong digital adoption, and diverse financial models. Studying this region therefore enriches global FinTech literature by filling a substantial geographical and contextual gap.

The study also contributes by examining how financial determinants behave across different economic phases, particularly before, during, and after the COVID-19 pandemic. The pandemic drastically accelerated digital finance adoption across China, Japan, and South Korea, creating shifts in consumer behavior, firm strategies, and investment dynamics. However, few studies have empirically assessed whether these external shocks altered the relationship between firm-level financial indicators and profitability. By introducing a temporal perspective, this research advances theoretical discussions on financial intermediation and organizational resilience within technology-driven financial firms.

Beyond academic contributions, this study carries strong practical value. For FinTech managers, the findings will offer evidence-based guidance on optimizing liquidity management, strengthening working capital strategies, and making effective leverage decisions to improve profitability and long-term sustainability. For investors, the results provide clearer visibility into the stability and growth potential of FinTech firms in East Asia, an increasingly attractive but volatile investment domain. For policymakers and regulators, the study delivers empirical insights that can support balanced regulatory frameworks that foster innovation while safeguarding financial stability. Understanding what drives profitability helps regulators identify areas where risk mitigation, transparency, consumer protection, and technological support are needed.

Ultimately, this study moves beyond descriptive trends to deliver a rigorous, data-driven examination of FinTech firm performance under varying economic conditions. Its contributions are twofold: it strengthens theoretical understanding of financial determinants in technology-driven financial firms, and it provides practical insights for improving profitability, investment decisions, and regulatory policy. By focusing on East Asia's FinTech sector and analyzing performance across pre-pandemic and post-pandemic periods, the study directly addresses the research objectives and establishes a strong foundation for the hypotheses developed in earlier chapters.

1.9 Outline of the Study

The remainder of this paper is organized as follows:

Chapter 1 introduces the fintech industry's growth in East Asia and outlines the research problems, objectives, questions, hypotheses, and significance of the study.

Chapter 2 reviews existing research on fintech, profitability, and financial ratios, with a focus on fintech firms in East Asia. It identifies theoretical frameworks and research gaps to provide context for the study.

Chapter 3 presents the details in research design, data collection, methods, sample selection, financial ratios (CR, WC/TA, D/E), variables, regression models, and analytical methods (including panel data analysis for 2016-2024, OLS regression) used to test the hypotheses, addressing issues like endogeneity and multicollinearity.

Chapter 4 presents the empirical findings, including descriptive statistics, correlation analyses, and regression results for COVID-19 periods as a moderating effect, interpreting their implications for fintech performance.

Chapter 5 concludes the paper with a summary of key findings, evaluates the hypotheses, and discusses theoretical and practical implications for fintech firms and policymakers. It provides recommendations for fintech firms, investors, and policymakers, acknowledges study limitations and suggests directions for future research.

CHAPTER 2: LITERATURE REVIEW

2.0 Introduction

This chapter covers the existing literature that supports the examination of FinTech firms' financial performance. It begins by outlining the theoretical foundations that explain firm profitability and financial behavior, followed by a discussion of profitability as a central indicator of performance. The review then explores how key financial determinants such as liquidity, working capital, and leverage influence profitability, drawing from prior studies in both traditional finance and emerging digital finance contexts. In addition, the chapter considers the impact of external shocks by examining how crisis periods shape financial outcomes, with particular attention to the years 2016 to 2024. By combining these approaches, the literature review emphasizes the significance of understanding financial strategies in various economic situations, reveals gaps in current knowledge, and lays the framework for the hypotheses and empirical analysis that follow.

2.1 Theoretical Frameworks

2.1.1 Pecking Order Theory

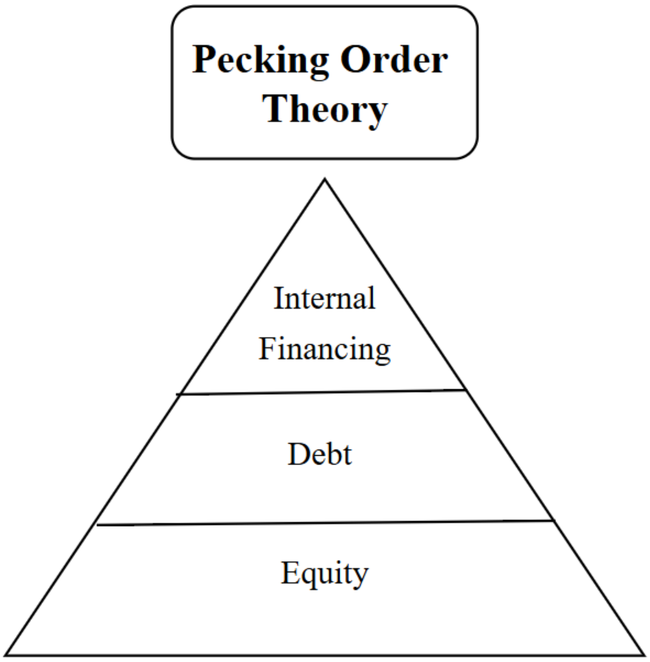


Figure 2.1. 1: Pecking Order Theory

The **Pecking Order Theory**, first introduced by Stewart C. Myers and Nicolas Majluf in 1984, explains how firms prioritize their sources of financing (CFI Team, n.d.). It suggests that businesses follow a hierarchy in which they first depend on internal funds, such as retained earnings, before seeking external financing (CFI Team, n.d.). When additional funding is required, firms generally prefer debt over equity, with equity considered the last option. This hierarchy is largely shaped by information asymmetry, since managers typically possess more accurate knowledge of a company's true value and prospects than outside investors. Issuing equity may therefore signal uncertainty or potential overvaluation of the market, making it a costly choice. In contrast, internal financing avoids signaling problems and ownership dilution, while debt is often less expensive and less disruptive than issuing new equity.

This model is evident in practice. For instance, multinational corporations like Apple often fund investments primarily through retained earnings rather than issuing new shares (Mark, 2024). Similarly, start-ups and rapidly developing businesses typically begin with internal funding, then transition to debt, and finally to equity as necessary. These patterns demonstrate the practical utility of the Pecking Order Theory in understanding corporate finance decisions in a variety of business situations.

In the context of this research, the Pecking Order Theory offers an important framework for analyzing the financing strategies of FinTech firms in East Asia. With the region's rapidly evolving economic landscape and the fast-paced growth of the digital financial sector, understanding how FinTech firms manage liquidity, working capital, and leverage is particularly important. The theory suggests that firms with sufficient internal resources, such as strong liquidity and efficient working capital, are less likely to rely heavily on debt or equity financing. As result this theory supports the expected positive impact between liquidity and working capital on profitability. However, during crisis periods like the COVID-19 pandemic, when internal funds may have been limited, firms were more likely to depend on debt financing, with equity as the last resort. This shift has direct implications for profitability, as excessive leverage increases financial costs and reduces overall performance. As a result, the Pecking Order Theory not only confirms the expected negative link between leverage and profitability, but also emphasizes the importance of liquidity and working capital in developing financial strategy over economic cycles.

2.1.2 Trade-Off Theory

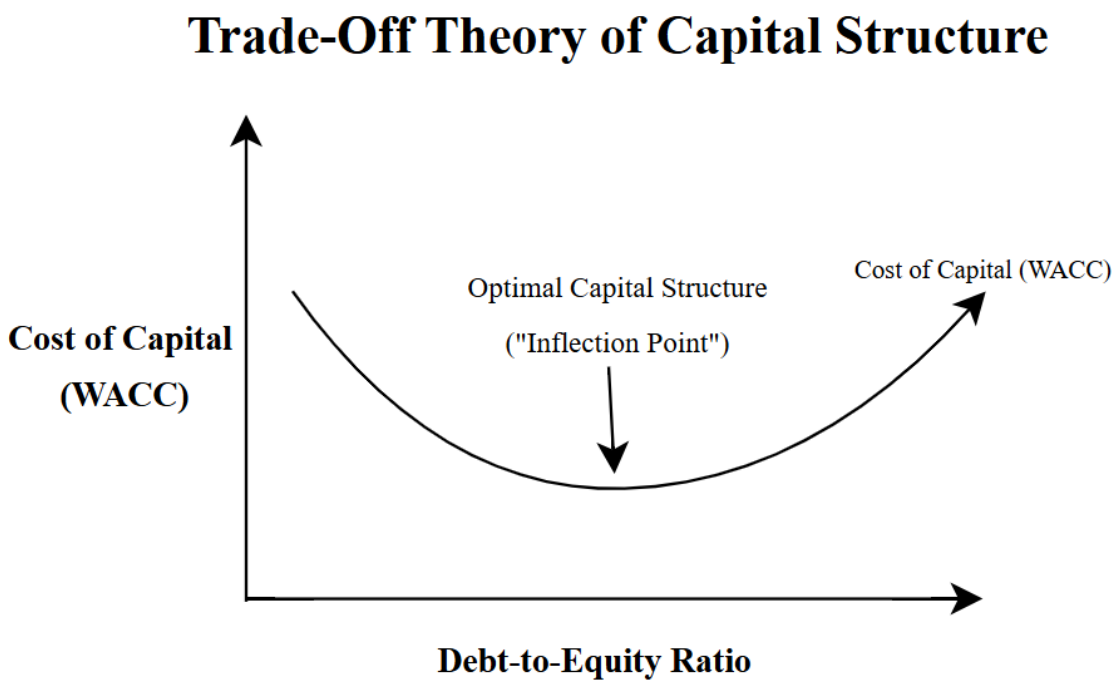


Figure 2.1. 2: Trade-Off Theory

The **Trade-Off Theory** provides another essential foundation for this research, as it explains how firms balance the advantages and disadvantages of debt financing when determining their capital structure (WallStreetPrep, 2024). Rather than avoiding debt totally, the theory proposes that enterprises seek for an optimal level of leverage in which the benefits of debt, such as tax savings from deductible interest payments, outweigh the accompanying costs, which include bankruptcy risk, financial distress, and agency issues.

One of the central advantages of debt is the tax shield it provides (capital.com, n.d.). Since interest payments are tax-deductible, borrowing can reduce a company's taxable income and increase after-tax profitability. However, debt also creates fixed obligations in the form of interest and principal repayments, which may constrain cash flow. Firms with high leverage can become especially vulnerable during periods of financial instability, facing risks of default, restructuring, or even liquidation. Therefore, the Trade Off Theory supports the expected negative impact of leverage on profitability and emphasizes that the costs of financial distress rise with higher debt levels (capital.com, n.d.). These costs extend beyond direct legal and administrative expenses to include reputational harm, loss of operational flexibility, and heightened risks of adverse selection and moral hazard. Consequently, firms must weigh whether the benefits of additional debt are sufficient to justify the risks that accompany it.

Empirical research suggests that modest leverage can boost profitability by saving on taxes and financing costs. However, once the ideal threshold is reached, the disadvantages of increased debt outweigh the benefits. While steady economic conditions may allow corporations to maintain modest leverage, periods of crisis or uncertainty, such as recessions or the COVID-19 epidemic, can force businesses to limit loan exposure in order to avoid financial difficulties. The Trade Off Theory is particularly important to the topic of this investigation. The hypothesis explains how financing tactics evolve in response to changing situations by evaluating the liquidity, working capital, leverage, and profitability of FinTech enterprises in East Asia during multiple economic cycles. It implies that, while leverage might boost profitability during stable times, excessive debt during crises or recovery periods can damage performance due to increased risks. In this regard, the Trade Off Theory supports the Pecking Order Theory by providing a balanced perspective on financing options and a useful lens through which to understand FinTech enterprises' financial actions prior to, during, and following the COVID-19 pandemic.

2.2 Profitability

Profitability is a key indicator of firm performance, showing a company's capacity to earn revenue from its operations. It is more than just an accounting result; it is a key measure of efficiency, competitiveness, and long-term viability. Hermanson and Edwards (2005) define profitability as a company's ability to generate income, but Seissian et al. (2018) define it as the net earnings remaining after subtracting liabilities during a given time period (Aldboush, Almasria, & Ferdous, 2023). In practice, profitability must be assessed both historically and, in the present, to provide a comprehensive picture of performance and to inform strategic decision-making. As Aldboush et al. (2023) point out, increasing shareholder value through measures like return on assets (ROA) remains a key goal of financial management.

Sustaining profitability is critical for a firm's survival and long-term growth. Companies must effectively combine and allocate resources to achieve their goals, as profitability represents one of the most important determinants of corporate endurance (Ohorella, 2019). For investors, it signals future potential and the capacity to generate consistent returns, while for creditors it reflects a firm's ability to meet obligations. Managers also rely on profitability to assess operational efficiency and shape strategic decisions (Ohorella, 2019; Osborne, Fuertes, & Milne, 2012). Beyond these roles, profitability is closely tied to financial stability. During times of economic stress, for instance, regulators such as the Federal Reserve and Japan's Financial Services Agency imposed stricter safeguards on banks, underscoring the importance of profitability in ensuring institutional resilience (Haas, Neely, & Emmons, 2020).

Profitability is influenced by both internal and external factors. Internally, firm size, efficiency, leverage, and working capital are key determinants, while externally, macroeconomic conditions, regulatory frameworks, and market structures play critical roles. Liquidity also has a close relationship with profitability, requiring firms to balance meeting short-term obligations with achieving long-term gain (Bibi & Amjad, 2017). Scholars have approached profitability from two primary perspectives. The structure-conduct-performance (SCP) model argues that market structure determines profitability, with concentration and barriers to entry shaping competitive behavior and outcomes. In contrast, the firm effect model emphasizes that profitability stems from unique firm characteristics and managerial practices, such as productivity, efficiency, and resource allocation (Aldboush, Almasria, & Ferdous, 2023; Stierwald, 2010). Together, these perspectives suggest that both industry-level and firm-level factors are essential in explaining profitability variations.

Measuring profitability has been a central concern in both research and practice, with accounting-based indicators being most used. Return on Assets (ROA), calculated as net income divided by total assets, is considered a key indicator of managerial efficiency because it demonstrates how effectively firms convert assets into earnings (Ohorella, 2019; Ercegovac

& Ivica Klinac, 2020).

The literature further indicates that the determinants of profitability vary across industries, regions, and periods. Some studies show that larger firms enjoy higher profitability due to economies of scale, while others present mixed or even negative results depending on the context (Nanda & Panda, 2017). Similarly, moderate levels of leverage may improve profitability through tax benefits, but excessive debt often increases financial risk and reduces performance. Liquidity and working capital also remain vital, as firms must manage them carefully to balance solvency with profitability. These diverse findings underscore the complexity of profitability and highlight the need for research that focuses on specific sectors and regional contexts.

In FinTech firms, particularly those operating in East Asia, profitability is shaped by unique dynamics such as technological innovation, rapid market expansion, and evolving regulatory frameworks. Understanding how profitability indicators, such as ROA, ROE, and EPS, interact with financial factors —namely, liquidity, working capital, and leverage — across different economic cycles is therefore crucial. Building on this discussion, the next section will examine in greater detail how these financial ratios influence the profitability of FinTech firms and how these relationships evolve across varying economic conditions.

2.3 Empirical Review

2.3.1 Liquidity and Profitability

Liquidity refers to a firm's ability to meet its short-term financial obligations in a timely manner (Bibi & Amjad, 2017). It is considered one of the most critical aspects of financial management because it ensures the smooth continuation of business operations and shields the organization from potential financial distress. Westhead et al. (2003) highlights that efficient liquidity management plays a central role in corporate strategy, as it contributes to maximizing shareholder wealth and enhancing the overall value of the firm.

From a managerial perspective, liquidity management is often described as the process of ensuring that current assets are adequate to cover current liabilities, a view supported by Harris et al. (2005). Nevertheless, liquidity should not be confined merely to financial ratios or numerical calculations. Hall et al. (2002) argues that a broader approach is necessary, one that incorporates all dimensions of a company's activities, including relationships with customers, suppliers, and product management. This perspective underscores that liquidity management is deeply interconnected with the operational and strategic decisions of the firm, rather than existing solely as an isolated financial task (Bibi & Amjad, 2017).

In this study, liquidity is quantified using the Current Ratio (CR), which represents the connection between current assets and current liabilities (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). This ratio is commonly regarded as an accurate predictor of a company's short-term financial health and ability to meet obligations while maintaining operating efficiency.

The relationship between liquidity and profitability is complex and has been extensively discussed in the literature, with research yielding both positive and negative results (Aldboush, Almasria, & Ferdous, 2023). Liquidity guarantees that enterprises can satisfy their short-term obligations, avoid financial difficulties, and continue operations. At the same time, how liquidity is managed determines whether it contributes to profitability or depletes business value. In essence, while keeping sufficient liquidity is critical for financial stability, the impact on profitability is ultimately determined by how well enterprises allocate and use their liquid resources.

From a positive perspective, maintaining sufficient liquidity is vital for ensuring operational flexibility and supporting strategic growth. It allows firms to meet unexpected obligations, seize profitable investment opportunities, and build confidence among investors and stakeholders. Liquidity holds particular significance for fintech companies, which operate in highly dynamic and innovative-driven environments. Easy access to liquid funds enables them to scale rapidly, invest in advanced technologies, and withstand financial shocks. Empirical studies reinforce this positive relationship: Nguyen & Nguyen (2019) found that liquidity positively influenced both ROA and ROE in industrial firms, while Mohd Zaid et al.

(2014) and Serrasqueiro & Nunes (2008) provided evidence that higher liquidity enhances profitability (Aldboush, Almasria, & Ferdous, 2023). Likewise, fintech-focused research demonstrated that liquidity and working capital significantly contribute to profitability, even during periods of crisis such as the global financial crisis and the COVID-19 pandemic (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). Collectively, these findings highlight liquidity's dual role as a safeguard against uncertainty and a driver of growth, enabling firms to remain resilient while capitalizing on long-term opportunities.

From a negative perspective, excessive liquidity can undermine profitability if it is not effectively managed. Large cash reserves that remain idle instead of being invested in productive assets create high opportunity costs, as resources fail to generate returns. Seissian et al. (2018) argued that surplus liquidity diminishes profitability, while Nanda and Panda (2018) observed that liquidity may initially reduce profits in the short term but eventually contribute positively over a longer period (Aldboush, Almasria, & Ferdous, 2023). At the macroeconomic level, research also highlights the risks of abundant liquidity. For example, during periods of low interest rates and monetary expansion, significant liquidity injections into financial markets have been shown to fuel speculative bubbles and increase market volatility (Calcagnini, Gardini, Giombini, & Carrera, 2020). These findings emphasize that although liquidity is essential for stability, excessive accumulation without strategic allocation can erode firm profitability and heighten systemic risks. Therefore, firms must carefully maintain a balance by keeping enough liquidity to safeguard operations and support growth while avoiding levels that result in inefficiency or financial instability.

Liquidity is a crucial determinant of corporate performance, particularly in the fintech industry where rapid technological advancement, intense competition, and constant regulatory shifts demand strong financial resilience. Empirical evidence consistently demonstrates that higher liquidity, as measured by the Current Ratio (CR), enhances profitability by providing firms with the flexibility to cover operating expenses, seize growth opportunities, and withstand economic shocks. For instance, studies on fintech firms in North America and Europe revealed a significant positive relationship between liquidity and key profitability indicators such as Return on Assets (ROA) (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). These findings indicate that sufficient liquidity enables fintech companies to operate efficiently and allocate resources strategically, even during periods of uncertainty such as the global financial crisis and the COVID-19 pandemic. Likewise, research on service firms in Jordan confirmed that liquidity positively influences ROA, ROE, and EPS, highlighting its role not only as a safeguard during financial distress but also as a driver of improved profitability (Aldboush, Almasria, & Ferdous, 2023).

While liquidity is widely recognized as a driver of firm performance, it is also important to acknowledge the risks associated with excessive liquidity. Macroeconomic research indicates that an overabundance of liquidity, particularly in environments of low interest rates and expansive monetary policies, may contribute to speculative bubbles and heightened market instability (Calcagnini, Gardini, Giombini, & Carrera, 2020). At the firm level, holding large amounts of idle cash without effective allocation can reduce profitability by increasing opportunity costs. Despite these concerns, evidence suggests that for fintech firms, higher levels of liquidity are generally advantageous, as they provide the financial flexibility required to sustain innovation, pursue growth opportunities, and maintain investor confidence. In the context of East Asian fintech firms, maintaining strong liquidity as measured by the Current Ratio is therefore expected to have a positive impact on profitability, as it enhances resilience, ensures operational continuity, and strengthens the ability to capitalize on emerging opportunities.

2.3.2 Working Capital and Profitability

Working capital is defined as the difference between a company's current assets and current liabilities, and it is quantified in this study using the Working Capital to Total Assets ratio. It is a key indicator of a company's short-term financial health, demonstrating its capacity to meet urgent obligations while maintaining day-to-day operations. Effective working capital management ensures that resources are not idle or overly limited, which is critical for preserving liquidity and overall profitability. Previous studies highlight that efficient working capital strategies can enhance earnings by improving operational efficiency and reducing financial risks (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). The importance of working capital is particularly pronounced in fintech firms, as they typically require greater liquidity than traditional businesses to drive innovation, adapt to rapid technological changes, and preserve stability in a competitive and highly regulated environment (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025).

Effective working capital management is critical for increasing firm profitability and maintaining total earnings. Firms with consistent cash flows are better able to meet short-term obligations, pay suppliers on schedule, and ensure the smooth execution of daily business activities. Such efficiency not only reduces financial risks and prevents liquidity gaps, but it also improves the firm's ability to create consistent and recurrent revenue.

Empirical evidence across both developed and emerging economies consistently highlights a positive relationship between effective working capital practices and firm performance. Studies from the United States, the United Kingdom, Finland, Egypt, Vietnam, Ghana, and Uganda demonstrate that well-managed working capital contributes significantly to profitability (Lyngstadaas, 2020; Goncalves, Gaio, & Robles, 2018; Enqvist, Graham, & Nikkinen, 2014; Nguyen & Nguyen, 2018; Kabuye, Kato, Akugizibwe, & Bugambiro, 2019). This link is rooted in the critical role of working capital in fostering growth: adequate liquidity allows firms to secure inventories, increase sales, and capture new revenue opportunities, while also serving as a safeguard against financial constraints.

Conversely, poor working capital management can hinder operations, delay payments, and erode profitability, particularly in businesses with low inventory cushions (Anton & Nucu, 2020). Within the fintech sector, the importance of working capital is amplified. Unlike traditional enterprises, fintech firms require greater liquidity to fuel innovation, adapt quickly to technological disruptions, and navigate complex regulatory environments. Therefore, maintaining an optimal level of working capital is not only essential for ensuring business continuity but also for sustaining agility, resilience, and competitiveness in today's fast-evolving financial landscape.

Empirical research consistently demonstrates that effective working capital management enhances firm performance across industries and regions. A study of FinTech firms in North America and Europe revealed that liquidity and working capital significantly strengthen profitability, while leverage tends to weaken performance during periods of crisis (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). In particular, the Working Capital to Total Assets (WC/TA) ratio was found to have a positive and significant effect on both Return on Assets (ROA), underscoring the importance of maintaining a solid working capital base for FinTech operations (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). These findings suggest that FinTech companies depend heavily on sufficient liquidity not only to sustain profitability but also to remain resilient during financial shocks.

Evidence from other economies reinforces this conclusion. For instance, Polish firms reported an average ROA of less than 1%, with working capital accounting for 19.71% of sales, indicating that even in low-return environments, efficient working capital management plays a crucial role in preserving profitability (Anton & Nucu, 2020). Similarly, research on Vietnamese listed companies found a positive relationship between working capital practices and corporate profitability, confirming that better liquidity and asset management enhance firm performance (Anton & Nucu, 2020).

Beyond traditional measures, the Cash Conversion Cycle (CCC) is widely applied to assess the efficiency of working capital management. The CCC reflects the time required to transform investments in raw materials into sales revenue, with longer cycles typically signaling weaker liquidity (Fan, Bae, & Liu, 2024). Prior studies consistently show that firms with shorter CCCs achieve higher profitability, as effective management of receivables, inventories, and payables reduces financing costs and supports stable cash flows (Enqvist, Graham, & Nikkinen, 2014). Cross-country evidence further validates this relationship, demonstrating that efficient CCC management strengthens both short-term liquidity and long-term profitability (Anton & Nucu, 2020).

Overall, these findings highlight that working capital efficiency, whether measured through WC/TA ratios or CCC, is a critical driver of profitability across diverse economic and institutional settings. This relationship is particularly relevant for FinTech firms, where liquidity constraints and operational agility are essential for maintaining a competitive edge.

Drawing on these insights, this study proposes that working capital, measured by the Working Capital to Total Assets (WC/TA) ratio, has a positive effect on the profitability of FinTech firms in East Asia. Profitability is assessed through both Return on Assets (ROA), which captures operational efficiency. Given that FinTech firms operate in highly dynamic environments requiring continuous innovation, technological adaptability, and strict regulatory compliance, maintaining an adequate level of working capital is expected to enhance both stability and profitability.

2.3.3 Leverage and Profitability

Leverage refers to the extent to which a firm depends on borrowed funds to finance its operations and expansion relative to the capital contributed by shareholders. It essentially reflects the balance between debt and equity financing within a company's capital structure. Leverage is commonly measured through the Debt-to-Equity Ratio (D/E), also expressed as Total Debt to Total Equity (TD/TE), which indicates the proportion of borrowed funds in relation to shareholder equity (Gupta, Jain, & Yadav, 2011). A higher leverage ratio suggests a stronger reliance on debt financing, whereas a lower ratio indicates greater dependence on internal resources.

In financial literature, leverage is widely acknowledged as a critical determinant of profitability across multiple industries, including banking, manufacturing, microfinance, consumer goods, and Internet finance (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). Empirical findings show that the Debt-to-Equity ratio often exerts a significant positive effect on Return on Assets (ROA), as debt financing provides firms with additional resources to invest, expand, and enhance operational efficiency. This suggests that while leverage can contribute to improved firm performance, excessive reliance on debt may elevate financial risk and hinder sustainable value creation.

The level of leverage also varies substantially across countries and industries depending on financing needs, growth strategies, and sector characteristics. For instance, a study on Indonesian listed firms reported an average leverage ratio of 1.91, indicating that companies in this sample relied more on debt than equity to fund their activities (Modjo, Loekman, & Limijaya, 2022). Such evidence highlights that leverage is not only a theoretical financial concept but also a practical indicator of how firms balance risk and growth in pursuit of profitability.

For FinTech companies, leverage holds particular importance due to the sector's dependence on continuous innovation, advanced technologies, and rapid market expansion. Debt financing enables these firms to secure the capital required to scale quickly and strengthen their competitive advantage. At the same time, the dynamic and often uncertain regulatory environments in which FinTech firms operate mean that overleveraging can expose them to heightened financial vulnerability and threaten long-term stability. In the East Asian context, where FinTech markets are expanding yet constrained by stringent regulations, maintaining an optimal level of leverage is crucial. It allows firms to capture growth opportunities while safeguarding financial resilience and ensuring sustainable profitability.

The relationship between leverage and profitability is strongly ingrained in corporate finance theories, particularly the trade-off and pecking order models. These concepts shed light on how debt financing affects business performance and why empirical findings might differ across industries, countries, and economic cycles.

According to the trade-off approach, corporations choose their capital structure by comparing the benefits of debt against its hazards. The fundamental benefit of debt is the tax shield effect, wherein interest expenditures lower taxable income and, hence, boost profitability (Phan, Narayanb, Rahman, & Hutabarat, 2020). However, this benefit is counterbalanced by the increased financial risk that comes with higher levels of leverage, including the threat of financial distress and bankruptcy. Excessive debt obligations can erode profitability, particularly during economic downturns or periods of revenue volatility. Prior research highlights this dynamic in the banking sector, where firms with higher equity ratios often enjoy lower funding costs and send positive signals of stability to investors (Holmstrom & Tirole, 1997). On the other hand, some studies argue that too much equity relative to debt may reduce profitability, as equity is viewed as costlier due to the loss of tax-shield benefits (Altunbas, Carbo, Gardener, & Molyneux, 2007; Osborne, Fuertes, & Milne, 2012). These opposing findings imply that leverage can boost or depress profitability, depending on whether the tax benefits of debt outweigh the costs of possible financial instability. In essence, trade-off theory suggests that organizations strive for an optimal level of leverage in which the marginal benefit of debt equals its marginal cost.

In contrast, the pecking order hypothesis prioritizes funding preferences over the pursuit of an optimal balance. It contends that organizations prioritize internal finance, such as retained earnings, above external sources due to information asymmetry and the greater costs of borrowing outside capital. When internal funds are insufficient, corporations typically turn to debt, with equity issues being considered only as a last resort. This financing hierarchy is especially significant for FinTech firms, which operate in environments that are highly dynamic and uncertain. Empirical evidence from crisis periods, including the 2007–2009 global financial crisis and the COVID-19 pandemic, shows that many firms increased their reliance on debt to sustain operations, even though this dependence sometimes reduced profitability (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025). These observations provide strong support for the pecking order theory, since firms tended to avoid issuing equity despite the risks involved and instead favored debt as a quicker and more flexible means of survival. While this strategy can help secure short-term stability, it also exposes firms to greater vulnerability when debt levels become excessive.

Taken together, these theories indicate that the impact of leverage on profitability is not universal but highly dependent on a firm’s financing choices and external conditions. For FinTech companies, the trade-off theory underscores the importance of carefully balancing debt to capture its tax and growth benefits while minimizing risks of instability in a tightly regulated industry. Meanwhile, the pecking order theory reflects the practical financing behavior of Fintech's, where internal funds are prioritized, debt is the preferred alternative when resources are constrained, and equity is used sparingly to avoid ownership dilution. Viewing leverage through these dual lenses helps explain why empirical evidence on its profitability effects is often mixed, and why the outcomes may be particularly sensitive to context in emerging FinTech markets.

A considerable body of empirical research has established the negative impact of leverage on business profitability in a variety of industries and regions. For example, evidence from North American and European FinTech enterprises suggests that the debt-to-equity (D/E) ratio has a considerable negative influence on both return on assets (ROA). These findings imply that excessive reliance on debt within the FinTech sector, which is defined by high risk and rapid innovation, heightens financial fragility, raises capital costs, and lowers investor trust, eventually diminishing profitability (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025).

Supporting this view, studies on Jordanian service firms and Indian manufacturing companies also reveal that rising debt levels diminish profitability. Such results reinforce the notion that while debt financing can provide short-term liquidity, it also amplifies the risk of financial distress, particularly during periods of crisis, thereby weakening overall financial performance (Nanda & Panda, 2017).

Nevertheless, the literature indicates that the effect of leverage is not uniform, as outcomes vary across institutional settings and industry structures. For example, research on Indonesian banks produced mixed evidence on the capital and performance relationship, highlighting the trade-off between the high cost of equity and the risk-reducing benefits of lower leverage (Phan, Narayanb, Rahman, & Hutabarat, 2020). Similarly, studies on Indian public sector enterprises found that debt remains the dominant source of financing, with non-disinvested firms exhibiting higher leverage ratios than their disinvested counterparts. These findings illustrate that the profitability implications of leverage are shaped by regulatory frameworks, financing practices, and market dynamics (Gupta, Jain, & Yadav, 2011).

Taken together, prior studies suggest that although moderate levels of leverage may support firms' survival during downturns, excessive debt generally impairs performance. This aligns with the pecking order theory, which emphasizes firms' preference for internal financing and cautions against heavy dependence on external debt because of its long-term negative impact on profitability.

Given this strong body of evidence and considering the highly volatile and risk-intensive environment in which East Asian FinTech firms operate, similar negative effects are anticipated. These firms, already exposed to heightened operational and market uncertainties, are especially vulnerable to the risks posed by excessive leverage.

2.3.4 The COVID-19 Pandemic

External shocks exert a profound influence on global financial markets and corporate stability, particularly during periods of economic crisis. Historical evidence, such as the Global Financial Crisis (GFC) of 2007–2009, illustrates how sudden disruptions in financial systems can alter performance dynamics across industries worldwide. Several studies (Berger & Bouwman, 2013; Vazquez & Federico, 2012; Olson & Zoubi, 2017) highlight that the GFC placed severe strain on the banking sector, where financial instability undermined corporate resilience. Although subsequent research confirmed that the negative impact of FinTech adoption on bank performance persisted even after accounting for the GFC, the episode demonstrated how external shocks can reshape the relationship between financial indicators and profitability.

The COVID-19 pandemic, beginning in early 2020, generated an even more disruptive and far-reaching shock. Unlike the GFC, which stemmed primarily from financial market failures, COVID-19 sparked an unprecedented global downturn through health-related disruptions, including lockdowns, social distancing measures, and the breakdown of supply chains (Anderson, Heesterbeek, Klinkenberg, & Hollingsworth, 2020; Chen, Qian, & Wen, 2020; Cutler, 2020). This dual crisis—both economic and health-driven—intensified financial instability, reduced demand, and magnified operational challenges for firms worldwide. In the United States, for instance, the recession officially began in March 2020, coinciding with the onset of severe financial turmoil (National Bureau of Economic Research, 2020). Similar disruptions were observed in other regions, where FinTech companies encountered heightened credit risks, liquidity constraints, and rapid shifts in consumer behaviour.

These developments underscore the importance of examining financial relationships across different phases of the economic cycle. The pre-COVID-19 era provides a relatively stable benchmark for assessing financial performance under normal conditions. In contrast, the crisis period was defined by volatility, liquidity shortages, and heightened risk aversion, all of which likely influenced the effects of working capital, leverage, and firm size on profitability. The post-COVID-19 phase, meanwhile, represents a period of recovery and adaptation, where firms must navigate structural market changes, regulatory reforms, and evolving consumer expectations.

For FinTech firms, which operate in highly dynamic and uncertain environments, understanding the moderating role of crisis periods is essential. By evaluating financial indicators across pre-crisis, crisis, and post-crisis stages, this study provides insights into how external shocks reshape profitability and financial strategies. This perspective not only highlights the value of context-specific performance evaluation but also emphasizes the long-term importance of crisis resilience for FinTech development, especially in emerging economies such as East Asia.

Linking to the hypotheses of this study, the moderating role of crisis periods provides a contextual layer that can either strengthen or weaken the proposed relationships. For instance, during stable periods, efficient working capital management is expected to positively influence profitability. However, during crises, disruptions in cash flows and liquidity constraints may reduce the strength of this relationship. Similarly, leverage may contribute positively to profitability in normal times by providing growth capital (H2), but in crisis periods high debt obligations could amplify financial vulnerability and diminish profitability. Firm size, meanwhile, is generally associated with higher profitability due to economies of scale (H3), yet crises may alter this relationship as larger firms often face more complex operational challenges compared to smaller, more flexible entities.

Thus, integrating the moderating role of crisis periods helps to contextualize the hypotheses by recognizing that the relationships between financial indicators and profitability are not static but shift according to the broader economic environment.

Pre-COVID-19 Period (2016-2019)

The pre-COVID-19 period (2016–2019) was characterized by relative economic stability, during which global financial systems expanded, and digital finance adoption accelerated. FinTech enterprises, particularly in North America and Europe, experienced rapid growth supported by innovations in payment technologies, online lending platforms, and blockchain applications. Evidence from the panel data analysis indicates that profitability among these firms was closely associated with financial ratios. Working capital, measured by the ratio of working capital to total assets (WC/TA), showed a significant and positive relationship with return on assets (ROA), suggesting that firms with efficient liquidity management and effective utilization of short-term resources were more likely to sustain profitability. Conversely, leverage, measured by the debt-to-equity (D/E) ratio, exhibited a negative association with firm performance, highlighting the risks of over-reliance on debt. This finding aligns with the pecking order theory, which emphasizes internal financing as a preferred strategy while cautioning against the long-term risks of excessive leverage (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025).

Beyond firm-level dynamics, the same period witnessed significant shifts in household financial behavior driven by digital finance. Empirical studies reveal that digital finance greatly improved household access to credit markets. Specifically, a one percent increase in the Digital Finance Index (DFI) was associated with a 2.93% higher likelihood of households obtaining loans and a 10.21% increase in average household debt (Yue, Korkmaz, Yin, & Zhou, 2022). This expansion of financial inclusion not only enhanced liquidity but also stimulated broader consumption patterns, thereby contributing to short-term economic activity.

However, the benefits of digital finance were accompanied by notable risks. Evidence suggests that financially illiterate households were particularly vulnerable to the adverse effects of increased borrowing, as many underestimated the long-term burden of debt and became more susceptible to financial distress. Prior research demonstrates that financial illiteracy, compounded by limited self-control, often led to over-indebtedness and repayment difficulties (Meyll & Pauls, 2019; Feng, Lu, Song, & Ma, 2019). As such, the pre-pandemic phase highlighted the dual nature of digital finance: while it enhanced inclusion and supported consumption, it also exposed disadvantaged households to the risks of unsustainable borrowing.

Taken together, the pre-COVID-19 period illustrates both the opportunities and vulnerabilities created by financial and technological developments. On the firm side, efficient working capital management improved profitability, whereas excessive leverage weakened performance. On the household side, digital finance promoted greater access and economic participation but simultaneously introduced new risks related to debt sustainability and financial literacy. These dynamics underscore how the pre-pandemic environment functioned as a crucial benchmark against which the disruptive effects of the COVID-19 crisis can be evaluated.

Post-COVID-19 Period (2021-2024)

The post-COVID-19 period (2021–2024) is characterized by gradual economic recovery and the transition of enterprises, particularly FinTech firms, into a "new normal." As the severe disruptions of the pandemic subsided, global and regional markets entered a phase of stabilization in which governments, businesses, and consumers sought to restore operations while reassessing long-term strategies. During this period, central banks began reversing the extraordinary monetary policies that had previously provided unprecedented liquidity support. For instance, the Bank of Japan (BOJ) and the Federal Reserve (Fed) scaled back their asset purchase programs, which had included equity ETFs, J-REITs, and agency mortgage-backed securities. Although these measures were effective in reducing systemic risks during the peak of the crisis, their prolonged continuation risked sustaining "zombie" firms that could only survive under ultra-low borrowing costs. The shift back toward conventional monetary policy therefore created new challenges for firms, particularly those in the FinTech sector that had benefitted greatly from the rapid acceleration of digital adoption during the pandemic (Haas, Neely, & Emmons, 2020).

For FinTech companies, the post-pandemic environment brought both opportunities and challenges. On one hand, digital adoption trends that had accelerated during the pandemic, including online payments, digital lending, and peer-to-peer finance, became embedded in consumer behavior. This structural shift-maintained demand for FinTech services and enabled many firms to expand their customer base. On the other hand, the longer-term consequences of pandemic-era FinTech lending began to surface, particularly in relation to rising delinquency rates and the sustainability of existing business models. Evidence suggests that during the pandemic, FinTech lenders were more willing than traditional banks to extend credit to new borrowers, but this strategy resulted in a sharper increase in default rates. As repayment practices began to normalize during the recovery phase, concerns emerged about whether FinTech firms could sustain profitability without taking excessive risks, especially in the context of higher interest rates and tighter investor scrutiny (Bao & Huang, 2020).

From a regulatory perspective, the post-COVID-19 period was also marked by reforms aimed at strengthening the resilience of the FinTech sector. Policymakers placed greater emphasis on consumer protection, market transparency, and the management of systemic risks. For example, in China, the rapid expansion of small-scale digital lending platforms without adequate risk management practices had previously generated vulnerabilities that spilled over into traditional finance. To mitigate such risks, regulators in the recovery period introduced stricter oversight mechanisms, promoted fair pricing practices, and emphasized consumer financial literacy. These measures were particularly important in reducing information asymmetry and ensuring that digital financial innovation could progress without undermining financial stability (Yue, Korkmaz, Yin, & Zhou, 2022; Bao & Huang, 2020).

East Asia provides valuable context for examining how financial relationships in the FinTech sector evolved during this recovery phase. With the region experiencing significant growth in digital finance adoption, it offers a natural setting to investigate whether liquidity, working capital, and leverage continue to influence profitability in the same way as during the crisis, or whether structural changes have led to new dynamics. Unlike the crisis years, when firms relied heavily on debt to remain operational, the post-COVID-19 environment tested whether FinTech companies could transition toward more balanced financial strategies that support long-term sustainability.

Overall, the post-COVID-19 period represents not only recovery but also adjustment and transformation. The withdrawal of emergency monetary policies, the correction of imbalances created during the pandemic, and the strengthening of regulatory frameworks are reshaping the way FinTech firms operate within a shifting economic landscape. Within this context, the financial strategies of FinTech firms, which involve managing liquidity, working capital, and leverage, are expected to differ significantly from those employed during both the pre-pandemic and crisis periods.

2.5 Conclusion

This chapter investigated the theoretical, conceptual, and empirical foundations that shaped the financial performance of FinTech organizations, with a specific emphasis on East Asia. Drawing on Pecking Order Theory and Trade-Off Theory, the review underlined how internal resources, external financing costs and risks, and the pursuit of an optimal capital structure influence organizations' financing decisions. Profitability was identified as a significant indicator of business performance, with ROA serving as an important benchmark for efficiency and shareholder value.

Empirical evidence highlighted liquidity and working capital as consistent drivers of profitability, supporting resilience, innovation, and growth in fast-evolving FinTech environments. In contrast, leverage produced mixed outcomes: while moderate debt levels may enhance performance through tax benefits and financing for expansion, excessive reliance on debt often undermines profitability by increasing financial vulnerability. The review further underscored the moderating role of external shocks, with the COVID-19 pandemic demonstrating how crisis conditions disrupt financial linkages. Liquidity constraints, cash flow disruptions, and heightened risk during such periods force firms to adjust strategies, a dynamic especially relevant in East Asia where FinTech enterprises operate in both rapidly expanding and tightly regulated markets.

In summary, this chapter found that liquidity and working capital are positively associated with profitability, whereas leverage requires cautious management to balance growth opportunities with financial risks. Moreover, external shocks like COVID-19 significantly reshape these relationships, reinforcing the importance of adaptive financial strategies. These insights establish the foundation for the hypotheses and empirical analysis developed in the next chapter.

CHAPTER 3: METHODOLOGY

3.0 Introduction

This chapter describes the methodology used to assess the financial performance of FinTech enterprises in East Asia. It covers the study's conceptual framework and describes the sample selection method, as well as the model specifications for empirical testing. The discussion expands on the dependent, independent, and control variables used in the analysis, explaining how they are measured and integrated into the research model. Robustness tests are used to guarantee that the findings are valid and reliable. Overall, this chapter gives a coherent explanation of the research strategy, establishing a clear foundation for the forthcoming empirical investigation and data analysis.

3.1 Conceptual Framework

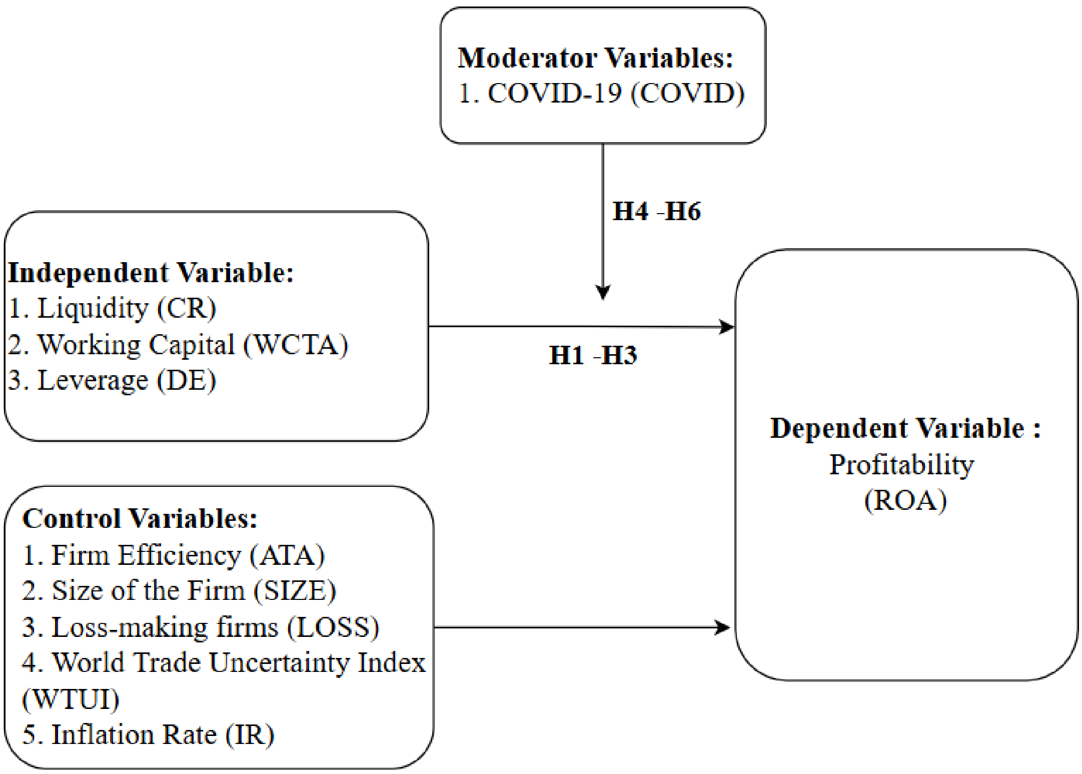


Figure 3. 1: Conceptual Framework of the Study

3.2 Sample Selection and Data Collection

To examine the influence of liquidity, working capital, and leverage on the profitability of FinTech firms, this study employs a dataset derived from the Refinitiv (LSEG) database, which provides comprehensive financial information on listed firms. The focus is placed on publicly listed FinTech companies operating in East Asian countries, as they represent a key and growing segment of the financial industry in the region. Out of a total of 33 FinTech firms identified in the database, 25 firms were selected for analysis. Firms that began operations after the observation period or that lacked consistent financial records were excluded to ensure the reliability of the dataset. Specifically, companies established after 2016 were not considered, as their data did not cover the full span of the study period. The analysis covers two distinct intervals, namely 2016 to 2019 and 2021 to 2024, thereby capturing both pre-pandemic and post-pandemic dynamics while excluding 2020 due to data inconsistencies arising from the peak of the COVID-19 crisis. Firm-year data with missing or incomplete values for the key variables were removed, and extreme outliers were adjusted at the upper and lower percentiles to prevent distortion of results. The final dataset comprises an unbalanced panel of 200 firm-year observations, which provides a robust foundation for empirical testing.

3.2 Model Specification

Data processing and statistical analysis were conducted using the STATA software package, which allows for advanced econometric modelling and ensures the accuracy of results. Accordingly, the following regression model was applied to evaluate the proposed hypotheses. The linear model was selected as it has been widely used in previous studies employing panel data regression and is well-suited for empirical investigations of this nature. The regression model applied in this study is presented below.

$$Profitability = \beta_0 + \beta_1\ LIQUIDITY + \beta_2\ WORKING\ CAPITAL + \beta_3\ LEVERAGE + \beta_4\ COVID\ 19 + \sum_{j=1}^{5} \beta_j\ CONTROL\ VARIABLES_{j,it} + \varepsilon it \quad \textbf{(1)}$$

Profitability is measured using return on assets (ROA) for firm *i* in year *t*. Liquidity is captured by the current ratio (CR), while working capital is represented by the working capital to total assets ratio (WCTA). Leverage is measured through the debt-to-equity ratio (DE). The model also incorporates several control variables, including firm efficiency, measured by the asset turnover ratio (ATA), firm size (SIZE), an indicator for loss-making firms (LOSS), the world trade uncertainty index (WTUI) and the inflation rate (IR). In addition, fixed effects for both year and continent are included to control for unobserved heterogeneity. Finally, Ɛit denotes the error term. The regression equations employed in this study are presented below.

$$ROA_{it} = \beta_0 + \beta_1\ CR_{it} + \beta_2\ WCTA_{it} + \beta_3\ DE_{it} + \beta_4\ ATA_{it} + \beta_5\ SIZE_{it} + \beta_6\ LOSS_{it} + \beta_7\ WTUI_{it} + \beta_8\ IR + \varepsilon it \quad \textbf{(2)}$$

$$ROA_{it} = \beta_0 + \beta_1\ CR_{it} + \beta_2\ WCTA_{it} + \beta_3\ DE_{it} + \beta_4\ ATA_{it} + \beta_5\ SIZE_{it} + \beta_6\ LOSS_{it} + \beta_7\ WTUI_{it} + \beta_8\ IR_{it} + \beta_9(CR\ x\ COVID) + \beta_{10}(WCTA\ x\ COVID) + \beta_{11}(DE\ x\ COVID) + \varepsilon it \quad \textbf{(3)}$$

3.3 Variables Measurement

3.3.1 Dependent Variable

3.3.1.1 Profitability

$$\boxed{\boldsymbol{Return\ on\ Assets = \frac{Net\ Income}{Total\ Assets}}}$$

Profitability is a relative measure of efficiency that assesses a company's ability to create profit in comparison to its size, indicating overall business success or failure (Horton, 2024). Profitability, generally measured by return on assets (ROA), is the dependent variable in this study, reflecting the primary purpose of profit-driven businesses (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025; Lyngstadaas, 2020). Prior research regularly used these indicators to assess firm success, particularly in the fintech sector. For example, Kayani et al. (2025) used ROA as profitability measures in their study of fintech companies in North America and Europe.

Similarly, Ohorella (2019) and Aldboush et al. (2023) used ROA to investigate the factors influencing profitability. The research demonstrates that profitability determinants fluctuate between geographies, timeframes, and industries, emphasizing the significance of this study's focus on East Asian fintech enterprises (Aldboush, Almasria, & Ferdous, 2023).

3.3.2 Independent Variable

3.3.2.1 Liquidity

$$\boxed{\boldsymbol{Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilities}}}$$

The ease with which an asset or security can be converted into available cash while maintaining its market price (Hayes, 2025). Liquidity is commonly acknowledged as a significant factor influencing corporate profitability. Previous research has shown that it has a good impact on financial success (A.Seissian, Gharios, & Awad, 2018). Kayani et al. (2025) postulated and confirmed that liquidity, measured by the current ratio (CR), had a considerable favorable effect on fintech firms' profitability, as assessed by ROA. Similarly, Aldboush et al. (2023) found a favorable and significant influence of liquidity on the profitability of service sector enterprises. Studies in the banking industry support this association, with Aggarwal et al. (2022) and Ercegovac et al. (2020) discovering a strong positive relationship between liquidity levels and profitability.

3.3.2.2 Working Capital

$$\boxed{\boldsymbol{Working\ Capital\ to\ Total\ Assets\ Ratio = \frac{Working\ Capital}{Total\ Assets}}}$$

A liquidity statistic calculated as the difference between a company's current assets and current liabilities (Fernando, 2025). Working capital has long been recognized as a key factor impacting corporate profitability (Aldboush, Almasria, & Ferdous, 2023; A.Seissian, Gharios, & Awad, 2018). Kayani et al. (2025) theorized and confirmed that working capital, as measured by the ratio of working capital to total assets (WC/TA), had a favorable and significant impact on profitability, notably ROA, in fintech companies. Growth in working capital results in better profitability. Similarly, Mathuva (2010) and Deloof (2000) found a positive association between working capital and profitability performance, supporting the idea that keeping adequate working capital levels promotes financial success. Efficient working capital management is especially important for fintech organizations because it improves operational agility, assures timely payments, prevents disruptions, and drives revenue growth through greater sales (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025).

3.3.2.3 Leverage

$$\boxed{\boldsymbol{Leverage = \frac{Total\ Liabilities}{Total\ Assets}}}$$

Leverage is an investment technique that involves leveraging borrowed money, specifically various financial instruments or borrowed cash, to improve the possible return on an investment (Hayes, 2025). Leverage is a popular financial measure in business profitability studies (Aldboush, Almasria, & Ferdous, 2023). Kayani et al. (2025) found that leverage, as measured by the debt-to-equity ratio (D/E), has a detrimental impact on the profitability of fintech firms, particularly during crises, which is consistent with the concepts of pecking order theory. Nanda and Panda (2017) reported similar findings, indicating a significant negative relationship between leverage and profitability in manufacturing enterprises. The pecking order theory highlights that organizations prefer internal finance over external debt due to the higher costs and risks associated with borrowing, implying that excessive dependence on leverage can harm profitability (Kayani, Dsouza, Husain, Nawza, & Hasan, 2025; Anton & Nucu, 2020).

3.3.3 Control Variable

Firm Efficiency

$$\boxed{\boldsymbol{Assets\ Turnover\ Ratio = \frac{Net\ Sales}{Average\ Total\ Assets}}}$$

Efficiency ratios assess how successfully a company manages its assets and liabilities, such as inventory, receivables, payables, and the cash conversion cycle, to optimize profits and inform shareholders how their investments are being used (Mcclure, 2024). Eling and Jia (2019) directly linked company efficiency and profitability, emphasizing the significance of operational effectiveness in financial performance.

Size of the Firm

Firm size is a quantitative indicator of a company's size and operational capabilities. Firm size can be measured in a variety of ways, including the number of employees, total revenue, and market share (Hulatt, 2023). Firm size has frequently been recognized in the literature as a significant predictor of profitability. Nanda and Panda (2017) found that business size had a significant positive impact on profitability. Stierwald (2010) found that larger enterprises in the United States and Australia were more profitable, highlighting the impact of economies of scale in improving performance. Akinlo and Asaolu (2012) confirmed this association in the Nigerian setting, demonstrating that larger enterprises are typically more lucrative. Kayani et al. (2025) found that firm size had a substantial impact on financial performance during the pre-listing stage, highlighting the importance of size in influencing firm results.

Loss-making Firms

The amount by which a company's operating expenses exceeds its gross profit (Kenton, 2022). In study on FinTech firm performance, a dummy variable for "loss-making firms" (Lo) is frequently added, with a value of 1 if a firm reports negative income in a particular year and zero otherwise. This variable illustrates the structural distinction between profitable and unprofitable organizations, noting that loss-making firms typically have a negative association with profitability. Kayani et al. (2025), for example, used firm-level features such ownership structure in their robustness tests to show how these factors affect performance outcomes. Similarly, accounting for loss-making status provides for a more accurate assessment of financial factors, as organizations that consistently lose money are more likely to experience operational inefficiencies, decrease investor confidence, and poor overall performance.

World Trade Uncertainty Index

The World Trade Uncertainty Index is an economic indicator developed by the International Monetary Fund (IMF) to measure trade policy uncertainty across nations and time periods. It is released quarterly and is available on the IMF's official website (Zinkpot, 2025). Kayani et al. (2025) found that the world trade uncertainty index has no significant relationship with firm performance.

This study includes nine variables, one explained or reliant on, while the other eight were independent and control variables. The three defining elements are liquidity, working capital, and leverage. Profitability is the dependent variable. The list of all potential variables, including control variables, is presented in *Table 1*, along with their measurement.

Inflation Rate

Inflation is described as a progressive loss of purchasing power, reflected in the overall rise in prices for goods and services over time. The inflation rate measures the average yearly price rise for a given basket of goods and services. When inflation is high, prices rise rapidly, whereas low inflation implies a slower pace of price growth. In contrast, deflation occurs when prices fall, resulting in increased purchasing power (Fernando, 2025). Inflation has been extensively researched as a significant macroeconomic element influencing corporate profitability. Biru (2021) points out that there is a negative relationship between the inflation rate and banks' profitability in European countries. The inflation rate had harmed the Return on Assets (ROA). Athanasoglou et al. (2006) found that the inflation rate has a strong effect on profitability. Inflation rate also identified a strong link between bank profitability and the prevailing level of inflation, suggesting that the ability of firms to adjust interest rates and costs plays a critical role.

Table 3. 1: Selected variables and their measurements.

Classification	Variables	Explanation	Measurement
Dependent variables	Profitability	Return on assets (ROA)	Net income / Total assets
Independent variables	Liquidity	Current Ratio (CR)	Current assets / Current liabilities
	Working Capital	Working capital to total assets ratio (WCTA)	Working capital / Total assets
	Leverage	Debt-to-equity ratio (DE)	Total liabilities / Total assets
Control variables	Firm Efficiency	Assets turnover ratio (ATA)	Net sales / Average total assets
	Size of the firm	Size of the Firm (SIZE)	The logarithm of Total assets
	Loss-making firms	Loss-making firms (LOSS)	Firms' years with negative income are measured as 1, and the others as 0.
	World Trade Uncertainty Index	World Trade Uncertainty Index (WTUI)	Sourced through https://worlduncertainty index.com/data/
	Inflation Rate	Inflation Rate (IR)	Sourced through https://databank.worldbank. org/source/world-development-indicators

Profitability is a measure of a business's performance. We observe the relationship between the independent variables mentioned as liquidity, working capital, and leverage with profitability in the presence of a set of control variables.

3.4 Diagnostic Checking

3.4.1 Normality Test

The normality test is a method for determining if data follows a normal distribution. Even minor variations in a large sample size might lead to the rejection of the normalcy assumption (Khatun, 2021). In this inquiry, the Jarque-Bera (JB) test will be utilized to establish normalcy by examining skewness and kurtosis. This idea is frequently applied in the field of economics. When the p-value exceeds 0.05, the data is normally distributed; when the p-value falls below 0.05, the data is skewed and does not follow the normal distribution.

3.4.2 Multicollinearity

Multicollinearity is a common statistical phenomenon in which independent variables in a multiple regression model are strongly or linearly connected. It results from strong correlations between variables in the model, which frequently leads to problems with the precision of regression estimations. It is a problem caused by a lack of data, which typically occurs in observational studies where researchers do not intervene. This issue can cause instability in the estimation of individual regression coefficients (Schreiber-Gregory & Foundation, 2017; Salmerón-Gómez, García-García, & García-Pérez, 2019), perhaps resulting in biased estimations.

The Variance Inflation Factor (VIF) is frequently used to detect multicollinearity; greater VIF values indicate more severe multicollinearity. A VIF greater than ten is generally regarded to indicate a high level of multicollinearity, signifying a high degree of correlation between independent variables and perhaps leading to incorrect regression predictions (Tay, 2017). However, while being highly associated, these variables should not be eliminated straight from the model because doing so may bring further bias issues (Tay, 2017).

3.4.3 Heteroscedasticity

Heteroscedasticity is the phenomenon in which the variance of the error term in a regression model varies with the independent variable. In other words, the residual variance is not constant. While the OLS estimates remain unbiased in the presence of heteroscedasticity, their efficiency is greatly diminished, and the accuracy of parameter inference suffers (Sani, Midi, & Babura, 2019).

The White test is a popular approach for finding heteroscedasticity and is frequently used to ensure the consistency of error variance in a model. It accomplishes this by running a regression of the squared residuals on the explanatory variables' squares and interaction factors. If these variables are significant, it implies heteroscedasticity. The test statistic uses a chi-square distribution to find non-linear correlations in the model (Sani, Midi, & Babura, 2019).

The White test, based on the chi-square distribution, is often produced using the sample's R^2 statistic. Furthermore, research has demonstrated that the White test works effectively in small samples (Clement & Olayemi, 2020).

3.4.4 Autocorrelation

Autocorrelation is the relationship between error terms at one point in time and those at later points. This violates the premise that linear regression errors are independent and identically distributed, resulting in biased regression estimates (Chaudhary, Nazir, Riaz, Sadiq, & Riaz, 2022; Arbabshirani, et al., 2014). In panel data models, autocorrelation frequently impacts time series, especially in fixed effects calculations. Thus, controlling autocorrelation is critical to ensuring the validity and reliability of research findings.

The Wooldridge Test, which was introduced in 2002 (Riveros, n.d.), is widely used to identify potential serial correlation concerns in models. It looks for autocorrelation in residuals to see if the model has serial correlation. This test has been used extensively in recent investigations (Born & Breitung, 2016). The Wooldridge test shows that when the p-value is less than 0.05, the null hypothesis is rejected, implying autocorrelation in the model. In contrast, a p-value greater than 0.05 indicates that there is no autocorrelation in the model.

3.5 Data Analysis

In empirical research, choosing a suitable model is critical since it affects not only the accuracy of the research results but also their applicability. A series of tests must be performed to determine the best algorithms or models for a given dataset and problem. These tests try to identify the optimum model for the study. Three commonly used models are introduced here, along with an explanation of how they are screened using various tests to determine which is best suited for this study.

3.5.1 Descriptive Statistics

This study uses secondary data covering the periods 2016–2019 and 2021–2024, resulting in a total of 200 observations. The analysis includes the dependent variable (ROA), all relevant independent variables, and control variables. The study examines the data in two stages: once without the moderating effect and once with the moderating effect.

Descriptive statistics such as mean, median, standard deviation, minimum, and maximum were calculated for all variables to provide an overview of their distribution. In addition, comparisons were made between the two periods to observe any changes in variable behavior. To further explore these differences, the study calculates the mean difference to test the significance of changes in variable means. This method helps to capture trends in variable changes across the periods and provides a foundation for the subsequent regression analysis, both with and without the moderating effect.

3.5.2 Pearson Correlation and Variance Inflation Factor

This study employs Pearson correlation analysis to examine the relationships among the variables and to assess the strength and direction of their linear associations. The Pearson correlation coefficient is used to identify whether a linear relationship exists between the variables, providing preliminary insights into how the explanatory variables are related to firm performance. In addition, a Variance Inflation Factor test is conducted to evaluate the robustness of the regression model. The VIF test is commonly used to detect multicollinearity in regression analysis, which can weaken the explanatory and predictive power of the model. The results of the VIF analysis indicate that multicollinearity is not a concern in this study, thereby confirming that the estimated coefficients are stable and that the empirical findings are reliable.

3.5.3 Panel Data Regression

Pooled OLS Model

The Pooled Ordinary Least Squares (POLS) model is a regression method that uses Ordinary Least Squares (OLS) on panel data to estimate the statistical association between dependent and independent variables by minimizing the sum of squared residuals (Lumivero, 2025). POLS is often used to assess the impact of numerous explanatory variables on economic growth. Its advantages include computational simplicity and efficiency when evaluating panel data over numerous years, especially when individual variation is neglected. POLS can be used with both cross-sectional and time series data (Lolemo & Pandya, 2023).

Fixed-Effect Model (FEM)

FEM is a popular method for panel data analysis in economics. This model takes heterogeneity across individuals and time as fixed factors. It tackles omitted variable bias in panel data by removing time-invariant heterogeneity between units and using within-unit variation to estimate the effects of the dependent variable (Mummolo & Peterson, 2018). When dealing with temporal changes among people, FEM produces more dependable results than POLS and delivers more exact estimates in analyses that account for individual heterogeneity over time (Bell & Jones, Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data, 2014). Furthermore, FEM surpasses REM and OLS in terms of addressing individual heterogeneity.

Random Effect Model (REM)

The REM is one of the most widely used models for dealing with panel data. This model treats inter-group disparities in observable data as random effects. It posits that individual effects between groups follow a distribution, making it appropriate for examining intergroup differences in multilevel data. It also takes into account within-group correlations while investigating heterogeneity (Bell, Fairbrother, & Jones, 2018). Thus, the approach efficiently resolves error correlation due to heterogeneity. REM provides more degrees of freedom than FEM for dealing with time-invariant variables (Zulfikar & STp, 2018).

F-Test

In the model selection procedure, this study first evaluates POLS, one of the most widely used regression methods in econometrics. An F-test will be used to compare POLS with the FEM. The F-test is a direct specification test that looks at the combined significance of the unit-specific effects estimated by the FEM (Plumper & Troeger, 2007). If the null hypothesis is rejected, it means that the FEM is preferable to the POLS model, which implies that individual-specific effects are important. In contrast, the POLS model is recommended if the null hypothesis is not disproved. This test determines if it is necessary to account for individual effects in the model in order to accurately represent variations between units in the data.

Breusch-Pagan Lagrange Multiplier Test (BPLM Test)

The Breusch-Pagan Lagrange Multiplier (BPLM) test, sometimes known as the BPLM test, is a widely used statistical approach for selecting between a REM and a POLS model. Specifically, the test is intended to detect whether random effects are substantial, which helps researchers choose the best model for data analysis (Breusch & Pagan, 1979).

When applying for the BPLM test, Breusch and Pagan (1979) first estimate the POLS model and calculate the residuals. By assessing the variance of these residuals, the BPLM test helps researchers determine whether there are systematic differences in variance, indicating the presence of random effects. The REM is considered more appropriate when test results indicate large random effects. If the outcome is not significant, random effects can be neglected, and the POLS model may be a more straightforward and effective strategy.

Hausman Test

The Hausman test is a versatile and popular statistical test that may be used to assess nearly any hypothesis. It is particularly beneficial when deciding between the FEM and the REM. The Hausman test is an effective tool for researchers to make sound conclusions (Chmelarova, 2002). This test compares the estimates from the FEM and REM to evaluate whether the model is better suited to the data.

The Hausman test is designed to determine whether the difference in estimates between two models is substantial. When the results of the Hausman test demonstrate that the p-value is less than a preset significance level (0.05), the FEM is regarded more acceptable. The premise that there is no association between individual effects and the explanatory variable in the REM is rejected. When the p-value is greater than the significance level, the REM is considered more appropriate, as the assumption of no correlation between the individual effects and the explanatory variables is acceptable.

3.6 Remedial Actions

3.6.1 Robust Standard Errors

The White test in STATA is used in this study to determine heteroskedasticity. When the p-value is less than 0.05, the regression model rejects the null hypothesis that there is no heteroskedasticity, indicating that it exists. Because heteroskedasticity reduces the trustworthiness of estimation results, additional precautions must be implemented. When heteroskedasticity is found, heteroskedasticity-robust standard errors are used to reduce its influence. This method recalculates standard errors to ensure that heteroskedasticity no longer influences the estimation findings. This method is appropriate for heteroskedasticity and yields more reliable estimates in the presence of outliers or uneven distribution. As a result, utilizing robust standard errors efficiently resolves heteroskedasticity in regression analysis, allowing for more trustworthy findings.

3.7 Summary of the Chapter

This chapter describes the empirical framework used to investigate how liquidity, working capital, and leverage affect the financial performance of publicly traded FinTech companies in East Asia. It described the sample selection approach, which yielded an unbalanced panel of 200 firm-year observations spanning the pre- and post-pandemic eras while removing unreliable 2020 data. The chapter also described the econometric model used, which included the use of fixed-effects regression to compensate for unobserved variation between businesses and years.

Clear definitions and measurement approaches were provided for all variables, including the dependent variable (ROA), the three main explanatory variables, and the five control variables that capture firm-level and macroeconomic characteristics. The justification for each variable was supported by relevant literature, ensuring strong theoretical grounding. Steps taken to clean and prepare the dataset, including the removal of incomplete entries and the handling of outliers, further enhance the reliability of the analysis.

Overall, the methodology presented in this chapter establishes a robust empirical foundation for the subsequent analysis. It ensures that the results in Chapter 4 are based on a transparent, systematic, and academically sound research design, enabling meaningful interpretation of how financial structure and economic conditions shape FinTech firms' profitability in East Asia.

CHAPTER 4: DATA ANALYSIS

4.0 Introduction

This chapter covers the data analysis carried out to investigate the factors influencing the performance of FinTech firms in East Asia, using Return on Assets (ROA) as the sole measure of firm performance. It begins with descriptive statistics, which outline the sample's characteristics and essential variables. The relationship between liquidity, working capital, leverage, and other control variables is then investigated using correlation analysis. Finally, regression analysis is used to test research hypotheses and evaluate the impact of these factors on ROA, including the moderating effect of COVID-19, shedding light on how the pandemic may have impacted FinTech firms' performance in the region.

4.1 Descriptive Statistics

Table 4.1 provides an overview of the data distribution for 200 observations. The analysis shows that the mean Return on Assets (ROA) is comparatively low at -0.040, indicating that, on average, the selected firms experienced a slight loss over the period. The standard deviation for ROA is 0.272, suggesting a moderate level of variation in profitability across the sample.

The mean Liquidity (CR) is 3.061, and the standard deviation is 3.068. CR represents the relationship between current assets and current liabilities. A CR greater than 1 indicates better liquidity on average across firms, but the mean of 3.061 suggests a reasonably high position in liquidity. A higher standard deviation of 3.068 indicates inconsistent liquidity behavior across the firms.

The mean Working Capital (WCTA) ratio is 0.222, and the standard deviation is 1.012. A positive mean of 0.222 indicates that, on average, firms hold positive net working capital, although the standard deviation of 1.012 explains the high diversity among firms with their working capital. The minimum value of -10.850 suggests some firms hold substantially negative working capital.

The mean Debt-to-Equity (DE) ratio is 0.662, and the standard deviation is 1.511. A mean of 0.662 suggests that, on average, the sample firms utilize approximately 66 cents of debt for every dollar of equity. A relatively high standard deviation of 1.511 identifies highly diverse leverage behavior across firms.

In contrast to the example, the skewness observations for ROA (-3.431), CR (3.568), WCTA (-8.172), and DE (6.503) are substantially far from zero, indicating that the data used in the sample are highly asymmetrical (skewed). Furthermore, the high kurtosis values across ROA (17.177), CR (20.123), WCTA (80.653), and DE (49.134) indicate that the sample data contains a significant presence of outliers (heavy tails). This high degree of non-normality supports the use of Fixed Effects panel regression over standard OLS, as FE is more robust to distributional assumptions.

Table 4. 1: Descriptive Statistics of the Variables

Variable	**Obs**	**Mean**	**Standard Deviation**	**Min**	**Max**	**Skewness**	**Kurtosis**
Return on Assets (ROA)	200	-.04	.272	-1.583	.328	-3.4308	17.1772
Liquidity	200	3.061	3.068	.04	24.757	3.5684	20.1226
Working Capital	200	.222	1.012	-10.85	.85	-8.1720	80.6534
Leverage	200	.662	1.511	.038	13.884	6.5033	49.1343
Firm Efficiency	200	.608	.579	0	3.66	2.4244	10.8207
Size of the Firm	200	9.443	.771	6.577	11.134	-.6256	5.0790
Loss-making Firms	200	.365	.483	0	1	.5608	1.3145
World Trade Uncertainty Index (WTUI)	200	.169	.098	.034	.377	.7976	2.6442
Inflation Rate	200	1.53	1.022	-.23	5.09	.2821	3.0139

NOTE. *Table 4.1* reports on the descriptive statistics. Descriptive statistics are based on the mean, standard deviation, minimum and maximum values, skewness, and kurtosis. Obs. reflects the observations. ROA: return on assets; CR: current ratio; WCTA: working capital to total assets ratio; DE: debt to equity ratio; ATA: asset turnover ratio; S: size of the firm; LOSS: loss-making firms; WTUI: world trade uncertainty index; IR: inflation rate. The study period is 2016 – 2024.

4.2 Pearson Correlation and Variance Inflation Factor

Correlation analysis was utilized to determine the linear correlations between variables, as well as the intensity and direction of association. Correlation analysis determines the dependence between variables. ***Table 4.2.1*** shows the pairwise correlations among the variables selected in this study.

The correlation matrix reveals diverse associations among the variables. Focusing on the relationship with Return on Assets (ROA), the results show that Liquidity (CR) (0.164) and Working Capital (WCTA) (0.553) are positively correlated with ROA. Conversely, leverage (DE) (-0.733) is strongly negatively correlated with ROA. The strong correlation coefficients for WCTA and DE suggest these variables are likely to have a significant influence on profitability, with DE being the strongest linear predictor.

The relationships between the independent variables themselves reveal vital information. Working Capital (WCTA) and Leverage (DE) have a notably strong negative association, measuring -0.782. This strong association is expected since enterprises with less debt may rely more on internal funding (working capital), and vice versa. Additionally, the control variable LOSS has a substantial negative association (-0.577) with ROA, as expected.

Although the correlation matrix paints a broad picture of the pairwise relationships between variables, we see substantial correlations between DE and WCTA. However, according to the VIF analysis (which is included in the OLS regression output), multicollinearity is not severe. Finally, we must conduct a regression analysis to assess the causal impact of our independent variables on ROA, while accounting for other factors.

Table4.2. 1: Pearson Correlation

Variables	ROA	CR	WCTA	DE	ATA	SIZE	LOSS	WTUI	IR
ROA	1.000								
CR	0.164	1.000							
WCTA	0.553	0.253	1.000						
DE	-0.733	-0.235	-0.782	1.000					
ATA	-0.174	-0.265	-0.283	0.453	1.000				
SIZE	0.469	0.195	0.290	-0.483	-0.348	1.000			
LOSS	-0.577	-0.044	-0.221	0.255	-0.035	-0.221	1.000		
WTUI	-0.017	-0.036	0.047	-0.030	-0.124	-0.087	0.045	1.000	
IR	-0.042	-0.041	-0.090	0.083	-0.012	0.072	-0.013	0.273	1.000

NOTE. *Table 4.2* reports the correlation results of the coefficients based on Pearson's pairwise correlation test. ROA: return on assets; CR: current ratio; WCTA: working capital to total assets ratio; DE: debt to equity ratio; ATA: asset turnover ratio; S: size of the firm; LOSS: loss-making firms; WTUI: world trade uncertainty index; IR: inflation rate. Statistically significant at the 5 percent level. The study period is 2016 – 2024.

As shown in ***Table 4.2.2***, the model achieved an R^2 of 0.7255 and an Adjusted R^2 of 0.7140, indicating that approximately 71.4% of the variation in Return on Assets (ROA) is explained by the independent and control variables. The OLS regression reveals a negative and highly significant coefficient for Leverage (DE). The coefficient for DE is -0.127. As DE moves in an inverse relationship with ROA, for every unit increase in DE, there will be a 0.127 unit decrease in ROA. The coefficient for Working Capital (WCTA) is -0.021, also indicating an inverse relationship with ROA. Conversely, the coefficient for Liquidity (CR) is 0.002, indicating a minor direct relationship with ROA, but this relationship is not statistically significant.

Hence, we conclude that Leverage (DE) negatively and significantly affects ROA, whereas CR and WCTA show weaker or statistically insignificant effects in the OLS context. In terms of control variables, SIZE (0.042) and ATA (0.075) have a direct (positive) relationship with ROA, while LOSS (-0.216) has an indirect (negative) relationship. WTUI (0.043) and IR (-0.002) have minor or non-significant relationships with ROA.

Furthermore, considering the Variance Inflation Factor (VIF) results in ***Table 4.3***, it can be concluded that the variables in the model are free from multicollinearity among themselves. The VIF for all independent variables is low, with the highest value for DE being 3.58. The Mean VIF for the model is 1.72. Since all individual VIF values are well below the conventional threshold of 10, and the mean VIF is close to 1, the stability and reliability of the regression coefficients are confirmed.

Table4.2. 2: Variance Inflation Factor

Variables	ROA	VIF	1/VIF
CR	.002	1.13	0.883589
	(.004)		
WCTA	-.021	2.75	0.363775
	(.017)		
DE	-.127	3.58	0.279437
	(.013)		
ATA	.075	1.44	0.694706
	(.021)		
SIZE	.042	1.47	0.679680
	(.016)		
LOSS	-.216	1.13	0.884310
	(.023)		
WTUI	.043	1.14	0.876181
	(.112)		
IR	-.002	1.13	0.888852
	(.0110		
-cons	-.325		
	(.163)		
Observations	200		
R^2	0.7255		
Adj R^2	0.7140		
Mean VIF		1.72	

NOTE. *Table 4.2.2* reports the Variance Inflation Factor. ROA: return on assets; CR: current ratio; WCTA: working capital to total assets ratio; DE: debt to equity ratio; ATA: asset turnover ratio; S: size of the firm; LOSS: loss-making firms; WTUI: world trade uncertainty index; IR: inflation rate. VIF is an alternative variance inflation factor test for measuring the correlation between the coefficients. The standard errors are shown in parentheses. *** p< .01, ** p< .05, * p< .1 reflects the statistical significance. The study period is 2016 – 2024.

4.3 Baseline Regression Results

4.3.1 Pre-Estimation Test

The Breusch-Pagan Lagrange Multiplier (BPLM) test was performed on Model 1 (without interaction) and Model 2 (with interaction) to assess whether Pooled OLS is preferable to Random Effects. The result has a p-value of 0.0000, showing significant cross-sectional variation. This confirms that Pooled OLS is improper and that a panel data model (RE or FE) should be employed.

Breusch-Pagan Lagrange Multiplier Test (BPLM Test)

Model	Chi2 Stat.	p-value	Conclusion
1	36.16	0.000	Reject H0, use REM

Finally, the Hausman test was used to determine whether to use the Random Effects (RE) or Fixed Effects (FE) estimators for Model 1 (without interaction) and Model 2 (with interaction). The test returns to a chi-square value of 110.08 with a p-value of 0.000, firmly rejecting the null hypothesis that the Random Effects estimator is consistent. This suggests that the unobserved individual effects are associated with the regressors, hence the Fixed Effects model is the most appropriate and consistent estimate for Models 1 and 2.

Hausman Fixed Random Test

Model	Chi2	p-value	Conclusion
1	110.08	0.000	Reject H0, use FEM

Therefore, Model 1 and Model 2 are confirmed with the FE Model, and the study proceeds with the Fixed Effects estimator for both models.

4.3.2 Result and Discussion

This study looks at the fixed effects of liquidity, working capital management, and leverage on business performance, which is assessed by return on assets. Table 4.3.2.1 shows the results of the Fixed Effects Model without interaction terms, which examines the relationship between liquidity, working capital management, leverage, and Return on Assets. The Current Ratio has a coefficient of -0.001 and a statistically insignificant p value of 0.719. Working Capital to Total Assets has a negative and statistically significant coefficient of -0.05 at the 1% level, with a p-value of 0.000. Debt to Equity similarly has a negative and statistically significant association with Return on Assets, with a coefficient of -0.126 and a p-value of 0.000. Overall, the Fixed Effects Model shows a strong explanatory power (R-squared = 0.606). This shows that the model's liquidity, working capital, leverage, and control variables explain approximately 60.6% of the variation in Return on Assets. The findings emphasize the importance of internal financial management and efficiency in determining the profitability of FinTech companies in East Asia.

Table 4.3.2. 1: Results of Fixed Effects of CR, WCTA, and DE on ROA, conducted as per panel data regression.

Return on Assets (ROA)	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
CR	-.001	.004	-0.15	.88	-.009	.008	
WCTA	-.05	.015	-3.37	.001	-.079	-.021	***
DE	-.126	.012	-10.53	0	-.15	-.103	***
ATA	.095	.038	2.50	.014	.02	.171	**
SIZE	.101	.049	2.07	.04	.005	.197	**
LOSS	-.177	.024	-7.26	0	-.225	-.129	***
WTUI	-.06	.103	-0.59	.559	-.264	.143	
IR	.002	.01	0.20	.843	-.017	.021	
Constant	-.882	.474	-1.86	.065	-1.818	.055	*

Mean dependent var	-0.040	SD dependent var	0.272
R-squared	0.606	Number of obs	200
F-test	32.116	Prob > F	0.000
Akaike crit. (AIC)	-288.627	Bayesian crit. (BIC)	-258.942

NOTE. *Table 4.3.2.1* reports the baseline regression results (Fixed Effects) of the CR, WCTA, and DE effects on ROA. ROA: return on assets; CR: current ratio; WCTA: working capital to total assets ratio; DE: debt to equity ratio; ATA: asset turnover ratio; S: size of the firm; LOSS: loss-making firms; WTUI: world trade uncertainty index; IR: inflation rate. VIF is an alternative variance inflation factor test for measuring the correlation between the coefficients. The standard errors are shown in parentheses. *** p< .01, ** p< .05, * p< .1 reflects the statistical significance. The study period is 2016 – 2024.

Table 4.3.2.2 shows the results of a Fixed Effects panel regression that includes interaction terms between COVID-19 and key financial variables such as the Current Ratio, Working Capital to Total Assets, and Debt to Equity, to investigate the pandemic's moderating effect on firm performance as measured by Return on Assets. The interaction between the Current Ratio and COVID-19 is negative and marginally significant, with a coefficient of -0.012 and p-value of 0.088. The interaction variables for Working Capital to Total Assets and Debt to Equity with COVID-19 are statistically insignificant, with coefficients of 0.12 and 0.005, and p values of

0.298 and 0.946, respectively. The constant term is negative and slightly significant. The model explains 61.3 percent of the variation in Return on Assets, according to a R squared value of 0.613, and the F test shows that the model is statistically significant at the one percent level. The regression is based on 200 observations.

Table 4.3.2. 2: Results of Fixed Effects with interaction on Moderating Effects of COVID-19 with CR, WCTA, and DE on ROA as per panel data regression.

Return on Assets (ROA)	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CR	.004	.006	0.69	.49	-.008	.016	
WCTA	-.052	.015	-3.48	.001	-.081	-.022	***
DE	-.126	.012	-10.42	0	-.15	-.102	***
ATA	.094	.039	2.45	.015	.018	.17	**
SIZE	.098	.05	1.94	.054	-.002	.197	*
LOSS	-.172	.025	-6.99	0	-.221	-.124	***
WTUI	-.085	.11	-0.78	.438	-.303	.132	
IR	.007	.011	0.66	.508	-.015	.03	
CR*COVID	-.012	.007	-1.58	.116	-.026	.003	
WCTA*COVID	.12	.072	1.68	.095	-.021	.261	*
DE*COVID	.005	.055	0.09	.932	-.105	.114	
Constant	-.876	.485	-1.81	.073	-1.834	.081	*

Mean dependent var	-0.040	SD dependent var	0.272
R-squared	0.613	Number of obs	200
F-test	23.665	Prob > F	0.000
Akaike crit. (AIC)	-286.438	Bayesian crit. (BIC)	-246.858

NOTE. *Table 4.3.2.2* reports the baseline regression results (Moderating Effects) of COVID-19 with CR, WCTA, and DE effects on ROA. ROA: return on assets; CR: current ratio; WCTA: working capital to total assets ratio; DE: debt to equity ratio; ATA: asset turnover ratio; S: size of the firm; LOSS: loss-making firms; WTUI: world trade uncertainty index; IR: inflation rate; COVID: COVID-19. VIF is an alternative variance inflation factor test for measuring the correlation between the coefficients. The standard errors are shown in parentheses. *** p< .01, ** p< .05, * p< .1 reflects the statistical significance. The study period is 2016 – 2024.

4.4 Robust Standard Error

4.4.1 Diagnosis Tests

Several diagnostic tests were run to assess the adequacy of the panel regression models and detect any violations of important assumptions.

The investigation began by doing the Cook-Weisberg heteroskedasticity test on both Model 1 (direct effects) and Model 2 (moderating effect). The results show a p-value of 0.0000 for both models, rejecting the null hypothesis of homoskedasticity. This validates heteroskedasticity, which means that the variance of the error term varies across data. Such a violation compromises the reliability of standard errors and significance tests, necessitating the usage of robust standard errors.

Cook-Weisberg Test for Heteroskedasticity

Model	Chi2 Stat.	p-value	Presence of Heteroskedasticity
1	15508.22	0.000	Yes
2	9040.45	0.000	Yes

Second, the Wooldridge test for autocorrelation in panel data was conducted. Both models returned p-values greater than 0.5000, indicating that the null hypothesis of no serial correlation could not be rejected. This suggests that there is no evidence of autocorrelation in the error terms across time. Ensuring the absence of autocorrelation is important because, if present and uncorrected, it can lead to biased standard errors and unreliable inference in panel data analyses.

Wooldridge Test for Autocorrelation

Model	F - Stat.	p-value	Presence of Autocorrelation
1	24.76	0.5787	No
2	18.43	0.9474	No

Since the FE model is proven for Model 1 and Model 2 has similar data features (heteroskedasticity and autocorrelation), the study uses the Fixed Effects estimator with robust standard errors for both models.

4.4.2 Results and Discussion

This section presents the findings from the Fixed Effects Model (FEM), which examined the influence of liquidity, working capital, and leverage on firm performance, as measured by Return on Assets (ROA). The choice of the FEM was justified by the Hausman test (Chi^2 = 110.08, $p = 0.000$), confirming that the Fixed Effects estimator provides a consistent and appropriate model for this analysis. The regression results with robust standard errors are summarized in ***Table 4.4.2.1***.

The results indicate that the Current Ratio has a coefficient of -0.001 with a p-value of 0.719, suggesting that it does not have a statistically significant effect on firm profitability. This implies that short-term liquidity, as measured by the ability to meet current liabilities with current assets, did not significantly influence the performance of fintech firms during the study period. This finding contrasts with prior studies by Al Nimer et al. (2015) and Lim and Rokhim (2021), who reported a positive relationship between the Current Ratio and financial performance.

Conversely, the Working Capital to Total Assets (WCTA) ratio exhibits a negative and highly significant effect, with a coefficient of -0.050 at the 1% level. This suggests that firms holding higher levels of working capital relative to total assets tend to experience lower profitability, potentially due to inefficient use of resources. While this result contradicts the findings of Anton and Afloarei (2020), it supports Nguyen and Nguyen's (2020) efficiency trade-off perspective, which argues that overly conservative working capital policies can adversely affect firm performance.

Similarly, the Debt-to-Equity (DE) ratio shows a negative and significant relationship with ROA. The coefficient of -0.126 at the 1% significance level indicates that higher leverage is associated with reduced profitability, likely due to increased financial obligations and risk exposure. This finding aligns with classical capital structure theory, which posits that excessive debt can hinder performance by raising financing costs.

Among the control variables, Asset Turnover has a positive and significant effect on firm performance (coefficient = 0.095, p = 0.044), demonstrating that firms that utilize their assets more efficiently tend to achieve higher profits. Firm size is marginally significant at the 10% level (coefficient = 0.101, p = 0.051), suggesting that larger firms may benefit from economies of scale or stronger competitive positioning. The LOSS variable has a strong negative and significant impact on ROA (coefficient = -0.177, $p < 0.01$), confirming that firms reporting losses experience substantially lower profitability. In contrast, the external macroeconomic variables, namely the World Trade Uncertainty Index and Inflation Rate, are statistically insignificant, indicating that broad economic conditions did not have a measurable impact on fintech profitability during the study period.

Overall, the model demonstrates high explanatory power, with an R-squared value of 0.606, indicating that the included liquidity, leverage, and control variables account for approximately 60.6% of the variation in firm performance. Collectively, these findings underscore the critical role of internal financial management, particularly working capital efficiency and leverage structure, in determining the profitability of fintech firms in East Asia.

Table 4.4.2. 1: Results of the Robust Standard Errors on the FEM Model of CR, WCTA, and DE on ROA, conducted as per panel data regression.

Return on Assets (ROA)	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CR	-.001	.002	-0.36	.719	-.004	.003	
WCTA	-.05	.004	-14.05	0	-.057	-.043	***
DE	-.126	.013	-10.04	0	-.152	-.1	***
ATA	.095	.045	2.12	.044	.003	.188	**
SIZE	.101	.049	2.06	.051	0	.202	*
LOSS	-.177	.028	-6.38	0	-.234	-.12	***
WTUI	-.06	.08	-0.76	.455	-.224	.104	
IR	.002	.008	0.25	.805	-.014	.018	
Constant	-.882	.459	-1.92	.066	-1.828	.065	*

Mean dependent var	-0.040	SD dependent var	0.272
R-squared	0.606	Number of obs	200
F-test	598.121	Prob > F	0.000
Akaike crit. (AIC)	-290.627	Bayesian crit. (BIC)	-264.240

NOTE. *Table 4.4.2.1* reports the robust standard error results (Fixed Effects) of the CR, WCTA, and DE effects on ROA. ROA: return on assets; CR: current ratio; WCTA: working capital to total assets ratio; DE: debt to equity ratio; ATA: asset turnover ratio; S: size of the firm; LOSS: loss-making firms; WTUI: world trade uncertainty index; IR: inflation rate. VIF is an alternative variance inflation factor test for measuring the correlation between the coefficients. The standard errors are shown in parentheses. *** p< .01, ** p< .05, * p< .1 reflects the statistical significance. The study period is 2016 – 2024.

This section presents the results of the second regression model, which incorporates the moderating effect of COVID-19 on the relationships between liquidity, working capital, leverage, and firm performance. The regression results with robust standard errors are displayed in ***Table 4.4.2.2***. The model shows an R-squared value of 0.613, slightly higher than the baseline model's 0.606, indicating that including the COVID-19 moderator improves the model's explanatory power and offers additional insight into firm behaviour during the pandemic period.

The results reveal that the interaction between the Current Ratio and COVID-19 is negative and significant at the 10% level (coefficient = 0.012), even though the direct effect of the Current Ratio on ROA remains small and statistically insignificant (coefficient = 0.004, p = 0.261). This suggests that the pandemic weakened the positive role of liquidity in sustaining firm performance. One plausible explanation is that holding liquid assets during an economic downturn can lead to higher opportunity costs, as firms face reduced commercial activity and limited investment opportunities. Consequently, liquidity appears less effective in generating returns during periods of crisis.

Regarding working capital, the interaction between the Working Capital to Total Assets ratio and COVID-19 is not statistically significant (coefficient = 0.012, p = 0.298). This indicates that the previously observed negative effect of working capital intensity on firm performance (coefficient = -0.052, significant at 1%) remained consistent throughout the pandemic. This finding implies that inefficiencies associated with high levels of working capital are structural characteristics of firm operations that are largely unaffected by external shocks. This aligns with Nguyen and Nguyen's (2020) assertion that excessive working capital reduces profitability regardless of broader economic fluctuations.

Similarly, the interaction between the Debt-to-Equity (DE) ratio and COVID-19 is not significant (coefficient = 0.005, p = 0.946), demonstrating that the negative effect of leverage on ROA (coefficient = -0.126, highly significant) persisted during the pandemic. This indicates that firms with higher debt levels continued to experience lower profitability due to financial risk and borrowing costs, and that the pandemic did not substantially amplify or mitigate this relationship. In other words, leverage remained a consistent predictor of financial performance, irrespective of the economic shock.

The control variables show patterns consistent with the baseline model. Asset Turnover remains positive and significant (coefficient = 0.094, $p = 0.032$), confirming that efficient use of assets continues to enhance profitability. Firm Size retains a positive effect (coefficient = 0.098, $p = 0.048$), suggesting that larger firms benefit from scale advantages or stronger market positioning. The LOSS variable remains highly significant and negative (coefficient = -0.172, $p < 0.01$), indicating that firms reporting losses experience substantially lower profitability. External factors, including the World Trade Uncertainty Index and Inflation Rate, remain insignificant in this model.

Overall, these findings suggest that COVID-19 had a limited moderating effect, slightly reducing the influence of liquidity on firm performance, while the roles of working capital intensity and leverage remained largely unchanged. This highlights that firm-specific characteristics, particularly internal financial management practices, continued to be the primary determinants of fintech firm performance between 2016 and 2024.

Table 4.4.2. 2: Results of the Robust Standard Errors with interaction on Moderating Effects of COVID-19 with CR, WCTA, and DE on ROA as per panel data regression.

Return on Assets (ROA)	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
CR	.004	.004	1.15	.261	-.003	.012	
WCTA	-.052	.005	-11.48	0	-.061	-.042	***
DE	-.126	.015	-8.65	0	-.156	-.096	***
ATA	-.094	.042	2.27	.032	.009	.180	
SIZE	.098	.047	2.08	.048	.001	.195	*
LOSS	-.172	.029	-5.96	0	-.232	-.113	
WTUI	-.085	.079	-1.08	.293	-.250	.079	**
IR	.007	.007	0.96	.344	-.009	.023	*
CR*COVID	-.012	.007	-1.78	.088	-.025	.002	*
WCTA*COVID	.12	.113	1.06	.298	-.113	.353	
DE*COVID	.005	.069	0.07	.946	-.139	.148	
Constant	-.876	.443	-1.98	.073	-1.791	.039	*

Mean dependent var	-0.040	SD dependent var	0.272
R-squared	0.613	Number of obs	200
F-test	23.665	Prob > F	0.000
Akaike crit. (AIC)	-286.438	Bayesian crit. (BIC)	-246.858

NOTE. *Table 4.4.2.2* reports the robust standard error results (Moderating Effects) of COVID-19 with CR, WCTA, and DE effects on ROA. ROA: return on assets; CR: current ratio; WCTA: working capital to total assets ratio; DE: debt to equity ratio; ATA: asset turnover ratio; S: size of the firm; LOSS: loss-making firms; WTUI: world trade uncertainty index; IR: inflation rate; COVID: COVID-19. VIF is an alternative variance inflation factor test for measuring the correlation between the coefficients. The standard errors are shown in parentheses. *** p< .01, ** p< .05, * p< .1 reflects the statistical significance. The study period is 2016 – 2024.

4.5 Robustness Check

The robustness test is conducted to examine the stability of the baseline regression results and to assess whether the estimated relationships are sensitive to alternative measurements of the key independent variables (Geeks for Geeks, 2025). In the baseline fixed effects model with robust standard errors, liquidity, working capital, and leverage are measured using Current Ratio (CR), Working Capital to Total Assets (WCTA), and Debt-to-Equity Ratio (DE), respectively. To verify the robustness of the findings, the model is re-estimated by substituting these variables with alternative proxies, namely Quick Ratio (QR) as an alternative liquidity measure, Net Working Capital (NWC) as an alternative working capital indicator, and Debt-to-

Assets Ratio (DA) as an alternative leverage proxy, while maintaining the same estimation technique and control variables.

Table 4.5.1 presents robustness test results and compares them with the baseline fixed effects model. The estimated coefficient for the alternative liquidity proxy, QR (-0.002), is negative and consistent with the coefficient of CR (-0.001) reported in the baseline model. Similarly, the alternative working capital measure, NWC (-0.017), also exhibits a negative coefficient, which aligns with the negative sign of WCTA (-0.050) in the baseline regression. These findings suggest that the estimated relationship between working capital management and firm performance remains stable across different working capital measurements.

In terms of leverage, the robustness specification indicates that DA (-0.125) carries a negative coefficient that is closely comparable in magnitude to DE (-0.126) in the baseline fixed effects model. The consistency in both sign and magnitude across alternative leverage proxies suggests that the estimated effect of leverage on firm performance is not materially affected by the choice of leverage measurement.

In summary, the robustness test results are consistent with the baseline fixed effects findings. The similarity in coefficient signs and magnitudes across alternative measures of liquidity, working capital, and leverage confirms that the main empirical results are robust to alternative proxy selections, thereby enhancing the credibility and reliability of the study's conclusions on the determinants of firm performance among FinTech firms in East Asia.

Table 4.5. 1: Results of the Robustness Check on the FEM Model of CR, WCTA, and DE on ROA, conducted as per panel data regression.

Return on Assets (ROA)	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
QR	-.002	.003	-0.50	.619	-.008	.005	
NWC	-.017	.032	-0.53	.598	-.084	.05	
DA	-.125	.01	-11.91	0	-.147	-.103	***
ATA	.114	.075	1.53	.139	-.04	.269	
SIZE	.144	.082	1.75	.092	-.025	.313	*
LOSS	-.175	.03	-5.95	0	-.236	-.115	***
WTUI	-.09	.093	-0.96	.344	-.281	.102	
IR	-.001	.01	-0.11	.912	-.022	.019	
Constant	-1.34	.778	-1.72	.098	-2.948	.265	*

Mean dependent var	-0.040	SD dependent var	0.272
R-squared	0.532	Number of obs	200
F-test	628.336	Prob > F	0.000
Akaike crit. (AIC)	-256.059	Bayesian crit. (BIC)	-229.672

NOTE. *Table 4.5.1* reports the robustness check of the QR, NWC, and DA effects on ROA. ROA: return on assets; QR: quick ratio; NWC: net working capital ratio; DA: debt to assets ratio; ATA: asset turnover ratio; S: size of the firm; LOSS: loss-making firms; WTUI: world trade uncertainty index; IR: inflation rate. VIF is an alternative variance inflation factor test for measuring the correlation between the coefficients. The standard errors are shown in parentheses. *** p< .01, ** p< .05, * p< .1 reflects the statistical significance. The study period is 2016 – 2024.

4.6 Summary of Empirical Results

This chapter investigates the determinants of FinTech firm performance in East Asia from 2016 to 2024, using Return on Assets (ROA) as the performance measure. The study employs panel data techniques, including descriptive statistics, correlation analysis, Fixed Effects regression, robust standard errors, moderating analysis of COVID-19, and robustness checks.

Descriptive statistics reveal that sampled firms exhibit positive ROA on average, indicating modest profitability over the study period. Significant variation is observed across firms in terms of liquidity, working capital, and leverage, with high skewness and kurtosis suggesting non-normality and the presence of outliers. These characteristics justify the use of Fixed Effects regression, which effectively accounts for unobserved firm-specific heterogeneity.

Correlation analysis indicates positive relationships between liquidity and working capital with ROA, while leverage is strongly negatively associated with firm performance. Although some independent variables, particularly working capital and leverage, are highly correlated, Variance Inflation Factor results show that multicollinearity is not a major concern.

Regression diagnostics confirm that pooled OLS is inappropriate, with the Hausman test strongly supporting the Fixed Effects Model. Baseline Fixed Effects results show that liquidity, measured by the Current Ratio, does not significantly affect ROA. In contrast, working capital management, proxied by Working Capital to Total Assets, negatively and significantly impacts performance. Similarly, leverage, measured by the Debt-to-Equity ratio, exerts a strong and significant negative effect on ROA. These findings suggest that higher working capital holdings and greater leverage are associated with lower profitability among FinTech firms. Among control variables, asset turnover and firm size are positively related to ROA, whereas loss-making firms consistently exhibit lower performance. External macroeconomic variables, including the World Trade Uncertainty Index and inflation, are generally insignificant.

Diagnostic tests detect heteroskedasticity but no serial correlation. After applying robust standard errors, the main results remain unchanged, confirming the reliability of the baseline findings. Moderating analysis of COVID-19 shows a limited impact, with only a marginally significant negative effect on the liquidity–ROA relationship, while working capital and leverage effects remain stable.

Robustness checks using alternative proxies for liquidity, working capital, and leverage yield consistent coefficient signs and magnitudes, confirming the stability of the empirical findings. Overall, internal financial management, particularly working capital efficiency and leverage structure, is the primary determinant of FinTech firms' performance in East Asia, whereas liquidity and external macroeconomic conditions play a more limited role.

CHAPTER 5: CONCLUSION AND IMPLICATIONS

5.0 Introduction

This chapter reviews and evaluates the findings reported in the previous chapter, relating them to the study's research aims and existing literature. It illustrates how liquidity, working capital, leverage, and the moderating effect of COVID-19 affect the performance of FinTech enterprises in East Asia as assessed by Return on Assets (ROA). The chapter also discusses the theoretical and practical consequences of the findings, recognizes the study's limits, and makes recommendations for further research. Overall, this chapter serves as a complete study conclusion, summarizing major observations and identifying future research possibilities.

5.1 Summary of Statistical Analyses and Major Findings

This study examined the factors influencing firm performance among FinTech companies in East Asia between 2016–2019 and 2021–2024, using Return on Assets (ROA) as the performance indicator. The analysis utilized secondary panel data comprising 200 firm-year observations. Both descriptive and inferential statistical techniques were applied, and a Fixed Effects Model with robust standard errors was employed following pre-estimation diagnostic tests to ensure the consistency and reliability of the results.

The baseline regression model assessed the direct effects of liquidity, working capital, and leverage on firm performance. The results show that the Working Capital to Total Assets ratio has a negative and highly significant effect on ROA, with a coefficient of -0.050 ($p < 0.01$). This supports Hypothesis 2, indicating that high working capital intensity can lead to operational inefficiencies and increased opportunity costs, ultimately reducing profitability. The finding highlights the critical role of effective working capital management in technology-driven financial firms, where idle resources can impede performance.

Leverage, measured by the debt-to-equity ratio, also has a substantial negative and significant impact on firm performance (coefficient = -0.126, $p < 0.01$), supporting Hypothesis 3. This result aligns with the Trade-Off Theory of Capital Structure, which posits that firms weigh the tax benefits of debt against the costs associated with financial distress. For FinTech firms, the costs of higher debt appear to outweigh potential advantages, leading to reduced ROA. This underscores the high financial risk and profit volatility in technology-driven financial organizations, where excessive leverage can quickly erode firm performance.

In contrast, liquidity, measured by the Current Ratio, does not show a statistically significant effect on ROA (coefficient = -0.001, $p = 0.719$), leading to the rejection of Hypothesis 1. Introducing a squared liquidity term to test nonlinearity did not alter this result, suggesting that liquidity is not a key driver of performance in this context. This may be because FinTech firms rely more heavily on technological capabilities, scalability, and market expansion than on traditional balance sheet liquidity.

The second regression model incorporated COVID-19 as a moderating variable to examine whether the pandemic altered the relationships between financial indicators and performance. The interaction between the Current Ratio and COVID-19 yields a negative coefficient of -0.012, marginally significant at the 10% level ($p = 0.088$). This provides some support for Hypothesis 4, indicating that during the pandemic, liquidity became less effective in sustaining profitability, potentially functioning as idle capital amid restricted economic activity.

By contrast, the interaction terms between Working Capital to Total Assets and Debt-to-Equity with COVID-19 are statistically insignificant ($p = 0.298$ and 0.946, respectively), failing to support Hypotheses 5 and 6. This suggests that the adverse effects of inefficient working capital management and high leverage on firm performance persisted throughout the pandemic.

One explanation for these findings lies in the structural and institutional features of the sampled countries—China, Japan, and South Korea—which host some of the most advanced and rapidly growing FinTech sectors in East Asia. These markets benefit from strong digital infrastructure, widespread technological adoption, and proactive government interventions during the pandemic. Many FinTech firms were able to adapt quickly through digital platforms, remote service delivery, and increased innovation, minimizing disruptions to their core financial operations.

Additionally, firms often entered the pandemic with robust risk management frameworks and access to diverse funding sources. Government support measures, flexible monetary policies, and targeted financial aid helped maintain credit market stability and reduce liquidity stress. Consequently, firms could sustain their working capital and leverage strategies without major structural adjustments, explaining why COVID-19 did not significantly alter these relationships with firm performance.

Overall, the evidence indicates that firm-specific financial management practices remain the primary determinants of FinTech performance in East Asia. The baseline model explains approximately 60.6% of the variation in ROA, while adding the COVID-19 moderating variable increases explanatory power slightly to 61.3%. Although this improvement is modest, it demonstrates that while crises like the COVID-19 pandemic can influence performance levels, they do not fundamentally alter the underlying financial mechanisms in technologically mature and resilient FinTech markets.

5.2 Implications of the Study

The findings of this study carry important implications for regulators, industry practitioners, and investors in the East Asian FinTech sector, particularly in China, Japan, and South Korea. By identifying key financial factors that drive firm performance and examining the moderating role of COVID-19, the study provides evidence-based insights that can inform more effective decision-making and regulatory policies.

For policymakers and regulators, the results underscore the need to monitor capital structure risks within the FinTech sector. The statistically significant negative impact of leverage on firm performance ($p < 0.01$) indicates that excessive reliance on debt can push firms beyond their optimal leverage levels, consistent with the Trade-Off Theory. Regulatory authorities should therefore promote prudent debt management and capital adequacy frameworks that account for the higher operational and technological risks inherent in FinTech firms. In contrast, the insignificance of the Current Ratio ($p = 0.719$) suggests that strict liquidity requirements alone may not directly enhance profitability. Regulatory focus should instead emphasize financial resilience, robust risk management practices, and sustainable growth strategies rather than traditional liquidity thresholds.

For FinTech managers and industry practitioners, the findings highlight the critical importance of internal financial management. The negative and highly significant association between Working Capital to Total Assets and ROA ($p < 0.01$) shows that excessive working capital can reduce profitability by tying up resources in non-productive assets. Managers should therefore prioritize operational efficiency by optimizing cash flow, accelerating receivables collection, and minimizing idle capital. Additionally, given the significant negative effect of leverage on performance, managers are encouraged to reassess their financing strategies and reduce reliance on debt. Greater use of internal financing or equity-based funding can mitigate financial distress risks while supporting long-term profitability, particularly in a sector characterized by rapid innovation and high profit volatility.

The moderating role of COVID-19 also offers practical insights for crisis management. While liquidity did not directly influence profitability, the slightly significant negative interaction between liquidity and COVID-19 suggests that holding excessive liquid assets during economic disruptions may hinder performance. Managers should adopt flexible and adaptive financial planning strategies that allow resources to be strategically deployed rather than left idle. This is especially relevant for FinTech firms in technologically advanced markets like China, Japan, and South Korea, where digital capabilities enable rapid operational adaptation.

For investors, the study provides guidance on firm evaluation and investment decisions. The results indicate that conventional liquidity ratios, such as the Current Ratio, are not reliable predictors of performance in the FinTech industry. Instead, investors should focus on leverage and operational efficiency metrics, which show strong and statistically significant correlations with firm success. Companies with lower debt exposure and effective working capital management are more likely to achieve stable and sustainable returns, even in the face of external shocks.

Overall, the findings emphasize that effective internal financial management remains the primary driver of FinTech firm performance in East Asia. While external shocks such as COVID-19 may affect short-term profitability, firm-specific financial structures and management decisions are the fundamental determinants of long-term success. These results enhance our understanding of financial resilience in the FinTech sector and offer practical guidance for strengthening stability and competitiveness in rapidly evolving digital financial markets.

5.3 Limitations of the Study

Despite the rigorous methodology and robust findings, this study has several limitations. First, the focus on publicly listed East Asian Fintech firms constrains the generalizability of results. Smaller, privately held startups or firms in other regions may exhibit different financial behaviors, and their responses to economic shocks might not align with those observed in large, listed entities.

Second, the measurement of the COVID-19 shock was operationalized as a binary variable, distinguishing pre-crisis (2016–2019) and post-crisis (2021–2024) periods. While this effectively captured structural changes, it does not account for variations in the pandemic's intensity over time, such as the contrast between initial lockdowns and subsequent recovery phases. A continuous, time-variant measure could provide a more nuanced understanding of firm adjustments during prolonged crises.

Third, the study focused on three independent variables: liquidity (CR), working capital (WCTA), and leverage (DE). Although these variables are important for internal financial management, external factors such as regulatory changes, product advances, and competition pressure also have an impact on business profitability. The absence of these elements may reduce the model's explanatory capacity and allow for more extensive future research. Despite these limitations, the study's results on the contingent function of working capital and the constant risk of leverage are useful for both academic research and practical applications.

5.4 Recommendations for Future Research

Building on the study's results and limitations, many options for further research are proposed to gain a better knowledge of the factors driving FinTech firm’s performance in East Asia. First, measure economic shocks at a granular level. This study used a binary pre- and post-crisis variable to assess the impact of the COVID-19 shock. While effective in capturing structural changes, such a simplistic measure cannot fully reflect the continuous fluctuations in economic uncertainty over time. Future research should adopt more granular, time-varying indicators of economic shocks, such as the World Trade Uncertainty (WTU) Index or regional policy uncertainty indices. By using continuous measures, researchers can better capture the intensity and duration of economic volatility, as well as its non-linear effects on working capital management and firm profitability. This approach would provide more precise insights into how firms adjust their financial strategies in response to evolving economic conditions, enabling more nuanced policy and managerial recommendations.

Second, disaggregation of working capital (WCTA). The empirical results of this study underscore the decisive role of the Working Capital to Total Assets ratio (WCTA) in determining firm resilience during crises and efficiency during stable periods. However, WCTA is an aggregated measure, which obscures the contribution of its individual components. Future studies should disaggregate working capital into Accounts Receivable, Inventory, and Cash Holdings to identify which components drive the observed effects. For instance, it may be that high cash holdings provide the most resilience during crises, while excessive inventory contributes to inefficiency during stable periods. Understanding the relative influence of each component would allow managers to implement more targeted and effective working capital strategies tailored to both ordinary operations and periods of economic turbulence.

Third, sectoral comparative analysis. While this study focused exclusively on FinTech firms, it remains unclear whether the contingency-dependent effects of working capital and leverage observed here are unique to the FinTech sector or reflect broader patterns in financial industries. Future research could conduct a comparative analysis between East Asian FinTech firms and traditional banking institutions. Using similar methodological frameworks, such as Fixed Effects models with moderating variables, such studies could empirically assess whether the dynamic role of working capital is an inherent characteristic of asset-light, innovation-driven firms or a generalizable phenomenon across financial sectors. Comparative insights could also inform both managerial strategies and regulatory policies by highlighting sector-specific vulnerabilities and resilience mechanisms.

In summary, these future research directions—improving the measurement of economic shocks, disaggregating working capital, and conducting sectoral comparisons—would provide a more detailed and nuanced understanding of the financial management strategies that drive firm performance. Such studies could strengthen the empirical foundation for evidence-based decision-making by managers, investors, and policymakers in the rapidly evolving East Asian FinTech ecosystem.

5.5 Conclusion

This Final Year Project investigates the financial determinants of business performance among FinTech enterprises in East Asia, with a particular focus on liquidity, working capital management, and leverage, as well as the moderating impact of the COVID-19 pandemic. Using panel data from FinTech firms in China, Japan, and South Korea covering 2016–2019 and 2021–2024, the study employed rigorous econometric techniques to address the research objectives and provide empirical insights into profitability dynamics in technologically advanced financial markets.

The first research objective—examining the relationship between liquidity, working capital, and leverage on FinTech profitability—was addressed using a Fixed Effects Model with robust standard errors. The results reveal that working capital management and leverage are significant determinants of firm performance. Specifically, the Working Capital to Total Assets ratio has a negative and statistically significant association with Return on Assets, indicating that excessive working capital reduces profitability due to operational inefficiencies and opportunity costs. Leverage, measured by the Debt-to-Equity ratio, also exerts a significant negative effect, suggesting that higher debt levels increase financial distress costs and constrain profitability. In contrast, liquidity, as measured by the Current Ratio, does not have a statistically significant impact on ROA, confirming that internal financial structure and efficiency play a more critical role in determining FinTech firm profitability than traditional liquidity measures.

The second research objectively exploring the moderating role of COVID-19 on the relationships between financial metrics and profitability—was similarly addressed. Interaction terms between the COVID-19 dummy variable and the key financial indicators reveal that the pandemic only slightly altered the effect of liquidity on performance. The negative and marginally significant interaction suggests that liquidity became less effective in supporting profitability during periods of economic disruption. However, COVID-19's moderating effects on working capital management and leverage were statistically insignificant, indicating that while the pandemic affected overall performance, it did not meaningfully change the sensitivity of profitability to working capital intensity or leverage.

Overall, the study demonstrates that both research objectives were successfully achieved. The findings underscore the importance of firm-specific financial management, particularly efficient working capital practices and prudent leverage decisions, as the primary drivers of profitability in East Asian FinTech enterprises. At the same time, external shocks like the COVID-19 pandemic have a limited moderating influence in technologically advanced and resilient FinTech markets.

In conclusion, this Final Year Project contributes to a deeper understanding of the factors driving financial performance in the East Asian FinTech sector by integrating firm-level financial analysis with the effects of crisis periods. The study provides valuable insights for policymakers, practitioners, and investors seeking to enhance financial resilience and support sustainable growth in the rapidly evolving digital finance industry.

References

A.Seissian, L., Gharios, R. T., & Awad, A. B. (2018). Structural and market-related factors impacting profitability: A cross sectional study of listed companiesa. *ScienceDirect*, 2-3, 8.

Aggarwal, M., Bamba, M., & Bansal*, I. (2022). Empirical Insights Into COVID-19 Impact on BSE Sectoral Returns. *Thailand and The World Economy*, 14-15.

Akinlo, O., & Asaolu, T. (2012). Profitability and Leverage: Evidence from Nigerian Firms. *Global Journal of Business Rsearch*, 1.

Aldboush, H. H., Almasria, N. A., & Ferdous, M. (2023). DETERMINANTS OF FIRM PROFITABILITY: EMPIRICAL EVIDENCE FROM JORDAN'S SERVICE SECTOR. *Vilnius Tech*, 1-3.

Altunbas, Y., Carbo, S., Gardener, E. P., & Molyneux, P. (2007). Examining the Relationship between Capital, Risk and Efficiency in European Banking. *European Financial Management*, 18.

Anderson, R. M., Heesterbeek, H., Klinkenberg, D., & Hollingsworth, T. D. (2020). How will country-based mitigation measures influence the course of the COVID-19 epidemic? *The Lancet*, 1-4.

Anton, S. G., & Nucu, A. E. (2020). The Impact of Working Capital Management on Firm Profitability: Empirical Evidence from the Polish Listed Firms. *Journal of Risk and Financial Managment*, 3-5,8.

Arbabshirani, M. R., Damaraju, E., Phlypo, R., Plis, S., Allen, E., Ma, S., . . . Calhoun, V. D. (2014). Impact of autocorrelation on functional connectivity. *ScienceDirect*, 1-15.

Athanasoglou, P. P., Delis, M. D., & Staikouras, C. K. (2006). Determinants of Bank

Profitability in the South Eastern European Region. *Journal of Finance Decision Making*, 2, 5-7, 16.

Bailey, A. (2020a, March 17). *Letter from the Governer to the Chancellor.* Retrieved from Bank of England: https://www.bankofengland.co.uk/-/media/boe/files/letter/2020/letter-from-the-governor-to-the-chancellor-march-2020.pdf

Bailey, A. (2020b, March 19). *Letter from the Governor to the Chancellor.* Retrieved from Bank of England: https://www.bankofengland.co.uk/-/media/boe/files/letter/2020/governor-letter-apf-march-2020.pdf

Bao, Z., & Huang, D. (2020). Shadow Banking in a Crisis: Evidence from FinTech During COVID-19. *SSRN*, 1, 5-7.

Bell, A., & Jones, K. (2014). Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data. *Political Science Research and Methods*, 2-39.

Bell, A., Fairbrother, M., & Jones, K. (2018). Fixed and random effects models: making an informed choice. *CrossMark*, 1-25.

Berger, A. N., & Bouwman, C. H. (2013). How does capital affect bank performance during financial crises? *ScienceDirect*, 27-28.

Bibi, N., & Amjad, S. (2017). The Realtionship between Liquidity and Firms' Profitability - A Case Study of Karachi Stock Exchange. *ResearchGate*, 3-4.

Born, B., & Breitung, J. (2016). Testing for Serial Correlation in Fixed-Effects Panel Data Models. *Institute of Econometrics and Operations Research*, 1-14.

Brealey, R., Myers, S., Allen, F., & Edmans, A. (2025). *Principles of Corporate Finance.* Evergreen.

Breusch, T. S., & Pagan, A. R. (1979). A SIMPLE TEST FOR HETEROSCEDASTICITY AND RANDOM COEFFICIENT VARIATION. *The Econometric Society*, 2-9.

Calcagnini, G., Gardini, L., Giombini, G., & Carrera, E. S. (2020). Does too much liquidity generate instability? *Journal of Economic Interaction and Coordination*, 4, 13-14.

capital.com. (n.d.). *What is a trade-off model of capital structure?* Retrieved from capital.com: https://capital.com/en-int/learn/glossary/trade-off-model-of-capital-structure-definition

Cedar_IBSi FinTech Labs. (2024, June 12). *FinTech Surge in MENA: 5 Key Enablers Driving Growth in the Industry*. Retrieved from Cedar_IBSi FinTech Labs: https://www.cedaribsifintechlab.com/fintech-surge-in-mena-5-key-enablers-driving-growth-in-the-industry/?utm

CFI Team. (n.d.). *Pecking Order Theory*. Retrieved from CFI: https://corporatefinanceinstitute.com/resources/valuation/pecking-order-theory/

Chaudhary, A. A., Nazir, N., Riaz, A., Sadiq, N., & Riaz, N. (2022). AUTOCORRELATION: WHAT HAPPENS IF THE ERROR OR DISTURBANCE TERMS ARE CORRELATED IN TIME-SERIES DATA. *Competitive Educational Research Journal*, 1-10. Retrieved from Competitive Educational Research Journal.

Chen, H., Qian, W., & Wen, Q. (2020). The Impact of the COVID-19 Pandemic on Consumption: Learning from High Frequency Transaction Data. *SSRN*, 23-24.

Chmelarova, V. (2002). THE HAUSMAN TEST, AND SOME ALTERNATIVES, WITH HETEROSKEDASTIC DATA . *Economics Commons*, 6-117.

Clement, O. O., & Olayemi, O. S. (2020). Investigating Performances of Some

Statistical Tests for Heteroscedasticity Assumption in Generalized Linear Model: A Monte Carlo Simulations Study. *Journal of Statistics*, 1- 35.

Cutler, D. (2020). How will COVID-19 affect the health care Economy? *JAMA Health Forum*, 1-2.

Deloof, M. (2000). Does Working Capital Management Affect Profitability of Belgian Firms? . *Journal of Business Finance & Accounting*, 2.

Eling, M., & Jia, R. (2019). Efficiency and profitability in the global insurance industry. *ScienceDirect*, 2.

Enqvist, J., Graham, M., & Nikkinen, J. (2014). The impact of working capital management on firm profitability in different business cycles: Evidence from Finland. *ScienceDirect*, 4, 13.

Ercegovac, R., & Ivica Klinac, I. Z. (2020). Bank Specific determinants of EU Banks Profitability After 2007 Financial Crisis. *ResearchGate*, 1-3.

Fan, C., Bae, S., & Liu, Y. (2024). Can FinTech transform corporate liquidity? Evidence from China. *ScienceDirect*, 1-3,5.

Feng, X., Lu, B., Song, X., & Ma, S. (2019). Financial literacy and household finances: A Bayesian two-part latent variable modeling approach. *ScienceDirect*, 17.

Fernando, J. (2025, February 25). *What Is Inflation?* Retrieved from Investopedia: https://www.investopedia.com/terms/i/inflation.asp

Fernando, J. (2025, June 14). *Working Capital: Formula, Components, and Limitations*. Retrieved from Investopedia: https://www.investopedia.com/terms/w/workingcapital.asp

FinCity Tokyo. (2021, January). *Japanese Fintech Market: Securities / Asset Management*. Retrieved from FinCity Tokyo: https://fincity.tokyo/wp-content/uploads/2021/01/1611286980-

b815978d395858892bde4954f81136b7.pdf

Fintech Galaxy. (2025, March 29). *MENA Fintech Funding: Poised to Hit $2.4B By 2029*. Retrieved from Fintech Galaxy: https://www.fintech-galaxy.com/media-center/news/mena-fintech-funding-poised-to-hit-24b-by-2029

Fintechnews Middle East. (2024, February 26). *Fintech Surges in MENA Though Talent and Capital Gaps Persist*. Retrieved from Fintechnews Middle East: https://fintechnews.ae/19864/fintech/fintech-surges-in-mena-though-talent-and-capital-gaps-persist/

Flinders, M., & Smalley, I. (2024, April 15). *What is fintech?* Retrieved from IBM: https://www.ibm.com/think/topics/fintech

Geeks for Geeks. (2025, July 23). *Robustness Testing*. Retrieved from Geeks for Geeks: https://www.geeksforgeeks.org/software-testing/robustness-testing/

Goncalves, T. C., Gaio, C., & Robles, F. (2018). The impact of Working Capital Management on firm profitability in different economic cycles: Evidence from the United Kingdom. *Economic and Business Letters*, 5.

Gupta, S., Jain, P. K., & Yadav, S. S. (2011). Generating Financial Flexibility and Financial Performance through Disinvestment: A Comparative Study Disinvested and Non-Disinvested Public Sector Enterprises in India. *Global Journal of Flexible Systems Management*, 6, 15.

Haas, J., Neely, C. J., & Emmons, W. R. (2020). Responses of International Central Banks to th COVID-19 Crisis. *Federal Reserve Bank of St.Louis Review, Fourth Quarter*, 8, 34-35, \37.

Hayes, A. (2025, May 31). *Understanding Liquidity and How to Measure It*. Retrieved from Investopedia: https://www.investopedia.com/terms/l/liquidity.asp

Hayes, A. (2025, June 2). *What Is Financial Leverage, and Why Is It Important?* Retrieved from Investopedia: https://www.investopedia.com/terms/l/leverage.asp

Holmstrom, B., & Tirole, J. (1997). Financial Intermedaition, Loanable Funds, and the Real sector. *The Quarterly Journal of Economics*, 27-29.

Horton, M. (2024, November 11). *The Difference Between Profitability and Profit*. Retrieved from Investopedia: https://www.investopedia.com/ask/answers/012715/what-difference-between-profitability-and-profit.asp

Hulatt, L. (2023, November 17). *Firm Size*. Retrieved from StudySmarter: https://www.studysmarter.co.uk/explanations/business-studies/managerial-economics/firm-size/#:~:text=Firm%20Size%20in%20Business%20Studies%20refers%20to%20the%20scale%20on,business's%20scale%20and%20operating%20capacity.

Hutchinson, & Jocelyn. (2024). *Dynamic capabilities (organizational theory)*. Retrieved from EBSCO: https://www.ebsco.com/research-starters/business-and-management/dynamic-capabilities-organizational-theory

Jurevicius, O. (2023, October 24). *Resource-Based View*. Retrieved from Strategic Management Insight: https://strategicmanagementinsight.com/tools/resource-based-view/

Kabuye, F., Kato, J., Akugizibwe, I., & Bugambiro, N. (2019). Internal control systems, working capital management and financial performance of supermarkets. *Cogent Business and Management*, 4, 16.

Kagan, J. (2025, July 25). *Financial Technology (Fintech): Its Uses and Impact on Our Lives*. Retrieved from Investopedia: https://www.investopedia.com/terms/f/fintech.asp

Kayani, U., Dsouza, S., Husain, Z., Nawza, F., & Hasan, F. (2025). Does the performance of financial technology (fintech) firms matter: evidence from North American and European fintech firms. *Cogent Economics and Finance*, 2-3,6.

Kenton, W. (2022, March 28). *Operating Loss (OL): Definition, How It's Calculated, and Causes*. Retrieved from Investopedia: https://www.investopedia.com/terms/o/operating-loss.asp

Kenton, W. (2025, July 15). *Financial Performance: Definition, How It Works, and Example*. Retrieved from Investopedia: https://www.investopedia.com/terms/f/financialperformance.asp

Khatun, N. (2021). Applications of Normality Test in Statistical Analysis. *Scientific Research Publishing*, 1-9.

KPMG. (2021, January). *2020 China Leading Fintech 50*. Retrieved from KPMG: https://assets.kpmg.com/content/dam/kpmg/cn/pdf/en/2021/01/china-fintech-50.pdf

Lolemo, S. E., & Pandya, D. H. (2023). THE IMPACT OF DIGITIZATION ON THE PROFITABILITY OF SELECTED INDIAN BANKS: POOLED OLS MODEL APPROACH. *International Journal of Management*, 1-9.

Lumivero. (2025). *Ordinary Least Squares regression (OLS)*. Retrieved from XLSTAT: https://www.xlstat.com/solutions/features/ordinary-least-squares-regression-ols

Lyngstadaas, H. (2020). Packages or systems? Working capital management and financial performance among listed U.S. manufacturing firms. *Journal of Management Control*, 3-4, 18-25.

MAGNiTT. (2019). *MENA Fintech Venture Report*. Retrieved from MAGNiTT: https://magnitt-live.s3.eu-west-2.amazonaws.com/files/research-files/2192019/5380223461751-

MAGNiTT_ADGM_2019_MENA_FinTech_Venture_Report_EN.pdf

MAGNiTT. (2022). *Fintech 2022 Venture Investment Report*. Retrieved from MAGNiTT: https://magnitt.com/research/fintech-2022-venture-report-50806

MAGNiTT. (2025, May 13). *Fintech Funding in MENA hits $644M in 2024, Maintaining its Dominance*. Retrieved from MAGNiTT: https://magnitt.com/news/fintech-funding-in-mena-hits-644m-in-2024-53994

Malyshev, A. (2025, August 20). *Step-by-Step Guide: How to Start a FinTech Startup (2025)?* Retrieved from SDK.finance: https://sdk.finance/how-to-start-a-fintech-company/

Mark. (2024, January 17). *Pecking Order Theory: Definitions, Concepts and Examples*. Retrieved from Capital City & Tarining Consulting: https://www.capitalcitytraining.com/knowledge/pecking-order-theory/

Mathuva, D. M. (2010). The Influence of Working Capital Management Components on Corporate Profitability : A Survey on Kenyan Listed Firms. *Research Journal of Business Management*, 2-11.

Mazzei, & Michael. (2024). *Resource-Based View (RBV)*. Retrieved from EBSCO: https://www.ebsco.com/research-starters/business-and-management/resource-based-view-rbv

Mcclure, B. (2024, December 20). *Measuring Company Efficiency To Maximize Profits*. Retrieved from Investopedia: https://www.investopedia.com/investing/measuring-company-efficiency/

Meyll, T., & Pauls, T. (2019). The gender gap in over-indebtedness. *ScienceDirect*, 5.

Modjo, M. I., Loekman, S., & Limijaya, A. (2022). The ICT Paradox in Indonesia:

ICT Investment and Firm Profitability. *ICIMTech*, 3-4.

Mummolo, J., & Peterson, E. (2018). Improving the Interpretation of Fixed Effects Regression Results. *Political Science Research and Methods*, 1-7.

Nanda, S., & Panda, A. K. (2017). The determinants of corporate profitability: an investigation of Indian manufacturing firms. *ResearchGate*, 3, 5-6.

National Bureau of Economic Research. (2020, June 8). *Business Cycle Dating Committee Announcement.* Retrieved from National Bureau of Economic Research: https://www.nber.org/news/business-cycle-dating-committee-announcement-june-8-2020

Nguyen, A. T., & Nguyen, T. V. (2018). WORKING CAPITAL MANAGEMENT AND CORPORATE PROFITABILITY: EMPIRICAL EVIDENCE FROM VIETNAM. *Foundations of Management*, 10.

Notta, O., & Vlachvei, A. (2014). The impact of Financial Crisis on firm performance in case of Greek food manufacturing firms. *Procedia Economics and Finance*, 5. Retrieved from Procedia Economics and Finance: 5

Ohorella, H. (2019). Factors Affecting Profitability of Pharmaceutical Companies Listed in Indonesia Stock Exchange. *ResearchGate*, 1.

Olson, D., & Zoubi, T. (2017). Convergence in bank performance for commercial and Islamic banks during and after the Global Financial Crisis. *ScienceDirect*, 1-3, 16.

Osborne, M., Fuertes, A.-M., & Milne, A. (2012). Capital and profitability in banking: Evidence from US banks. *Cass Business School*, 1, 12, 48-49.

Phan, D. H., Narayanb, P. K., Rahman, R. E., & Hutabarat, A. R. (2020). Do financial technology firms influence bank performance? *ScienceDirect*, 1, 4.

Plumper, T., & Troeger, V. E. (2007). Efficient Estimation of Time-Invariant and

Rarely Changing Variables in Finite Sample Panel Analyses with Unit Fixed Effects. *Oxford University Press*, 1-16.

Riveros, J. M. (n.d.). *Wooldridge Serial Correlation Test for Panel Data using Stata.* Retrieved from MS Research Hub: https://blog.ms-researchhub.com/2021/02/24/wooldridge-serial-correlation-test-for-panel-data-using-stata/

Salmerón-Gómez, R., García-García, C., & García-Pérez, J. (2019). A Guide to Using the R Package "multiColl" for Detecting Multicollinearity. *Springer*, 3-9.

Sani, M., Midi, H., & Babura, B. I. (2019). ROBUST WHITE'S TEST FOR HETEROSCEDASTICITY DETECTION IN LINEAR REGRESSION. *Journal of Sciences*, 1-4.

Schreiber-Gregory, D. N., & Foundation, H. M. (2017). Multicollinearity: What Is It, Why Should We Care, and How Can It Be Controlled? *SESUG*, 1-12.

SCMP. (2020, October). *China Fintech Report 2020*. Retrieved from SCMP: https://www.hkira.com/en/resources/views202012_fintechreport_sample.pdf?utm_

Sleiman, M. (2020, December 31). *Pandemic creates surge for MENA fintech development*. Retrieved from Executive: https://www.executive-magazine.com/fintech-2/pandemic-creates-surge-for-mena-fintech-development?utm

Son, S. K. (2024, April 24). *Korea Fintech Industry Overview and Introduction to Major Policies*. Retrieved from Fintech Center Korea: https://www.itu.int/en/ITU-T/webinars/dfs/sc/20240424/Documents/Sung%20Kyun%20Son%20v2.pdf

Stierwald, A. (2010). Determinants of Profitability: An Analysis of Large Australian

Firms. *The University of Melbourne*, 4, 16.

Tay, R. (2017). Correlation, Variance Inflation and Multicollinearity in Regression Model . *Journal of Eastern Asia Transportation Societies*, 1-10.

Tenity. (2024, June 17). *Fintech in South Korea: An intro to the country's fintech scene*. Retrieved from Tenity: https://www.tenity.com/blog/fintech-korea

Thi Ngoc Lan NGUYEN, V. C. (2019). The Determinants of Profitability in Listed Enterprises: A Study from Vietnamese Stock Exchange . *Journal of Asian Finance, Economics and Business*, 9.

Vazquez, F., & Federico, P. (2012). Bank Funding Structures and Risk: Evidence from the Global Financial Crisis. *ResearchGate*, 3, 5-9, 18-19.

WallStreetPrep. (2024, September 20). *Trade-Off Theory*. Retrieved from WallStreetPrep: https://www.wallstreetprep.com/knowledge/trade-off-theory/

Westhead, C. H. (2003). The focus of working capital management in UK small firms. *Academic Press*, 5.

Weygandt, J. J., Kimmel, P. D., & Kieso, D. E. (2009). Financial Accounting (9th ed.). In J. J. Weygandt, P. D. Kimmel, & D. E. Kieso.

World Economic Forum. (2025, June). *The Future of Global Fintech: From Rapid Expansion to Sustainable Growth*. Retrieved from World Economic Forum: https://reports.weforum.org/docs/WEF_Future_of_Global_Fintech_Second_Edition_2025.pdf

Yue, P., Korkmaz, A. G., Yin, Z., & Zhou, H. (2022). The rise of digital finance: Financial inclusion or debt trap? *ScienceDirect*, 2, 4-6.

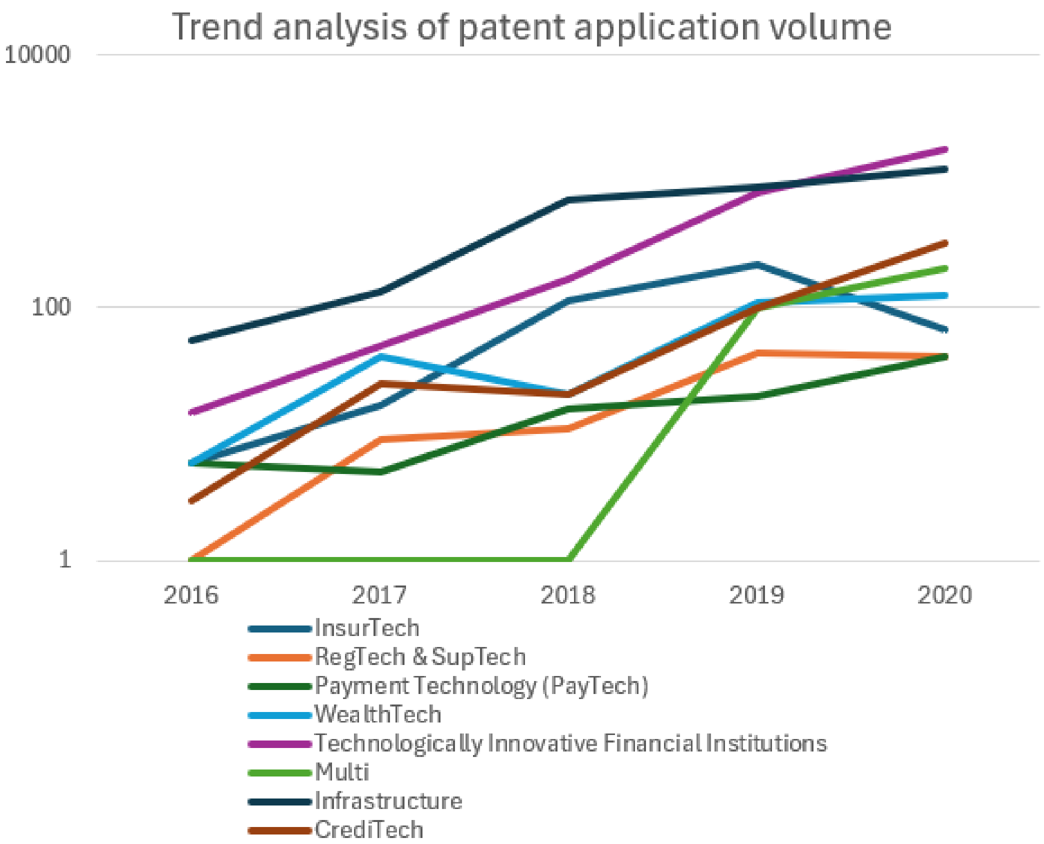
Zinkpot. (2025, May 13). *What is World Trade Uncertainty (WTU) Index?* Retrieved from Zinkpot.AI: https://www.zinkpot.com/?page=news&news=what-is-world-trade-

uncertainity-index

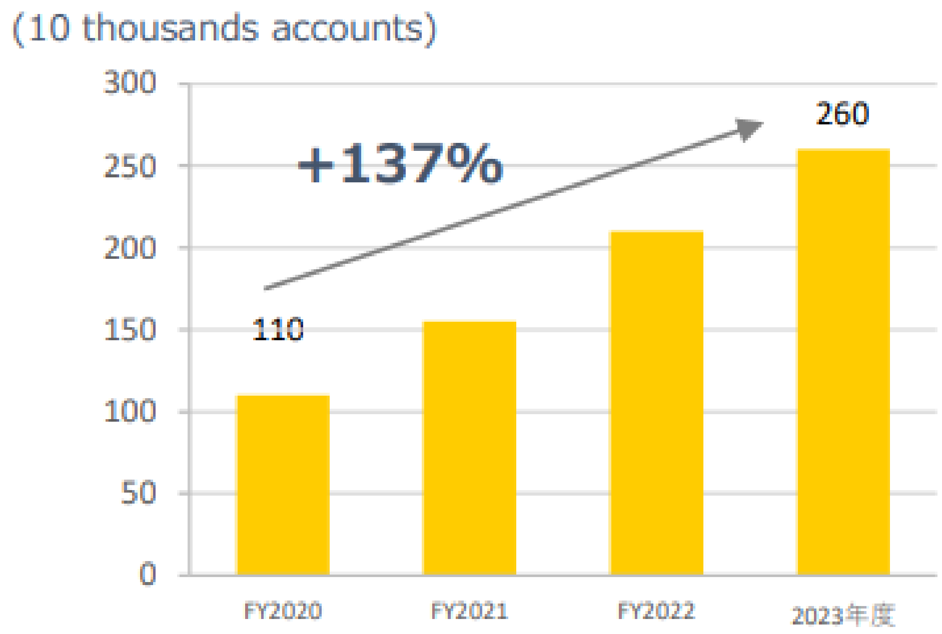
Zulfikar, R., & STp. (2018). ESTIMATION MODEL AND SELECTION METHOD OF PANEL DATA REGRESSION : AN OVERVIEW OF COMMON EFFECT, FIXED EFFECT, AND RANDOM EFFECT MODEL. *Universitas Islam Kalimantan MAB Banjarmasin*, 1-10.

Appendices

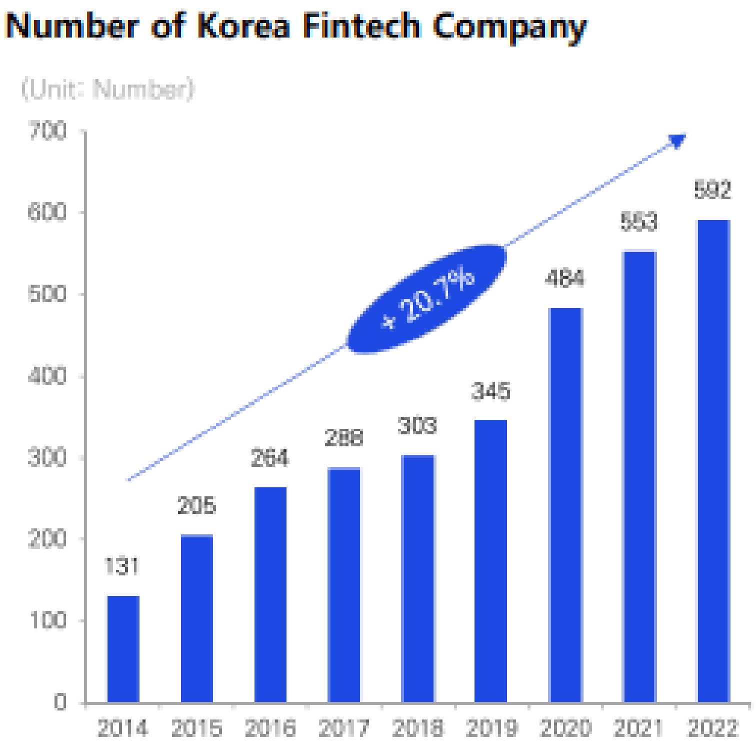
Appendix 1. 1: China Fintech Trend Analysis (2016 – 2020)



Appendix 1. 2: Japan Fintech Trend Analysis (2020 – 2023)



Appendix 1. 3: Number of Korea FinTech Companies (2014 – 2022)



Companies grew 20.7% annually
from 131 in 2014 to 592 in 2022.

Source : Korea Fintech Company Directory

Appendix 4. 1: Result of Descriptive Statistics from STATA

```
. *-------------------------

.
. * 2. Descriptive statistics

.
. *-------------------------
```

	e(count)	e(mean)	e(sd)	e(min)	e(max)	e(skewn~)	e(kurto~)
roa	200	-.0397865	.2720133	-1.5827	.3276	-3.43075	17.17723
liquidity	200	3.060992	3.067915	.04	24.757	3.568394	20.12256
workingcap~l	200	.222139	1.011833	-10.85	.85	-8.171981	80.65336
leverage	200	.661927	1.510891	.0376	13.8836	6.503322	49.13429
firmeffici~y	200	.6079365	.5787124	0	3.66	2.424443	10.82069
sizeofthef~m	200	9.442677	.7714344	6.5775	11.1338	-.6255949	5.078988
lossmaking~s	200	.365	.4826383	0	1	.560829	1.314529
wtui	200	.168657	.0982868	.0337	.3772	.7976155	2.644207
inflationr~e	200	1.53015	1.022301	-.23	5.09	.282108	3.013855

Appendix 4.2. 1: Result of Person Correlation from STATA

```
. *------------------------
.
. * 3. Pearson pairwise correlation
.
. *------------------------

. pwcorr roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms wtui i
> nflationrate, sig obs
```

	roa	liquid~y	workin~l	leverage	firmef~y	sizeof~m	lossma~s	wtui	inflat~e
roa	1.0000								
	200								
liquidity	0.1642	1.0000							
	0.0202								
	200	200							
workingcap~l	0.5531	0.2527	1.0000						
	0.0000	0.0003							
	200	200	200						
leverage	-0.7326	-0.2353	-0.7822	1.0000					
	0.0000	0.0008	0.0000						
	200	200	200	200					
firmeffici~y	-0.1738	-0.2653	-0.2828	0.4530	1.0000				
	0.0139	0.0001	0.0000	0.0000					
	200	200	200	200	200				
sizeofthef~m	0.4689	0.1945	0.2897	-0.4834	-0.3477	1.0000			
	0.0000	0.0058	0.0000	0.0000	0.0000				
	200	200	200	200	200	200			
lossmaking~s	-0.5769	-0.0437	-0.2206	0.2547	-0.0350	-0.2208	1.0000		
	0.0000	0.5387	0.0017	0.0003	0.6227	0.0017			
	200	200	200	200	200	200	200		
wtui	-0.0165	-0.0360	0.0468	-0.0301	-0.1238	-0.0874	0.0446	1.0000	
	0.8161	0.6131	0.5102	0.6722	0.0807	0.2183	0.5305		
	200	200	200	200	200	200	200	200	
inflationr~e	-0.0423	-0.0409	-0.0902	0.0827	-0.0125	0.0722	-0.0132	0.2731	1.0000
	0.5518	0.5651	0.2038	0.2446	0.8608	0.3097	0.8523	0.0001	
	200	200	200	200	200	200	200	200	200

Appendix 4.2. 2: Result of Variance Inflation Factor from STATA

```
. *------------------------

.
. * 4. Pearson Correlation

.
. *------------------------

.
. reg roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms wtui infl
> ation
```

Source	SS	df	MS			
				Number of obs	=	200
				F(8, 191)	=	63.10
Model	10.6821552	8	1.3352694	Prob > F	=	0.0000
Residual	4.04210057	191	.02116283	R-squared	=	0.7255
				Adj R-squared	=	0.7140
Total	14.7242558	199	.073991235	Root MSE	=	.14547

roa	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
liquidity	.0018368	.003576	0.51	0.608	-.0052167	.0088902
workingcapital	-.0213201	.016898	-1.26	0.209	-.0546507	.0120106
leverage	-.1270229	.0129117	-9.84	0.000	-.1524908	-.101555
firmefficiency	.0746463	.0213795	3.49	0.001	.0324761	.1168166
sizeofthefirm	.0420464	.0162147	2.59	0.010	.0100635	.0740293
lossmakingfirms	-.2156794	.0227215	-9.49	0.000	-.2604966	-.1708622
wtui	.043016	.1120903	0.38	0.702	-.1780779	.2641098
inflationrate	-.0016662	.0106996	-0.16	0.876	-.0227707	.0194384
_cons	-.324986	.1628173	-2.00	0.047	-.6461369	-.0038351

```
. estat vif
```

Variable	VIF	1/VIF
leverage	3.58	0.279437
workingcap~l	2.75	0.363775
sizeofthef~m	1.47	0.679680
firmeffici~y	1.44	0.694706
wtui	1.14	0.876181
liquidity	1.13	0.883589
lossmaking~s	1.13	0.884310
inflationr~e	1.13	0.888852
Mean VIF	1.72	

Appendix 4.3.1. 1: Result of BPLM from STATA

```
. *------------------------

.
. * 5. BPLM Checking

.
. *------------------------

. reg roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms wtui infl
> ation
```

Source	SS	df	MS			
				Number of obs	=	200
				F(8, 191)	=	63.10
Model	10.6821552	8	1.3352694	Prob > F	=	0.0000
Residual	4.04210057	191	.02116283	R-squared	=	0.7255
				Adj R-squared	=	0.7140
Total	14.7242558	199	.073991235	Root MSE	=	.14547

roa	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
liquidity	.0018368	.003576	0.51	0.608	-.0052167	.0088902
workingcapital	-.0213201	.016898	-1.26	0.209	-.0546507	.0120106
leverage	-.1270229	.0129117	-9.84	0.000	-.1524908	-.101555
firmefficiency	.0746463	.0213795	3.49	0.001	.0324761	.1168166
sizeofthefirm	.0420464	.0162147	2.59	0.010	.0100635	.0740293
lossmakingfirms	-.2156794	.0227215	-9.49	0.000	-.2604966	-.1708622
wtui	.043016	.1120903	0.38	0.702	-.1780779	.2641098
inflationrate	-.0016662	.0106996	-0.16	0.876	-.0227707	.0194384
_cons	-.324986	.1628173	-2.00	0.047	-.6461369	-.0038351

```
. xtreg roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms wtui in
> flation, re

Random-effects GLS regression                   Number of obs     =        200
Group variable: firmid                          Number of groups  =         25

R-squared:                                      Obs per group:
     Within  = 0.5987                                         min =          8
     Between = 0.8315                                         avg =        8.0
     Overall = 0.7225                                         max =          8

                                                Wald chi2(8)      =     397.81
corr(u_i, X) = 0 (assumed)                      Prob > chi2       =     0.0000
```

roa	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
liquidity	.0009106	.0037516	0.24	0.808	-.0064423	.0082636
workingcapital	-.0358114	.0154621	-2.32	0.021	-.0661165	-.0055063
leverage	-.1274555	.0121026	-10.53	0.000	-.1511761	-.1037348
firmefficiency	.077187	.024853	3.11	0.002	.0284761	.125898
sizeofthefirm	.050937	.0198952	2.56	0.010	.0119431	.089931
lossmakingfirms	-.2017774	.0228204	-8.84	0.000	-.2465046	-.1570501
wtui	.0054542	.1028982	0.05	0.958	-.1962226	.2071311
inflationrate	-.0011265	.0097963	-0.11	0.908	-.020327	.0180739
_cons	-.4037065	.1970296	-2.05	0.040	-.7898774	-.0175356
sigma_u	.04959303					
sigma_e	.12302802					
rho	.13977938	(fraction of variance due to u_i)				

```
. xttest0

Breusch and Pagan Lagrangian multiplier test for random effects

        roa[firmid,t] = Xb + u[firmid] + e[firmid,t]

        Estimated results:
                        |       Var     SD = sqrt(Var)
                ---------+-----------------------------
                     roa |   .0739912       .2720133
                       e |   .0151359        .123028
                       u |   .0024595        .049593

        Test: Var(u) = 0
                             chibar2(01) =    36.16
                          Prob > chibar2 =   0.0000
```

Appendix 4.3.1. 2: Result of the Hausman Test from STATA

```
. *-------------------------

.
. * 6. Hausman Test Checking

.
. *-------------------------

. hausman FE RE
```

	Coefficients (b) FE	(B) RE	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
liquidity	-.0006458	.0009106	-.0015564	.0020352
workingcap~l	-.0500815	-.0358114	-.0142701	.
leverage	-.1264173	-.1274555	.0010382	.
firmeffici~y	.0952024	.077187	.0180153	.0289431
sizeofthef~m	.1008729	.050937	.0499359	.0444336
lossmaking~s	-.1767907	-.2017774	.0249867	.0084674
wtui	-.0603883	.0054542	-.0658425	.0081433
inflationr~e	.0019431	-.0011265	.0030696	.0002091

```
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(8) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            = 110.08
Prob > chi2 = 0.0000
(V_b-V_B is not positive definite)
```

Appendix 4.3.2. 1: Result of the FEM without Interaction from STATA

```
. *------------------------

.
. * 7. FEM Test

.
. *------------------------

. xtreg roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms wtui in
> flation, fe

Fixed-effects (within) regression               Number of obs     =        200
Group variable: firmid                          Number of groups  =         25

R-squared:                                      Obs per group:
     Within  = 0.6061                                         min =          8
     Between = 0.7535                                         avg =        8.0
     Overall = 0.6892                                         max =          8

                                                F(8, 167)         =      32.12
corr(u_i, Xb) = -0.0027                         Prob > F          =     0.0000
```

roa	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
liquidity	-.0006458	.0042681	-0.15	0.880	-.0090721	.0077805
workingcapital	-.0500815	.0148527	-3.37	0.001	-.0794046	-.0207583
leverage	-.1264173	.0120058	-10.53	0.000	-.15012	-.1027145
firmefficiency	.0952024	.0381494	2.50	0.014	.0198851	.1705196
sizeofthefirm	.1008729	.0486843	2.07	0.040	.0047569	.196989
lossmakingfirms	-.1767907	.0243407	-7.26	0.000	-.2248458	-.1287355
wtui	-.0603883	.10322	-0.59	0.559	-.2641724	.1433959
inflationrate	.0019431	.0097986	0.20	0.843	-.0174019	.0212881
_cons	-.881653	.4742232	-1.86	0.065	-1.817898	.0545921
sigma_u	.1032776					
sigma_e	.12302802					
rho	.41338646	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(24, 167) = 4.17                     Prob > F = 0.0000
```

Appendix 4.3.2. 2: Result of the FEM with Interaction from STATA

```
. *------------------------

.
. * Covid-19 as a moderating Effect

.
. * 2. FEM Test

.
. *------------------------

.
. xtreg roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms wtu inf
> lation liquidity_covid workingcapital_covid leverage_covid, fe

Fixed-effects (within) regression               Number of obs     =        200
Group variable: firmid                          Number of groups  =         25

R-squared:                                      Obs per group:
     Within  = 0.6135                                         min =          8
     Between = 0.7682                                         avg =        8.0
     Overall = 0.7007                                         max =          8

                                                F(11, 164)        =      23.67
corr(u_i, Xb) = 0.0276                          Prob > F          =     0.0000
```

roa	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
liquidity	.0042331	.0061186	0.69	0.490	-.0078482	.0163144
workingcapital	-.051778	.0148999	-3.48	0.001	-.0811983	-.0223576
leverage	-.1260897	.0120965	-10.42	0.000	-.1499748	-.1022047
firmefficiency	.09431	.0385482	2.45	0.015	.0181953	.1704247
sizeofthefirm	.0978279	.0503275	1.94	0.054	-.0015456	.1972013
lossmakingfirms	-.172361	.0246516	-6.99	0.000	-.2210365	-.1236855
wtui	-.0854737	.1100527	-0.78	0.438	-.3027765	.1318291
inflationrate	.0074785	.0112625	0.66	0.508	-.0147597	.0297167
liquidity_covid	-.0115548	.0073035	-1.58	0.116	-.0259758	.0028662
workingcapital_covid	.1199962	.0715361	1.68	0.095	-.0212543	.2612468
leverage_covid	.0047345	.0554219	0.09	0.932	-.1046981	.114167
_cons	-.8762883	.4849867	-1.81	0.073	-1.833911	.0813347
sigma_u	.10021705					
sigma_e	.12297083					
rho	.39909972	(fraction of variance due to u_i)				

```
F test that all u_i=0: F(24, 164) = 4.05                   Prob > F = 0.0000
```

Appendix 4.4.1. 1: Result of Heteroskedasticity Test without Interaction from STATA

```
. *-------------------------

.
. * 8. Test for Heteroskedasticity

.
. *-------------------------

. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (25)  =       15508.22
Prob > chi2 =          0.0000
```

Appendix 4.4.1. 2: Result of Heteroskedasticity Test with Interaction from STATA

```
. *-------------------------

.
. * 3. Test for Heteroskedasticity

.
. *-------------------------

.
. xttest3

Modified Wald test for groupwise heteroskedasticity
in fixed effect regression model

H0: sigma(i)^2 = sigma^2 for all i

chi2 (25)  =        9040.45
Prob > chi2 =          0.0000
```

Appendix 4.4.1. 3: Result of Autocorrelation Test without Interaction from STATA

```
. *-------------------------

.
. * 9. Test for Autocorrelation

.
. *-------------------------

. xtreg roa L.roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms w
> tui inflationrate, fe

Fixed-effects (within) regression               Number of obs     =        150
Group variable: firmid                          Number of groups  =         25

R-squared:                                      Obs per group:
     Within  = 0.6576                                         min =          6
     Between = 0.8583                                         avg =        6.0
     Overall = 0.7767                                         max =          6

                                                F(9, 116)         =      24.76
corr(u_i, Xb) = 0.1483                          Prob > F          =     0.0000

. testparm L.roa

 ( 1)  L.roa = 0

       F(  1,   116) =    0.31
            Prob > F =    0.5787
```

Appendix 4.4.1. 4: Result of Autocorrelation Test with Interaction from STATA

```
. *-------------------------

.
. * 4. Test for Autocorrelation

.
. *-------------------------

. xtreg roa L.roa liquidity workingcapital leverage liquidity_covid workingcapital_covid leverage_
> covid, fe

Fixed-effects (within) regression               Number of obs     =        150
Group variable: firmid                          Number of groups  =         25

R-squared:                                      Obs per group:
     Within  = 0.5222                                         min =          6
     Between = 0.8230                                         avg =        6.0
     Overall = 0.6478                                         max =          6

                                                F(7, 118)         =      18.43
corr(u_i, Xb) = 0.4485                          Prob > F          =     0.0000

. testparm L.roa

 ( 1)  L.roa = 0

       F(  1,   118) =    0.00
            Prob > F =    0.9474
```

Appendix 4.4.2. 1: Result of the Robust Standard Error without Interaction from STATA

```
. *------------------------

.
. * 10. Robust Standard Error

.
. *------------------------

. xtreg roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms wtui in
> flationrate, fe vce(cluster firmid)

Fixed-effects (within) regression               Number of obs     =        200
Group variable: firmid                          Number of groups  =         25

R-squared:                                      Obs per group:
     Within  = 0.6061                                         min =          8
     Between = 0.7535                                         avg =        8.0
     Overall = 0.6892                                         max =          8

                                                F(8, 24)          =     598.12
corr(u_i, Xb) = -0.0027                         Prob > F          =     0.0000

                                 (Std. err. adjusted for 25 clusters in firmid)
```

roa	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
liquidity	-.0006458	.0017768	-0.36	0.719	-.0043129	.0030213
workingcapital	-.0500815	.003565	-14.05	0.000	-.0574393	-.0427236
leverage	-.1264173	.0125869	-10.04	0.000	-.1523952	-.1004393
firmefficiency	.0952024	.0448329	2.12	0.044	.0026718	.1877329
sizeofthefirm	.1008729	.0490326	2.06	0.051	-.0003253	.2020712
lossmakingfirms	-.1767907	.0276985	-6.38	0.000	-.2339577	-.1196237
wtui	-.0603883	.0795067	-0.76	0.455	-.224482	.1037055
inflationrate	.0019431	.0077645	0.25	0.805	-.0140821	.0179683
_cons	-.881653	.4585768	-1.92	0.066	-1.828109	.0648031
sigma_u	.1032776					
sigma_e	.12302802					
rho	.41338646	(fraction of variance due to u_i)				

Appendix 4.4.2. 2: Result of the Robust Standard Error with Interaction from STATA

```
. *------------------------

.
. * 5. Robust Standard Error

.
. *------------------------

.
. xtreg roa liquidity workingcapital leverage firmefficiency sizeofthefirm lossmakingfirms wtui in
> flationrate liquidity_covid workingcapital_covid leverage_covid , fe vce(cluster firmid)

Fixed-effects (within) regression               Number of obs     =        200
Group variable: firmid                          Number of groups  =         25

R-squared:                                      Obs per group:
     Within  = 0.6135                                         min =          8
     Between = 0.7682                                         avg =        8.0
     Overall = 0.7007                                         max =          8

                                                F(11, 24)         =    1170.43
corr(u_i, Xb) = 0.0276                          Prob > F          =     0.0000

                                   (Std. err. adjusted for 25 clusters in firmid)
```

roa	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
liquidity	.0042331	.0036768	1.15	0.261	-.0033554	.0118216
workingcapital	-.051778	.0045111	-11.48	0.000	-.0610883	-.0424676
leverage	-.1260897	.014579	-8.65	0.000	-.1561793	-.0960001
firmefficiency	.09431	.0415451	2.27	0.032	.0085651	.1800549
sizeofthefirm	.0978279	.0469904	2.08	0.048	.0008446	.1948112
lossmakingfirms	-.172361	.0289279	-5.96	0.000	-.2320651	-.1126568
wtui	-.0854737	.0794783	-1.08	0.293	-.2495088	.0785614
inflationrate	.0074785	.0077499	0.96	0.344	-.0085166	.0234736
liquidity_covid	-.0115548	.0065007	-1.78	0.088	-.0249717	.001862
workingcapital_covid	.1199962	.1128096	1.06	0.298	-.1128314	.3528239
leverage_covid	.0047345	.0694177	0.07	0.946	-.1385366	.1480056
_cons	-.8762883	.4433489	-1.98	0.060	-1.791315	.0387388
sigma_u	.10021705					
sigma_e	.12297083					
rho	.39909972	(fraction of variance due to u_i)				

Appendix 4.5. 1: Result of the Robustness Test without Interaction from STATA

```
. *------------------------

.
. * 10. Robust Standard Error

.
. *------------------------

.
. xtreg roa qr nwc da ata size loss wtui ir, fe vce(cluster firmid)

Fixed-effects (within) regression               Number of obs     =        200
Group variable: firmid                          Number of groups  =         25

R-squared:                                      Obs per group:
     Within  = 0.5317                                         min =          8
     Between = 0.6226                                         avg =        8.0
     Overall = 0.5808                                         max =          8

                                                F(8, 24)          =     628.34
corr(u_i, Xb) = -0.1405                         Prob > F          =     0.0000

                                (Std. err. adjusted for 25 clusters in firmid)
```

roa	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
qr	-.001582	.0031405	-0.50	0.619	-.0080637	.0048997
nwc	-.0172904	.0323755	-0.53	0.598	-.0841101	.0495294
da	-.1249999	.0104913	-11.91	0.000	-.1466528	-.1033469
ata	.1144305	.0748713	1.53	0.139	-.0400963	.2689572
size	.1438113	.0819721	1.75	0.092	-.0253708	.3129933
loss	-.1754475	.0295037	-5.95	0.000	-.2363402	-.1145547
wtui	-.0895379	.0928192	-0.96	0.344	-.2811072	.1020315
ir	-.0011146	.0099801	-0.11	0.912	-.0217125	.0194834
_cons	-1.341531	.7782415	-1.72	0.098	-2.947743	.26468
sigma_u	.12973167					
sigma_e	.13413305					
rho	.4833242	(fraction of variance due to u_i)				