MERGERS AND ACQUISITIONS IN THE FOOD AND AGRI-BUSINESS INDUSTRY: TIME TO COMPLETION, ROLES OF ADVISERS, AND PREDICTION OF ACQUIRERS

By

Ramyani Mukhopadhyay

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food and Resource Economics - Doctor of Philosophy

2022

ABSTRACT

MERGERS AND ACQUISITIONS IN THE FOOD AND AGRI-BUSINESS INDUSTRY: TIME TO COMPLETION, ROLES OF ADVISERS, AND PREDICTION OF ACQUIRERS

By

Ramyani Mukhopadhyay

Mergers and Acquisitions (M&A) are corporate actions pursued with the intention of achieving significant synergistic gains. They are also often considered a successful component of an expansionary business strategy. However, M&A have higher failure rates and can lead to significant diminution of shareholder wealth. Given the high risk and high reward of M&A, the factors responsible for their high failure rates are worthy of study. In this dissertation, I have identified some of the factors responsible for M&A failures in the global agribusiness industry. These include longer time-to-completion (TTC), possible asymmetric information (AI) in M&A deals, and high competition amongst acquirers. Therefore, in this dissertation, components studies include 1) the determinants of TTC, 2) the value added by financial and/or legal advisory firms to participating companies in an environment of AI, and 3) the profile and characteristics of successful acquirers.

The first area, TTC, is highly and directly correlated with the probability of deal failure. However, the literature has not sufficiently addressed the factors that accelerate or delay the deal process. The second area, the role of legal and financial advisory firms, has been effectively analysed in the literature against the backdrop of the risk of adverse selection due to the presence of AI. The literature has also not sufficiently addressed the contribution of advisory services companies in an opaque business environment. Finally, the third area, the profile and characteristics of successful acquirers, has also not been effectively dealt in the literature.

However, it is of immense importance from the point of view of potential targets. This dissertation addresses all these three issues with the intent of better understanding the global food and agri-business industry.

M&A are a complex business strategy that involves several stakeholders, including acquirers, targets, investment banks, regulators, investors and advisory service firms. The objective function of each stakeholder is different and the strategic action of one stakeholder may impact upon other stakeholders. AI results in longer TTC which results in reduced deal profitability. It should be noted that 90% of the M&As turns our financially nonviable. Therefore, in the current complex economic situation, it is very challenging for the stakeholders to navigate through the M&A process and make it economically profitable for themselves if AI and TTC challenges are nor well understood.

This dissertation should make significant contributions to the literature on M&A economics and the stakeholders in the M&A process. For example, the three component essays should be helpful to academic and other stakeholders in identifying the factors that lead to greater likelihood of the success of M&A deals through reduced TTC and mitigated risks of adverse selection and should help to improve understanding on the part of acquirers of the nature and potential for contemporaneous bidders. Practitioners in M&A process will find these results useful due to their practical applicability. For example, the analysis on TTC from the first essay of this dissertation suggests that a target should expect a non-cash deal involving an efficient acquirer to take a longer amount of time. Targets can also use the data to identify potential acquirers. Acquirers might also find the findings of this dissertation helpful in implementing their M&A strategies, navigating environments of AI, and anticipating the TTC of an M&A deal. M&A practitioners, especially financial advisory firms, may find this study helpful.

ACKNOWLEDGEMENTS

The research for this dissertation was carried out between 2017 and 2022 during the period of my Ph.D. studies at the Department of Agricultural Food and Resource Economics (AFRE) at Michigan State University (MSU). The research and my graduate study were supported by (1) a Graduate Assistantship provided by the Office of the John A. Hannah Distinguished Professor in Land Policy through most of my stay at MSU, (2) a Graduate Teaching Assistantship from the Department of AFRE, (3) a Dissertation Completion Fellowship from the College of Agriculture and Natural Resources (CANR) at MSU, and (4) emergency assistance funds from the office of the Dean of the MSU Graduate School.

I am deeply grateful to my graduate adviser and dissertation committee chairperson, Dr. Adesoji O. Adelaja, the John A. Hannah Distinguished Professor in Land Policy at MSU, for his significant insights, guidance, and endless support. He constantly inspired me and was always there to help me through major ups and downs over the past five years. He has contributed to this dissertation with his great patience, enthusiasm, immense knowledge and undivided motivation. Professor, thank you for your patience and for guiding me through the subtleties of analytical thoroughness and effective writing.

I also wish to convey my appreciation to the three other members of my dissertation committee for their guidance and mentoring: Dr. Dave Weatherspoon, Associate Provost and Professor of AFRE; Dr. Brent Ross, Associate Professor and Associate Chair at AFRE; and Dr. Charles D. Hadlock, the Frederick S. Addy Distinguished Chair in Finance and Associate Dean for Faculty and Doctoral Programs, Department of Finance, MSU. The quality and depth of this dissertation reflects the strength of my dissertation committee.

My department, AFRE, provided me with an enabling and stimulating environment for research through its extraordinary faculty and staff. These include Dr. Robert Myers, former Professor, Associate Chairperson, and Graduate Program Director for AFRE; and Dr. Nicole Mason-Wardell, the current Associate Chairperson, Graduate Program Director, and Associate Professor at AFRE. They helped me address administrative difficulties, departmental funding, and other critical issues during the period of my Ph.D. studies.

I would like to thank my parents, Dr. Arup Ratan Mukhopadhyay and Mrs. Maitreyee Mukherjee for their undying love and lifelong commitment to shaping my future. I can honestly say that this dissertation and the achievement of a doctoral degree would have been impossible without their stellar efforts. They believed in me even when I stopped believing in myself. I would also like to thank my grandmothers, Ira Banerjee and Arati Mukherjee, and my aunt, Atreyee Banerjee, who have always kept their faith in me. They gave me the extra strength to get things done. My grandfather, the late Prafulla Ratan Mukhopadhyay, was always proud of me and always wanted to witness me holding a doctorate degree.

Finally, I would also like to thank my friends, Dr. Sukrit Pal, Shayonee Chakraborty, Dr. Christine Sauer, Dr. Aishwarrya Deore, Charuta Parkhi, Jill Steiner, Dr. Ahmed Salim Nuhu, and Aniruddha Paranjpe for their irreplaceable presence during the period of my academic studies.

For their sacrifice, unconditional love and unequivocal support, I dedicate this dissertation to my parents, Dr. Arup Ratan Mukhopadhyay and Mrs. Maitreyee Mukherjee.

PREFACE

This dissertation consists of three essays, all of which represent original scholarship and distinct contributions to the Mergers and Acquisitions literature. The research and analysis in this dissertation is primarily my own, with the guidance and other contributions of Dr. Adesoji Adelaja, my graduate program adviser and chair of my dissertation committee at Michigan State University.

The first essay, “Time-to-Completion of Mergers and Acquisitions in the Global Food and Agribusiness Industry,” has been published in *Agribusiness: An International Journal* in January of 2022. That article is co-authored with Dr. Adelaja, with me as the second author. The primary data used in the paper was collected from Bloomberg’s Mergers and Acquisition Database and Thomson Reuters. The second essay, titled “Impact of Advisory Services on the Success of M&A in the Food and Agribusiness Industry,” has some writing contributions made by Dr. Adesoji Adelaja. The data sources of the second essay are the same as the first. The third essay, “Predicting Acquirers in Food and Agribusiness Industry Mergers and Acquisitions,” also has some writing contributions by Dr. Adelaja. Dr. Adelaja. As with the first and second essays, data sources of the third essay are the same as the first two essays.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

KEY TO ABBREVIATIONS

2SLS	Two Stage Least Square Model
AI	Asymmetric Information
ATE	Average Treatment Effect
AUD	Australian Dollar
BAS	Bid-Ask Spread
BMAD	Bloomberg Merger and Acquisition Database
Bn	Billion
BSM	Black-Scholes-Merton
C.I.	Confidence Interval
CAD	Canadian Dollar
CEO	Chief Executive Officer
CIFAR	Canadian Institute for Advanced Research
CNY	Chinese Renminbi
DC	Deal Completion
DV	Disposal Value
EBIT	Earnings Before Interest and Taxes
EPS	Earnings Per Share
EUR	European Union Euro
EY	Ernst and Young
FABI	Food and Agri-Business Industry

FDI	Foreign Direct Investment
FE	Fixed Effect
GBP	British Pound Sterling
GDP	Gross Domestic Product
GFABI	Global Food and Agri-Business Industry
IB	Investment Bank
ILLIQ	Illiquidity Ratio
IR	Individual Rationality
IV	Instrumental Variable
JPY	Japanese Yen
KMO	Kaiser-Meyer-Olkin
KPMG	Klynveld Peat Marwick Goerdeler
KV	Keep Value
LR	Liquidity Ratio
M&A	Mergers and Acquisitions
NPV	Net Present Value
NYSE	New York Stock Exchange
OLS	Ordinary Lease Square
PCA	Principal Component Analysis
PE	Private Equity
PSM	Propensity Score Matching
PWC	Price Waterhouse Coopers

Q1	Quarter 1
Q2	Quarter 2
Q3	Quarter 3
Q4	Quarter 4
R&D	Research and Development
RE	Random Effect
ROA	Return on Assets
ROC	Return on Capital
ROE	Return on Equity
ROI	Return on Investment
ROWC	Return on Working Capital
S&P	Standard & Poor
SAQ	Scaled Accruals Quality
SD	Superior Deal
SEC	Securities Exchange Commission
SIC	Standard Industrial Classification
SPELL	Solvency, Profitability, Efficiency, Leverage, Liquidity
T	Trillion
TNC	Transnational Corporations
TRD	Thomson Reuters Database
TTC	Time-To-Completion
US/USA	United States of America

USD	United States Dollar
USDA	United States Department of Agriculture
VIF	Variance Inflation Factor

CHAPTER 1. INTRODUCTION

The COVID-19 pandemic catalyzed a major worldwide economic crisis by disrupting production, logistics, supply chains, markets, and employment, leading to inflationary pressures upon the price of many goods and services. In the food industry, businesses were stressed by the health, safety, and logistical challenges resulting from the pandemic. While the pandemic is not yet over, the world entered an economic bubble in which macro-economic managers and regulators are increasingly concerned about achieving market correction and avoiding a major recession. High competition, along with high inflation in the global market, has made it harder for companies to survive.

In this new environment, companies are striving to recalibrate their operations and transform themselves for the post-pandemic era. Mergers and Acquisitions (M&A) have been a crucial strategy with immense promise to accelerate the growth of a company. In an environment where drastic changes are not always easy to achieve, companies look toward M&A as a means of achieving transformational change when feasible and appropriate. But it comes with risks.

Specifically, M&A activities, which slowed down with the advent of the COVID-19 pandemic, have now begun to rise again. This rise is due to the need for portfolio diversification, a strategy often used by companies to position themselves for the future. However, research shows that M&A do not always yield the expected results, and many fail. Therefore, it is important to understand the associated risks and appropriate precautionary measures to mitigate these risks. As will be discussed below, this is particularly important in the food and agribusiness industry (FABI) due to its importance and uniqueness.

This dissertation investigates two critical risks associated with M&A. These risks are also among the most important reasons for M&A failure. The first is the time to completion (TTC) of M&A transactions. The second is the asymmetry of information (AI) in M&A transactions. The third is the role of competition in M&A and the characteristics of competing acquirers.

Specifically, this research raises three critical questions regarding the success of M&A. The first question is how to understand the probable time to complete a transaction in a complex global economy, and, along with this, whether TTC adversely affects the success of M&A. The second question is, assuming that AI plays a major role in the failure of M&A deals, what are possible strategies to reduce AI? The third question is how to characteristically predict the competition among acquirers in an M&A deal. These three questions are related to both the characteristics of the acquiring company in the FABI and also answer the question of why a particular organization might still struggle for growth through M&A, especially in the context of TTC, AI, and global competition.

This dissertation concludes that the vast majority of M&A cases will struggle to achieve financial gain until they manage to understand the motivation of the other M&A stakeholders. For example, acquirers need to analyze the objective of the target, investment bank, and regulators in order to design and implement a strategy to accelerate or delay a deal or to suppress information. In order to achieve desirable growth, acquirers need to have a fair understanding of probable TTC before entering into an M&A transaction or making a conscious acquisition decision, and strategically apply instruments to reduce the IA. These recommendations will help acquirers in carefully selecting and examining their targets as far as the management, financials, operations are concerned.

This dissertation advances the understanding of what mergers and acquisitions are. M&A are the most common strategy used in business expansion, yet they are subject to significant failure rates. By investigating this issue, this dissertation addresses a gap in the literature. The findings of the research reveal that success in mergers and acquisitions is more complex and harder to achieve than previously assumed, especially in the context of TTC and asymmetric information (AI).

1.1. Background

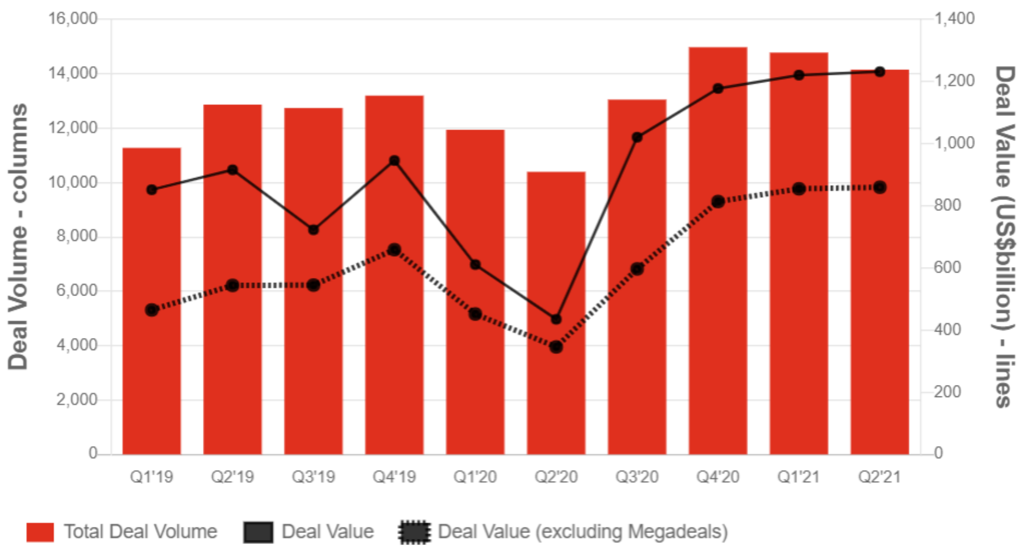
In the context of corporate strategy, the term "acquisition" generally refers to the act of purchasing the assets of another company. More precisely, it is used to describe the purchase of shares or assets in companies during the merger process. An acquisition can take the form of purchasing the stock of the target entity or acquiring a substantial amount of its assets. In this process, the acquired company ceases to exist, leaving its assets and liabilities to the acquiring company. From the legal perspective, an acquisition extinguishes the target corporation as a legal entity, and the surviving acquiring corporation assumes all the merged corporation's rights, privileges, and liabilities.

In contrast, "a merger is a strategy-driven corporate agreement between two existing companies of approximately the same size which enables them to join forces as a new single entity. The two corporations lose their separate legal identities and combine to form an entirely new corporation. The stocks of both companies are surrendered, and new stocks are issued in the new entity. In a merger, two involved CEOs and their boards agree to integrate their two companies in order to serve the best interest of both of the companies" (Investopedia, 2022).

M&A are being extensively used across the globe. Table-1 presents the recent trend in M&A in terms of deal volume (frequency) and deal value. The global economy witnessed around ten thousand M&A deals per quarter in 2019 Q1, which increased to 15 thousand M&A deals per quarter in 2021 Q1. The COVID-19 pandemic had a major global impact on M&A deal activity:

both the deal volume and deal value of M&A hit rock bottom in Q2 of 2020. The aggregate value of the mega deals (M&A deals that are large and costly transaction that valued $5B or more) was $500Bn, and non-mega deals were $400Bn, which is approximately half of the deal value in Q2 of 2019. However, M&A activities recovered very fast, as exponential growth from the third quarter of 2020 brought the value up to $1200Bn for mega deals and $900Bn for non-mega deals. (PWC, 2021).

Figure 1.1: Recent Trend of Mergers and Acquisitions (Deal Volume and Deal Trend)



Source: Refinitiv, Dealogic, and PwC analysis

M&A are one of the most critical business decisions, involving several risks and uncertainties. Acquirers, targets, investment banks, advisory service firms, and regulators always make effort to improve the M&A process. Over time, these M&A practitioners have adopted the best available practices to strengthen the businesses (Cristerna and Ventresca, 2020). Despite that, almost 90% of M&A deals fail to deliver management's promise of increased shareholder value. Specifically, about 42% of deals do not increase shareholder value while about 45% of deals decrease shareholder value (KPMG, 2008). This dissertation makes an effort to understand the causes of failure in the context of the global food and agri-business industry (GFABI).

The term “agribusiness and food industry” was first coined in 1957 by Goldberg and Davis to refer to industries that are linked in some way or other in the food and agribusiness chain. It includes all the sectors within the agriculture and food value chain, including the production agriculture, food manufacturing, food processing, food wholesale, food service, and food retail. The reason for choosing the GFABI as the focus of this dissertation lies in its importance in terms of market size, consumer spending, and global employment.

The GFABI has a market size of $5 trillion globally. GFABI represents 10% of global consumer spending and 40% of global employment (Goedde, Horii & Sanghvi, 2015). The agribusiness industry in Africa, currently valued at $313 billion yearly, has the potential to turn into a $1T food market by 2030 (USDA, 2018). In the US, on average, citizens spend 12.6% of the household budget on food alone (World Bank, 2013). The contribution of agriculture, food, and related industries to gross GDP in the US in 2015 was $992B. Agriculture and the associated sectors alone provided 11% of US employment. Food manufacturing alone accounts for 14% of all US manufacturing employees. The biggest program of the USDA is the Food and Nutrition Assistance programs (USDA, 2018). These figures establish that the FABI has a major share of the global market.

The Food Industry Review (2015) revealed that food-based retailing accounts for 28% of all retail trade in the US, amounting to $1.46 Trillion in 2014. Snack sales in the US are up from $34.2 Billion in 2005 to $47.5 Billion in 2015. Snacks constitute everything from healthy food to fast food. About 81% of Americans snack once a day, with 49% snacking twice or more daily. World foreign direct investment (FDI) flows into agriculture exceed $3 Billion annually but constituted less than 1% of total FDI. A significant volume of the FDI comes through M&A. In the less developed countries such as Cambodia, Lao People's Democratic Republic, the United

Republic of Tanzania, and Mozambique, the FDI inflow into agriculture is relatively high, compared to its public investment. These figures demonstrate the significance of the food and agri-business industry in the global economy that significantly influences the economy's inflation, employment, consumer demand and choice and price competition.

1.2. Issues in GFABI Mergers and Acquisitions

The post-pandemic era of 2021 proved to be challenging for trading due to the disruption of global supply chains. Labor shortages and high inflation emerged at rates not seen in decades. While M&A are a rising trend in all industries, its nature is especially worthy of study in the GFABI. GFABI is one of the most essential industries and demand is typically consistent, irrespective of whether or not there is an economic crisis. In fact, the pandemic increased the demand for food due to the fear of scarcity. Therefore, the GFABI is one of the most risk-neutral industries during a global recession. For this reason, to diversify their portfolios, inter-industry acquirers are now investing in food companies through M&A. This is particularly true of financial, technology, and e-commerce companies. Another characteristic of the GFABI is that often small food companies get acquired by the large food companies or by inter-industry acquirers. These small food companies are often privately or publicly owned and are not listed in New York Stock Exchange (NYSE).

Major global firms pursue a variety of strategies to manage competition with their peers. One approach is through mergers with or acquiring another company to gain access to new technology, facility, or market. In 2017, of the total of 14,196 mergers and acquisitions in the USA, 640 (4.5%) involved the food industry. Of these 640 firms, 37 involved agricultural chemicals, 43 involved food services, 143 involved agriculture, 123 involved beverage, 372 food non-cyclical, and 14 agricultural biotechnology involved combinations thereof (Bloomberg, 2018).

GFABI has witnessed significant vertical, horizontal, and other forms of M&A in recent years. Notably, large companies lead in multiple sectors simultaneously. Transnational corporations (TNCs) which dominate the chemical market, are also the market leader in the seed sector. For example, Monsanto is at the top of the seed industry and is second in the agri-chemical industry (Access to Seeds, 2021). This phenomenon is not restricted to the input sector but is also pervasive in the output sector. The food manufacturing, retail, and wholesale segments of the GFABI show similar trends in market concentration. Indeed, the degree of concentration is growing, raising concerns about monopoly power.

Digitalization is another very critical aspect of GFABI. GFABI is entering a new era of online purchase when the pandemic hit and further intensified online activities. Retail and IT industries pioneered the e-commerce of the GFABI. Existing large food companies were not left behind digitally, as many expanded their positions in e-commerce. However, the perishability of food products makes food e-commerce challenging, as does global competition, low profitability, and increasing inflation. While large food companies have an advantage of industry knowledge over inter-industry acquirers, finance, and technology (fintech) companies tend to have higher technological expertise and liquidity, making it easier for them to brand, promote, and market online food businesses.

With this in mind, we can see that while the GFABI is characterized by a high degree of competition and low profitability, it still represents a low risk for investors. On one hand, the amalgamation of food companies (in other words, M&A) is leading to a more oligopolistic industry. On the other hand, the interest of inter-industry and intra-industry acquirers in the food industry is growing, leading to a higher benefit to the consumers. However, being an essential industry, any structural changes in the GFABI often lead to a significant socio-economic impacts, compared to other industries. GFABI is highly regulated to ensure consumer welfare, which means that regulatory approval is required for any M&A deal to sail through. Therefore, the GFABI M&A have multifold risk and benefit to consider not only before getting into a deal, but also during and after completion of the deal.

Farm to plate, a global trend toward amalgamation in the form of M&A, is observed along the food chain (Kristins, 2019). Businesses often get into M&As as a survival strategy in a highly competitive environment. GFABI is one of the highly competitive and low profitable industry. Therefore, food companies often get into M&As driven by several motivations. The conventional motivations for M&A include: (a) increased market share, (b) increased market power (ability to influence prices), (c) desire to ward off competition, (d) vertical integration in the resource and input control, (e) vertical integration to establish more control of the consumer market, (f) strategic integration to enter a new market, (g) strategic integration to improve logistics (CFI, 2021), and (h) technology takeover or patent ownerships (PWC, 2021). All the above-mentioned motivations for M&A are aimed at making the parent company more profitable in the industry. However, M&A is a very complex corporate strategy that could involve high expense and time.

In GFABI, as in every industry, the motivation for M&A is to make the parent company more competitive in the industry. However, M&A can also increase the financial exposure of the acquiring firm, which creates complexity. Complexity attracts regulatory and financing scrutiny that results in a longer time to completion (TTC). Long TTC increases the probability of deal termination. The second chapter of the dissertation identifies the characteristics of the deals that take longer to get completed and the impact of the prolonged TTC on the likelihood of the deal termination.

Another critical issue in M&A activities is the diverse cultures of multiple organizations, industries, and countries. Such diversity can increase asymmetry of information (AI) which can ultimately affect the probability of achieving the desired result of the M&A activities (Gencheva & Davidavičienė, 2016). A better understanding of these issues can provide much-needed guidance to actors in the M&A game. The opacity of the business environment raises the risk of adverse selection that can be partially addressed through different screening and signaling strategies. One such strategy is to hire an advisory service firm to help navigate through the AI. The role of advisory service firms in the M&A process is identified and discussed in the third chapter of this dissertation.

Finally, profitability and attractiveness are the two critical observations in the recent M&A trend, which work as essential catalysts for increased investment in M&A (PWC, 2021). Intra-industry acquirers have been active investors in the GFABI. The share of deals with the acquirers from private equity, retail, investment banking, and e-commerce increased from 27% in early 2019 to 38% in the first half of 2021, indicating increased appetite for larger and more complex deals. This is also true of the GFABI: in the last 10 years, the number of inter-industry acquisitions has risen more than 120%. With this in mind, the fourth chapter of the dissertation identifies the characteristics of the acquiring firms interested in acquiring food companies. A possible justification for the inter-industry acquisition in the food industry is to hedge the investment risk: though the food industry is not one of the most profitable industries, it is less susceptible to the economic crisis. To balance the investment portfolio and make a safe investment from recession, PEs, IBs, IT, e-commerce and retailer industry investors are increasingly getting interested in investing in the food sector (Food Drive, 2019).

1.3. Problem Statement

Time to Completion (TTC) is a critical issue in the M&A process. While it has received some research attention in recent years, the literature is limited. Specifically, while a few studies have focused on specific TTC determinants, a comprehensive analysis of factors that determine TTC has never been attempted. The previous studies lacked theoretical and conceptual rigor. These gaps in the literature motivated the first essay (Chapter Two).

This chapter presents a conceptual/theoretical model of TTC determinants, breaking TTC into three time-dimensions: negotiation and due diligence, financing, and regulatory approval. In Chapter 2, a model is developed to identify buyer and seller behavior that shapes optimal TTC for each of these actors. These theoretical models also identify company-specific characteristics, complexity characteristics of the deal, financing characteristics, and regulatory characteristics that shape TTC. The empirical analysis further showed the relationship between TTC and its key determinants. It establishes a direct relationship between TTC and the probability of deal termination.

The literature on asymmetric information (AI) in M&A is broadly divided into three major different components of firm-specific AI, deal-specific AI, and country-specific AI. The economic environment at the time of a specific deal can contribute to the level of AI. In cross-border M&A or cross-industry M&A, the acquirer might have less information regarding the economic environment of that country or industry. On the other hand, in an M&A, the labour-market behaviour and the socio-political environment of the host country can create an environment of deal opaqueness. For example, a deal involving a developing country may create uncertainty and anxiety due to strict labour market regulations. Therefore, the presence of AI could reduce the likelihood of deal success. This is true across the board: AI creates opacity and, thus, a greater risk of failure in an M&A deal.

Chapter 3 seeks to bridge a major gap in the literature by considering a more detailed and broader picture of the sources of AI. While some studies have measured AI and addressed the impact of advisory service firms on the likelihood of success of M&A deals, these studies have not controlled for the inherent level of AI in an M&A deal that could adversely impact the deal's success and therefore neutralize the effect of advisory service firms on the deal. The second essay (Chapter 3) of this dissertation estimates the impact of the advisory service firms on the TTC and the post-M&A deal performance for a given level of inherent AI.

Finally, while there is a vast literature on the prediction of M&A, no studies have predicted which firms are likeliest to become acquirers. More specifically, the characteristics of the acquirers in the GFABI have never been studied. Additionally, the literature has not explored the importance of understanding acquirer prediction in the M&A process. The existence of a wide variety of acquirers is very evident from previous M&A examples. However, how the characteristics of one type of probable acquirer possibly influences decision and strategy in the M&A process has never been previously discussed. For example, does the abundance and mobility of liquidity of a private equity (PE) firm possibly make it a more probable food-industry acquirer? Or, in the era of food-tech, is the technological inclination of IT firms considered a more desirable quality in an acquirer, compared to a traditional intra-industry acquirer? The third essay (Chapter 4) of this dissertation discusses the changing dynamics of the food industry acquirers and their characteristics. This essay will help to predict the probable acquirers interested to acquire food and agribusiness firms in the USA.

1.4. Dissertation Chapters

Based on the problem statement presented above, I study three specific topics in this dissertation. In Chapter 1 of my dissertation, I discuss the background of the M&A in the food and agri-business industry, the recent trends, and the relevance of this dissertation in the context of the current economic environment. Chapter 2 focuses on the critical determinants of the TTC of M&A in the GFABI. Chapter 3 identifies the impact of advisory service firms on the success of M&A deals in the context of GFABI. Chapter 4 predicts the acquirers in the food and agribusiness industry (FABI) in the USA specifically. Finally, in Chapter 5, the dissertation discusses its contributions to the field and the scope of future research. In every chapter, I conduct a topic-specific literature review to find gaps in existing research. I then develop a hypothesis to bridge those gaps. I also outline a theoretical framework in each chapter to justify the hypotheses to be tested empirically. Finally, I provide the results and explain them in the context of economic theory.

1.5. Contributions to the Literature

Each chapter of this dissertation makes significant contributions to the literature. The conceptual/theoretical model presented in Chapter 2, which analyzes TTC in three-time dimensions, contributes by understanding the TTC process and its determinants. The empirical models in chapter-2 capture underlying buyer and seller behavior that ultimately shape optimal TTC for each of the stakeholders. These theoretical models also helped in identifying company-specific characteristics, complexity characteristics, financing characteristics, and regulatory characteristics that shape TTC. To investigate whether longer TTC is detrimental to the companies involved in an M&A transaction, survival analysis was utilized to show that delayed TTC increases the likelihood of deal failure. This result is crucial as it underscores the value of expediated TTC.

The empirical analysis further showed the relationship between TTC and its key determinants. Firstly, due-diligence or negotiation factors such as acquirer solvency and leverage, which imply acquirer execution ability, accelerate the TTC. Secondly, deals involving payment in cash and in hard currency conclude faster, while deals involving both an acquirer and target from the same country or the same industry do not. Thirdly, the presence of legal or financial advisers lengthens the TTC. Delays in financing are not caused by limited transparency or the degree of risk involved. Deals during a recession take longer while regulatory phase factors such as deal size and acquirer history of repeated M&A activities neither accelerate nor delay TTC. These results are significant because they prove better understanding to the acquirer, target and the regulators about the factors that could potentially accelerate or slow down the TTC, allowing stakeholders to plan their business strategy accordingly.

Chapter 3 identifies three different dimensions of AI in M&A: company-specific AI, deal-specific AI, and macro-economic-related AI. To navigate through a deal that involves AI, screening mechanisms are important to make better and more informed decisions. This essay evaluates screening mechanisms such as hiring financial and legal advisory service firms, non-cash payment for the deal, and incorporating a termination fee clause in the agreement. An adverse selection model is used to conceptualize the impact of screening mechanisms on the performance of an M&A deal in the presence of AI. The model demonstrates that hiring advisory service firms improves the performance of the acquirer. This conceptual model is also empirically tested using the Blomberg M&A data. Principal component analysis (PCA) is used to index the identified sources of AI. Propensity Score Matching (PSM) is then used to compare the impact of screening mechanisms on the performance of the acquirer for a given level of AI. It is found that employing advisory service firms significantly improves the profitability of an acquirer. Treatment group acquirers (those that hired a financial and/or legal advisory service firms) have a profit that is 600 points higher, on average, compared to a control group acquirer (those that did not). Other screening mechanisms (non-cash payment and termination fee) do not have significant impacts on deal performance when advisory service firms are not hired. As the literature had not addressed this issue, Chapter 3 provides a much-needed contribution to scholarship in this area.

Chapter 4 presents a theoretical framework for understanding the characteristics of firms that make them frequent acquirers. The empirical analysis showed that M&A decisions are highly dependent on individual-specific characteristics. Therefore, using a fixed-effect model was the most appropriate choice to predict the acquirers. The results suggest that acquirers get into the acquisition to improve their low solvency, attractiveness, and liquidity. However, they need to be less leveraged to be eligible for a loan from the investment bank to pay for the acquisition. Therefore, this chapter provides a broad understanding of the characteristics of the acquirers of FABI bridging a significant gap of the M&A literature.

This dissertation contributes to the literature on (M&A), especially in the FABI, by theoretically and empirically unpacking the determinants of TTC, thereby improving its predictability. It also contributes to this literature by theoretically and empirically explaining the role of AI in M&A and answering the questions of why and how acquirers engage legal and financial advisory services firms. Finally, this dissertation contributes to the extant literature by providing a theoretical and empirical basis for acquirer prediction, therefore improving the ability to identify those firms that are likely to become acquirers and bringing the literature at par with the literature on target prediction.

Overall, the findings are useful to a wide variety of audiences. This includes (1) regulators and policymakers who have responsibility for M&A oversight (e.g., the Securities and Exchange

Commission); (2) academics in economics, finance and industrial relations who are involved in industrial organization research, in GFABI and beyond; (3) financial advisory services firms (e.g., Goldman Sachs, Morgan Stanley, JP Morgan, Citigroup, and Deutsche Bank); (4) legal advisory services firms (e.g., Wachtell et al, Skadden, Cravath et al LLP, Swaine & Moore LLP, and Sullivan & Cromwell LLP); and (5) auditing and accounting services firms (e.g., KPMG, Ernst and Young (EY), Deloitte, PricewaterhouseCoopers (PwC)). Investment bankers and lenders in particular will find the predictive models useful in identifying probable acquiring firms and developing loans and other financial strategies to support such clients. The findings of this dissertation not only fill significant gaps in the literature, but provides practical and immediately applicable steps and solutions for stakeholders in M&A.

CHAPTER 2: ESSAY 1: TIME-TO-COMPLETION OF MERGERS AND ACQUISITIONS IN THE GLOBAL FOOD AND AGRIBUSINESS INDUSTRY

2.1. Introduction

In general, the time to completion (TTC) is the period it takes to complete a merger and/or acquisition transaction. Most mergers and acquisition (M&A) deals (~70%) are completed within 180 days (Lavelle, 2019), but complex deals can take up to 20 years as per the Bloomberg M&A data. It is widely accepted that the longer it takes to complete an M&A transaction, the more likely it is for the deal to fall through (Li et. al., 2017). Therefore, TTC is an important concept in determining M&A deal success, and the factors that affect it are of significant interest to M&A practitioners and scholars.

The importance of TTC in determining the probability of deal completion/success was formally recognized by Luypaert & Maeseneire (2015). Since then, few studies have explored specific TTC determinants and their roles. Most of these merely focused on deal-specific factors (factors related to the nature of the M&A transaction), including deal size, payment mode, and whether or not participants are from the same industry or country). To date, however, few studies have comprehensively examined the roles of a broad range of factors that affect TTC (e.g., the role of financial advisory service firms, market conditions, the financial status of firms). Furthermore, no study has advanced a theoretical or conceptual framework for understanding the complexity of TTC or justified their analysis, despite the importance of the issue.

These are important gaps in the literature. Longer TTC can be costly if it delays the gains from synergy, which is a key motivation for M&A transactions in the first place (Luypaert & Maeseneire, 2015). The faster a deal and its post-acquisition integration are completed, the sooner the realization of return on investment or ROI (Dauksts, 2018). Furthermore, longer TTC can increase overall M&A costs due to the time value of initial funds. Also, perceptions of M&A success fall over time (Angwin, 2004) while the likelihood of deal failure increases with TTC (Li et. al., 2017).

In this chapter, for analytical purposes, TTC is more precisely defined as the period of time between an M&A deal announcement (usually the bid date), and the receipt of approval to go ahead by the regulatory authority. Note, however, that in a few cases, the bid date may differ from the announcement date and that regulatory approval requests are sometimes denied. Figure 1 specifically depicts the official start and stop of the TTC. By the time a deal is announced, work has already gone into the M&A process. The preliminary (pre-announcement) phase of an M&A process starts with an assessment of finding gaps in the acquirer's portfolio and ends when a feasible target is found. This period is not included in the defined notion of TTC. In the pre-TTC period, the acquirer would have conducted a portfolio gap assessment, sought and obtained approval from its shareholders and board that the gap warrants an investment, verified that the proposed investment will yield reasonable returns, select an acquisition target, and carefully study the selected target. It is difficult to predict or explain the time consumed in the pre-TTC period since this depends on the volume of needed preliminary research and gap analysis, and the nature of the industry, acquirer, and target.

The food and agribusiness industry (FABI) was used as the case study because of the critical importance of TTC to the success of M&A transactions and the absence of existing studies on TTC in the industry. While several studies have examined specific components of TTC in other industries, including pharmaceuticals, no study has explained TTC in the FABI. This study, therefore, places the literature at least at par with other industries in which TTC has been studied.

For FABI, it further explains the factors that determine TTC in a more comprehensive way than previous studies have for other industries and demonstrate the value of shorter TTC. This moves the literature even further than what exists for other industries.

There are five additional reasons for selecting FABI. First, like the pharmaceutical industry, FABI firms are highly regulated and M&As involving them are highly time sensitive. FABI firms are also highly dependent on leveraging "first-mover advantages" to pursue their competing interests in a market, where responding quickly to consumer demand can add to their competitive advantage and research and new product development can make a huge difference. However, research in the pharmaceutical industry requires huge capital investments, a longer period of clinical trials, and a longer period of regulatory scrutiny and regulatory approval. Therefore, for the FABI, when a merger or acquisition is chosen as a strategy to achieve "first-mover advantage", time is of the essence and timely completion of the deal is critical to short and long-term success. Also, TTC in the FABI tends to be much shorter (e.g., average TTC is 180 days in FABI, but 250-280 days in the pharmaceutical industry). Note that for FABI M&As, TTC is more evenly distributed between negotiation, financing, and regulatory approval, while it is more skewed in the direction of regulatory approval for the pharmaceutical industry. Again, it is noteworthy that studies exist on TTC in the pharmaceutical industry, but none exists in the FABI.

Second, the economic contributions of FABI are quite substantial Adelaja et. al., 1999). FABI accounts for 10-20% of the GDPs of most developing countries (Nash et. al., 2013). For the US, on average, 12.6% of the household budget is spent on food, and agriculture-related industries contributed $992 billion to GDP and 11% to employment in 2015. Nearly 70% of the global population still depends on FABI for their livelihood (Zavatta, 2014). FABI also has a significant global footprint (total sales in 2018 reached $8.7 trillion, with $5 trillion coming from agribusiness and \$3.4 trillion from food). Third, FABI has featured major M&A activities. For example, 6% of global M&A transactions are attributable to FABI (the global value of M&As in 2018 was the US \$3.9 trillion, with \$1.6 trillion (41%) for US deals (Szmigiera, 2019)). Agri-businesses alone ranked 4th in the value of M&A deals (Martinez & Elitzak, 2019). Fourth, the GFABI has strong consumer links. For example, food alone accounts for 10% of global consumer expenditures and 40% of employment (Goedde et al., 2015).

Finally, while companies spend over \$2 trillion on acquisitions annually, the M&A failure rates are typically between 70% and 95% (Christensen et.al., 2011). Deal failures in FABI are also quite rampant). About 83% of FABI M&A transactions fail to deliver management-promised shareholder value increases (PR Newswire, 1999 and cited in Nguyen and Kleiner, 2003) - 42% fail to increase shareholders' values while 45% decrease it. A key reason is excessive TTC (Thompson and Kim, 2020), which translates into costlier transactions, deal failures, or delayed benefits realization. Lavelle's (2019) finding that average TTC rose more than 30% in the last decade is also concerning, implying that transaction costs and deal failures will increase over time.

2.2. Literature Review

It is important to understand the key component of TTC, the factors that determine them, and the effects of TTC determinants. As shown in Figure 1, the three phases of overall TTC include time devoted to (a) negotiation, (b) financing the deal by an investment bank, and (c) obtaining regulatory approval. Delays can occur in any of these phases. In Phase 1, it is expected that as each party seeks to maximize the benefits to itself, it is concerned about the future profitability of the deal or resulting entity, the amount and mode of payment, tax benefits, and in the case of a merger, the post-integration synergies, etc. Based on the literature, it is expected that delays in this phase are attributable to the characteristics of the deal, of both the buyer and seller, and of the market

(Adelaja et al, 1999), including willingness to sell (De Bodt, et al., 2014). As suggested by Maqbool & Zameer (2018), the financial statements of both companies and the nature of the deal, including deal complexity indicators, reflect future performance possibilities.

Deal complexity (e.g., more than one country or industry, hidden information, etc.) could complicate the due diligence process and lead either company to hire a legal or financial adviser to make the deal sounder and more sustainable. Note that the performance of a company indicates not only firm success, but firm objectives and strategy (Khudhair et al., 2019), and regulatory compliance (Maqbool & Zameer, 2018; Gan et al, 2015; Chang & Taylor, 2016). The extant literature identifies some of the factors that explain deal complexity, including bid value or deal size (Grinstein & Hribar, 2004); cross-border cultural differences (Popli & Kumar, 2016); degree of government control in the target sector (Reddy et. al., 2016); limited knowledge of business practices (Luypaert & Maeseneire, 2015; Dikova, Sahib & Witteloostuijn, 2006); cross-country/cross-sectoral nature of a deal (Coakley & Iliopoulou, 2006 and Bugeja et al, 2012); using stocks instead of cash as payment (Reddy et al, 2016); degree of deal hostility (Walter et al, 2008); weak shareholder support (Luypaert & Maeseneire, 2015); and market uncertainties (Graff et al., 2020). It is expected that the more favorable these factors are, the shorter the TTC.

How transparent the participants in an M&A deal affect the TTC. The literature shows that "financial factors are significant determinants of the transparency of a company" (Ahmed, 2015; Arsov & Bucevska, 2017). The extant literature identifies three determinants of the transparency of a deal: (1) nature of ownership, (2) financial reports, and (3) board and management structure. These factors include financial leverage or the proportion of assets financed (Chow and Wong-Boren, 1987), ratios of market value to book value (Berglöf & Pajuste, 2005), acquirer's growth rate (Berglöf & Pajuste, 2005), concentrated ownership (Hanifa & Rashid, 2005), firm size (Hanifa

& Rashid, 2005), liquidity (Trabelsi et al., 2008), expected performance (Trabelsi, et al, 2008), R&D expenditure (Trabelsi et al, 2008), age of the company (Bokpin, 2013), profitability (Bokpin, 2013) and the audit quality (Bokpin, 2013). When a company's SPELL (solvency, profitability, efficiency, leverage, liquidity) ratios (e.g., return on assets (ROA), return on equity (ROE), and return on investment (ROI),) are used to explain its performance, they also explain the transparency and complexity of the deal (Maqbool & Zameer, 2018). To be sure, SPELL is a standard acronym used to describe Solvency, Profitability, Efficiency, Liquidity, and Leverage. The literature, therefore, provides a sufficient basis for the development of a formal model or framework for understanding the time required to conclude negotiation and due diligence.

Phase 2, the time required by an investment banker to conclude financing, is affected by several factors, including risk (Cai et al., 2016) and transparency factors from phase 1 (Marquardt & Zur, 2015). SPELL ratios reflect the acquirer's payment capacity. For example, for public companies which are usually more transparent, the Investment Bank (IB) is more confident, and TTC is likely to be shorter (Cain et al., 2011; Marquardt & Zur, 2015; Cai et al., 2016; Dhaliwal et al., 2016). Again, the literature provides some guidance on how to conceptualize the time required for financing.

Phase 3, the regulatory compliance phase, is equally complicated. Stringent regulatory and policy requirements can slow down the completion of M&A deals. Regulatory approval delays could emanate from three possible sources (Bushman, et. al., 2004). The first, anti-trust policies, aim to protect an industry from excessive consolidation and the exercise of monopoly power. Oligopoly behavior can diminish consumer utility by increasing the price-fixing power of the firm (Röller, Stennek & Verboven, 2001). As M&As can make an industry less competitive (Gomes-Casseres, 2018) by increasing the market share of the acquirer, regulators seek to protect public interests while supporting economic growth and industry investments, identified in the Harvard business review. The second is international cross-border regulations (Utesch-Xiong, 2021). Acquirers are likely to face added regulatory scrutiny in both domestic and foreign markets due to bureaucracy, self-interest/dealing, and the desire to protect domestic firms (Bittlingmayer and Hazlett, 2000). The third is monetary policy constraints. The need for foreign exchange to complete an M&A transaction may complicate the transaction. Country financial authorities may not always be willing to part with foreign exchange to finance an international acquisition (Adra et. al., 2020).

To prevent monopoly power, the literature suggests that regulators also consider the size of the deal and the absence of transparency, which suggests greater monopoly power (Thijssen, 2005). The more favorable the values of these factors, the shorter the approval time. For cross-border M&As, complexity can simply be explained by the cross-border nature of such deals vis-à-vis domestic deals. The currency in which the deal was transacted matters. Hence, the TTC of the regulatory approval phase may be explained through appropriate analysis.

In essence, the existing literature lays the foundation for a more deliberate, theoretically sound, and comprehensive investigation into TTC determinants. Since M&A involves two players (target & acquirer), optimal TTC determination necessarily involves optimization by each party at each TTC phase and overall. Thijssen (2005) describes this as dual-party profit maximization under a perfect information scenario. However, no study has yet advanced a coherent conceptual or theoretical explanation for the entire TTC period, especially the time is taken for investment banking and regulatory approval decisions. Also, most studies zero in on one or two causes of delay, rather than explore, more comprehensively, the processes involved in TTC. In this chapter, these gaps in the literature were addressed while advancing knowledge about how deals get delayed or accelerated.

2.2.1. Gaps in the Literature and Testing Hypothesis

Most studies zero in on one or two causes of delay rather than explore comprehensively the processes involved in TTC. Literature also does not account for the time taken for investment banking and regulatory approval decisions and gives it a theoretical framework. This chapter seeks to address these gaps in the literature while advancing knowledge about how deals get delayed or accelerated. Specifically, I explain the factors that determine TTC in the global FABI more comprehensively than in previous studies and demonstrate the value of shorter TTC.

In phase 1, the essay assumes that the acquirer has a positive attitude and wants a shorter TTC. For company-specific variables, the acquirer's and target's measures of solvency, profitability, liquidity, leverage, and efficiency, as well as non-SPELL characteristics (e.g., tax implications, assets under management, and risk factors) are expected to affect TTC. I hypothesize that the better the SPELL ratios of the acquirer, vis-à-vis the target, the greater the ability to expedite the process, thereby lowering TTC. I consider such factors as cash payments, advisory service firms, and deal size as critical determinants for deal-specific variables. Deal-specific factors describe the deal's complexity, and I assume that the higher the complexity of the deal, the longer the TTC. The market-specific variables such as GDP growth of the country, the presence of recession, etc. These variables could have both a positive and a negative relation with TTC.

In phase 2, I identified the factors such as loan size, deal size, and length of the loan, the risk factors associated with the deal, the creditworthiness of the acquirer, along with the SPELL variables of the subject firm, to determine TTC. In contrast, better values of the first three components delay financing, better SPELL ratios, and higher creditworthiness expedite the time for funding.

Finally, in phase 3, regulators consider the market share, market power, and price-setting power of the acquirer company after the M&A deal. The better the values of these parameters, the more time-consuming is the approval process.

2.3. Conceptual Framework and Mathematical Model

In chapter 2, I provide a theoretical foundation for how both the acquirer and target make optimization decisions at each phase of decision-making that ultimately shapes TTC. My preliminary thoughts about this are presented next.

2.3.1. Phase 1: Negotiation and Due Diligence

In Phase 1, the acquirer and the target must arrive at mutually agreeable terms, considering the transaction's mutual costs and benefits. I expect that the larger, more profitable, more liquid, less leveraged, and/or more efficient acquirers try to use their financial powers to accelerate the TTC by offering better deal terms. However, financially viable targets may have the ability to delay the transaction to attract higher bids (or better suitors) if they believe that they are not adequately compensated. However, since the decision to target a firm is made prior to the TTC time frame, it is conceivable that the target's characteristics may not matter by the time the negotiation and due diligence phase starts. The acquirer would ordinarily pursue targets that it believes has low resistance capacity.

I assume that each of the primary actors in Phase 1 has a preferred *TTC*. The seller (target) chooses a *TTC* that optimizes the net present value (*NPV*) of all its costs and revenues from the transaction and net revenues from current operations. The buyer (acquirer) chooses a *TTC* that maximizes the gap between the *NPV* of the company acquired and all costs incurred in the acquisition process, in addition to the net revenues from its current operations. Therefore, the actual *TTC* is the time frame that is optimal for both the bidder (acquirer or buyer) and the target (seller).

i. Buyer's (Acquirer's) Optimization Problem:

Superscript "*B*" is used to denote the buyer whose optimization problem is to select a single deal completion date (T^{B*}) that maximizes the value of the transaction to its shareholders. Recall that the buyer pays the price P^X to the seller to acquire the assets valued previously at A^S. Denote the buyer's discount rate as r^B, the net price or per-unit profit from the devotion of the new fixed assets to the ongoing or current buyer's operation in time "*t*" (i.e., per unit revenue minus cost) as P^B, $f^B(\cdot)$ as the new production function of the buyer using seller's old assets and Θ^B is a vector capturing the negotiation and due-diligence factors. Note that Θ^B includes the SPELL variables of the buyer, deal characteristics, and transparency variables.

The buyer's optimal completion date (T^{B*}) depends on the net present value (*NPV*) of future income streams from the purchase[15]. However, the stream of income to the buyer from buying the company (KV^B) is essentially the sum of revenue it earns from devoting the acquired assets to its operations after the sale, transaction costs it incurs, and the opportunity cost of the money it ties down (interest loss) for the acquisition. The interest income lost from tying down company assets for the duration of the transaction can be expressed as:

$$PV^B = \int_t^T e^{-r^B t}\,[i^B \; P^X(T^B)\,A^S]dt. \qquad (1)$$

In equation (1), the buyer loses interest income by tying up resources to buy the seller's assets. The transaction cost incurred by the sale of the assets in time T^B is also considered to be fixed at the point of discounting. That is,

$$C^B = e^{-r^B T^B} C_1^B, \qquad (2)$$

where C^B is the present value of the total purchase transaction cost of the buyer (C_1^B). Now,

$$TTC^B = T^B - t, \tag{3}$$

The stream of income after the purchase of assets, purchase value (PV^B), can be specified as:

$$PV^B = \int_T^{\dot{T}^B} e^{-r^B t} \, [P^B(t) f^B(A^S, \Theta^B) \,] dt, \tag{4}$$

where P^B is unit profit when the acquirer devotes the target's assets to its production function f^B. $\dot{T}^B$ is the acquirer's financial planning horizon that decides to buy at T^B.

The dynamic optimal acquisition problem of the buyer can be specified as:

$$\underset{\{T^B\}}{Max\ PV^B} = -\int_t^{T^B} e^{-r^B t} \, [i^B(P^X(T^B)A^S)] + \int_{T^B}^{\dot{T}^B} [e^{-r^B t} \ [P^B(t) f^B(A^S;\ \Theta^B)] \,] dt \ - \ e^{-r^B t} C_1^B \,. \tag{5}$$

The optimal completion time depends on the marginal relationship between transaction costs and returns. Differentiating equation 5 with respect to A_a and re-arranging the terms, I obtain:

$$P^B(t) \frac{\partial f^B(A^S;\Theta^B)}{\partial A^S} = \ -i^B \frac{\partial P^X(t)\, A^S}{\partial A^S} \tag{6}$$

From equation 6, the acquirer buys the target's company as long as the return from buying it is sufficient to compensate for the opportunity cost of the stream of costs associated with the transaction. The problem can be solved by differentiating equation 5 with respect to T^B. Again, following the Leibniz integral rule and rearranging this expression yields:

$$-i^B(P^X(T^B)A^S) - r^B C_1^B = \ P^B(t)\, f^B(A^S\,;\ \Theta^B). \tag{7}$$

At the optimal end, (T^B) in equation 7, the return from owning and managing the company equals the net costs associated with the transaction, including the price paid for the seller's assets. The conditions in equation seven also define the factors that determine the span of the preferred *TTC* of the buyer (TTC^B). The end time T^B can be defined, as optimal, in terms of the parameters that define the optimal condition in equation eight as follows:

$$T^{B^*} = T^{B^*}(P^X, A^S, P^B, i^B, \Theta^B). \tag{8}$$

From equation (8), *TTC* changes with the buyer's bid price, current profitability, interest rate, anticipated market conditions, company characteristics, regulations, the industry of the company, and the business environment. Each of these effects on TTC^B can be shown by differentiating equation 5 with respect to T^B, using the Leibniz integral rule, totally differentiating the resulting expression, and solving for the effective relationship with each parameter. The total derivative of equation (5) with respect to T^B (denoted by PV^B) yields:

$$dPV^B = f^B(A^S;\, \Theta^B)dP^B + P^B(t)[\frac{\partial f^B(\cdot)}{\partial A^S}\,\partial A^S + \frac{\partial f^B(\cdot)}{\partial \Theta^B}\,\partial\Theta^B] - [P^X(T^B)A^S]di^B$$

$$- i^B[(\frac{\partial P^B}{\partial T^B}\,dT^B)A^S] - i^B[P^X(T^B)\partial A^S] + r^B dC_1^B + C_1^B dr^B = 0 \tag{9}$$

The comparative statistics suggest that each of the parameters in equation (8) shows that these parameters affect the length of the TTC.

$$\frac{\partial T^B}{\partial i^B} < 0,\ \frac{\partial T^B}{\partial P^X} < 0,\ \frac{\partial T^B}{\partial P^B} < 0, \frac{\partial T^B}{\partial A^S} \lesseqgtr 0, \text{ and } \frac{\partial T^B}{\partial \Theta^S} \lesseqgtr 0. \tag{10}$$

In equation 10, P^X is assumed to be a function of T^B and other exogenous factors (z^B). Ceteris paribus, an increase in the potential interest rate earned if funds tied down in the acquisition process were invested at the market rate decreases the benefits from the purchase and reduces the TTC ($\frac{\partial TTC^B}{\partial i^B} < 0$). Hence, a longer TTC^B reduces the price of the assets to be purchased (i.e., ${\partial P^X}/{\partial T^B} > 0$). Hence, a positive future economic outlook shortens the TTC.

The higher the bid price, the lower the TTC^B (${\partial T^B}/{\partial P^X} < 0$). A modification can simply be made to accommodate higher closing than the initial bid price. Buyers are more willing to accelerate a deal that offers a high bid price than a low bid. The effect of the seller's asset value is uncertain, as it depends on the profitability from purchasing the company, vis-a-vis investing in the market. If the buyer's return from keeping its money than from closing the deal, TTC^B is longer. The effect of the current net profitability of the buyer on TTC is negative ($^{\partial T^B}/_{\partial P^B} < 0$). A profitable buyer is more eager to assimilate the target and not drag on the process. Finally, the effects of specific companies, industries, markets, regulations, and other characteristics depend on each characteristic.

ii. Seller's (Target's) Optimization Problem:

"S" is used as a superscript to denote a variable or parameter that is associated with the seller that seeks to select a completion date (T^{S*}) that maximizes the value of its company. I make a simplifying assumption that the seller expects the deal to close. The choice of an optimal T^{S*} for the seller, however, depends on the net present value (*NPV*) of future streams of income from (a) the sale and (b) earning between the initial deal announcement date and the completion of the sale. Transaction costs represent an outflow, which must be netted against the income streams discussed above.

The seller's income stream from keeping the company is expressed as follows:

$$KV_t^S = \int_t^T e^{-r^S t}\,[P^S(t) f^S(A^s;\,\Theta^S)]dt, \tag{11}$$

where KV_t^S denotes seller's keep value, r^S is the seller's discount rate, P^S is the net price or per-unit profit from devoting the seller's fixed assets to the ongoing or current operation in time "t" (i.e., per unit revenue minus cost), $f^S(\cdot)$ is the production function for seller company's total output using a given level of company's assets (A^S). Θ^S is a vector capturing the negotiation and due-diligence factors. Note that Θ^S includes the seller's SPELL variables, deal characteristics, and transparency variables. I simplify the assumption that fixed assets are used in fixed proportions with other inputs and are devoted to ongoing operations until time T^S. The seller's TTC (TTC^S) can be expressed as:

$$TTC^S = T^S - t, \tag{12}$$

where t is the date of the deal announcement and T^S is the date of deal closure.

The benefit of selling the company at time T^S is the return (interest income) on funds derived by selling its assets if invested elsewhere in the economy. Assuming that, a deal which closes at the preferred TTC^S, closes at the bid price, the stream of income from the sale or disposal of company assets, or disposal value (DV^S), can be specified as follows:

$$DV^S = \int_T^{\dot{T}^S} e^{-r^S t} [i^S P^X(T^S) A^S] dt, \tag{13}$$

where i^S is the rate of interest that applies to the seller, P^X is the final price per unit of fixed assets at which the company is sold to the buyer (depends on the time of sale (T^S), and $\dot{T}^S$ is the financial planning horizon of the seller which sells at T^S. Note that $\dot{T}^S$ could be equal to ∞. P^X embodies seller, buyer, and industry characteristics (z^S) and the time of sale. Also, in equation 13, A^S denotes fixed seller assets managed by the seller's management until time T^S but made available for sale at time T^S. P^X is the same for both; it ties both the buyer and seller together (seller pays what the buyer gets), except for transaction cost (discussed next).

The sale of the assets in time T^S imposes transaction costs that are charged to the seller (C^S). This includes costs associated with staff efforts, extra deal-related costs, filing fees, legal advisory fees, financial advisory fees, possible capital gains taxes, commissions to agents, and other transaction costs. To simplify, it is assumed that the company considers the transaction cost to be fixed at the time of discounting. Therefore, transaction costs can be expressed as:

$$C^S = e^{-r^S T^S} C_1^S, \tag{14}$$

where C^S is the present value of the total sale transaction cost (C_1^S).[13] The seller's TTC^S problem is determined by factors that influence the flow of benefits from continuing to operate independently and selling, as well as transaction costs.

The dynamic optimal sale problem of the seller can be specified as:

$$\underset{\{T^S\}}{Max\ DV^S} = \int_t^{T^S} e^{-r^S t}\,[P^S(t) f^S(A^S;\ \Theta^S)]d + \int_{T^S}^{\dagger^S}\ [e^{-r^s t}\ [i^S(P^X(T^S)A^S)]\,]dt - \ e^{-r^S t}C_1^S. \tag{15}$$

Therefore, the optimal keep or sell decision depends on the marginal relationship between the returns from keeping the company versus the returns from selling it, affected by the transaction costs. This is derived by differentiating equation 15 with respect to fixed asset A^S and re-arranging the terms:

$$P^S(t)\frac{\partial f^S(A^S;\Theta^S)}{\partial A^S} = \ -i^S\frac{\partial[P^X(T^S)\ A^S]}{\partial A^S}. \tag{16}$$

From equation 16, the seller retains its company if the return from keeping it is sufficient to compensate it for the opportunity cost of the stream of benefits if the company were to be sold. The *TTC* problem of the target company (TTC^S) can be solved by differentiating equation (15) with respect to T^S. Following the Leibniz integral rule and rearranging this expression yields:

$$i^S(P^X(T^S)A^S) - r^S C_1^S = \ P^S(t)\ f^S(A^S\ ;\ \Theta^S). \tag{17}$$

In equation 17, the optimal end time, T^S, the return from keeping the company and not selling, equals the net benefit from selling it. It is the optimal switch point where the target sells or does not sell. The conditions in equation (17) also define the factors that determine the timespan of the preferred *TTC* of the seller (TTC^S). The end time (T^S) can be defined, as optimal, in terms of the parameters that define the optimal condition in equation (17):

$$T^{S^*} = T^{S^*}(P^S, A^S, P^X,\ i^S, \Theta^S). \tag{18}$$

From equation 18, *TTC* changes with the bid price, current profitability, interest rate, anticipated market conditions, company characteristics, regulations, the industry of the company, and the business environment. The effect of each TTC^S is seen by differentiating equation 15 with respect to T^S, using the Leibniz integral rule, totally differentiating the resulting expression, and solving for the effective relationship with each parameter. Using total differentiation, the derivative of equation 15 with respect to T^S (denoted by DV^S) yields:

$$dDV^S = f^S(A^S;\, \Theta^S)dP^S + P^S[\frac{\partial f^S(\cdot)}{\partial A^S}\,\partial A^S + \frac{\partial f^S(\cdot)}{\partial \Theta^S}\,\partial \Theta^S] - [P^X(T^S)A^S]di^S - i^S[(\frac{\partial P^S}{\partial T^S}\,dT^S)A^S]$$

$$- i^S[P^X(T^S)\partial A^S] + r^S dC_1^S + C_1^S dr^S = 0. \qquad (19)$$

The comparative statistics with respect to each of the parameters in equation (18) show that these parameters affect the length of the TTC.

$$\frac{\partial T^S}{\partial i^S} = -\frac{[(P^X(T^S,\ z^S)A^S)di^S]}{i^S A^S\left[\partial P^S/_{\partial T^S}\right]} < 0\ , \qquad (20)$$

$$\frac{\partial T^S}{\partial P^X} = -\frac{i^S A^S}{i^S A^S\left[\partial P^S/_{\partial T^S}\right]} = -\frac{1}{\partial P^X/_{\partial T^S}} < 0\ , \qquad (21)$$

$$\frac{\partial T^S}{\partial A^S} = -\frac{\left[P^S(\partial f^S(\cdot))/_{\partial A^S} - i^S(P^X(T^S,\ z^S))\right]}{i^S A^S\left[\partial P^S/_{\partial T^S}\right]} \lesseqgtr 0\ , \qquad (22)$$

$$\frac{\partial T^S}{\partial P^S} = -\frac{f^S(\cdot)}{i^S A^S\left[\partial P^X/_{\partial T^S}\right]} > 0\ \text{, and} \qquad (23)$$

$$\frac{\partial T^S}{\partial \Theta^S} = -\frac{[P^S]}{i^S A^S\left[\partial P^X/_{\partial T^S}\right]}\,\frac{\partial f^S(\cdot)}{\partial \Theta^S} \lesseqgtr 0. \qquad (24)$$

In equations 20 to 24, P^X is assumed to function of $\dot{T}^S$ and other exogenous factors (z). Equation 20 suggests that ceteris paribus, an increase in the rate of interest earned from investing sale proceeds, increases the benefits from the sale, thereby reducing the TTC ($\frac{\partial TTC^S}{\partial i^S} < 0$). This assumes that a higher TTC^S increases the sale price of the assets (i.e., $\partial P^X/_{\partial T^S} > 0$). Hence, a positive future economic outlook shortens the TTC. Equation 21 shows that a higher the bid price lowers the TTC^S ($\partial T^S/_{\partial P^X} < 0$). Sellers are more willing to accelerate a deal that offers a higher bid price. From equation 22, the effect of the company's asset value is uncertain. It depends on the returns from keeping the company versus selling it. If the former is greater than the latter, TTC^S is longer. From equation 23, the effect of current net profitability on TTC is positive ($\partial T^S / \partial P^S >$ 0). A seller is less willing to sell a profitable company and drags on the M&A process. Finally, from equation 24, the effects of specific company, industry, market, regulatory and other characteristics depend on each specific one. These are further discussed below, where specific hypotheses are discussed.

iii. Optimal Time to Completion in Phase 1:

Equations (8) and (18) define the demand and supply sides of TTC. Hence, at equilibrium T^*,

$$T^* = (P^S, P^X, P^B, A^S, i^B,\ i^S, \Theta^S, \Theta^B). \qquad (25)$$

In equation (25), P^B is the acquirer's profitability when it devotes the purchased asset of the target to its management. The pre-deal profitability of the acquirer is a reasonable proxy. P^S denotes the seller's profitability in its current operations. A reasonable proxy for this is the historical profit of the target. P^X is the equivalent profitability implied by the premium price associated with the bid. A reasonable proxy for this is the price paid for the target (deal size). Note that for the transaction to make economic sense to the seller if all profit-related factors are measured in equivalent terms, $P^X > P^S$. Similarly, the buyer assumes that it can create an improved management scenario where $P^B > P^X > P^S$. In equation (25), the seller's and buyer's discount rates, r^B *and* r^S are also assumed to be purely exogenous and can be proxied by several macroeconomic indicators. Based on the opportunity cost concept, it is expected that each party's discount rate is directly related to its profitability, such that $\frac{\partial r^S}{\partial P^S} > 0$ and $\frac{\partial r^B}{\partial P^B} > 0$. Please note that P^B, $P^{X,}$ and P^S can be proxied by standard profitability ratios such as return on assets, investments, earnings per share, and investment turnover.

Also, in equation (25), Θ^S denotes seller-related characteristics while Θ^B denotes buyer-related characteristics along with deal-specific factors and transparency factors in both Θ^S and Θ^B. Finally, A^S can be proxied by such measures as tangible and intangible assets, intellectual property, and brand value. The following sub-section shows the relationships between TTC and specific financial ratios and other essential factors in the M&A process.

2.3.2. Phase 2: Time to Finance: Profit Maximization of the Investment Bank

The investment banker (IB) of the acquirer arranges to finance in phase 2. The relevant factors that shape the IB's timeframe include the assessment of capital need (assessment of tangible assets of buyer and seller), shareholder approvals for both the acquirer and the target, and macroeconomic indicators such as interest rate, inflation rate, and sectoral GDP (Davis, 2009). Since asymmetric information implies risk, the IB tries to minimize risk by gathering more information. This involves time and, therefore, a constraint on R

In the Black-Scholes-Merton (BSM) model, if the IB may in a riskless bond that pays a fixed rate of return, the deterministic reward function can be written as:

$$R_t = e^{-rt} R_0, R_0 > 0, \tag{26}$$

where r is the risk-free return on a riskless bond. Otherwise, it can invest in an alternative that involves risk due to asymmetric information in the deal (Ludkovski, 2009). The monetary loss from asymmetric information follows the following geometric Brownian Motion (Alsmeyer & Jaeger, 2005):

$$X_t = X_0 \, exp\left(\sigma \, B_t(\mu_X - \frac{\sigma^2}{2})t\right), \, t \geq 0, \tag{27}$$

where X_t is the monetary loss from the risk associated with asymmetric information in time t; X_0 is the monetary loss from asymmetric information at the initial level when the bank has not had time to reduce asymmetric information and follows Ito's drift-diffusion process $dY_t = \mu_Y dt + \sigma_Y W_t$;

μ_X is the drift parameter such that $\mu_X \in IR$ and volatility $\sigma_X > 0$, and (B_t), for all $t \geq 0$ denotes standard Brownian Motion (Wiener Process) starting at 0. In equation (27), the volume of asymmetric information reduces over time as the IB exercises more discovery time. In other words, the bank takes time to make its decision to reduce the asymmetric information until time t, and for the time period (T-t), it invests its capital K in a particular M&A deal. So, the discounted reward to the investment bank in investing is:

$$Ke^{-r(T-t)} - X_t\, e^{-r(T-t)} = (K - X_t)e^{-r(T-t)} \tag{28}$$

if the bank decides to finance the deal at the time t.

To determine optimal information collection as a function of time, to maximize profits, the following optimal stopping problem needs to be solved:

$$V(x) = \sup_{\tau} \mathbb{E}_x \left[(K - X_t)e^{-r(T-\tau)}\right], \ x > 0, \tag{29}$$

where "sup" defines supremum, which is evaluated over the stopping time τ for $(X_t)_{t\geq 0}$. Note that $[(K - X_t)e^{-r(T-\tau)}]_{t\geq 0}$ is a super-martingale for $r \geq \mu$ and a martingale for $r = \mu$, when there is no arbitrage. It is assumed, in the case of this study, that $r = \mu$. The case of martingale is only considered here.

To find the optimal stopping time, Alsmeyer & Jaeger (2005) suggested to look within the set of threshold rules. That is,

$$\tau_a \stackrel{\text{def}}{=} \mathbb{E}_x[(K - X_t)e^{-r(T-t)}] \text{ , when } 0 < a \leq K \tag{30}$$

where τ_a is a given stopping time. Following the procedure above, the first step is to compute

$$V_a(x) \stackrel{\text{def}}{=} \mathbb{E}_x[(K - X_t)e^{-r(T-t)}], \ 0 < a \leq K \tag{31}$$

In the Brownian motion $(B_t)_{t\geq 0}$, the first epoch *t* is denoted by the stopping time τ_a and B_t is usually on or below the following line $\sigma^{-1}(\log\left({}^{a}/_{X_0}\right) - \left(r - {}^{\sigma^2}/_2\right) t)$.

The density of $P_x(\tau_a \in \cdot, \tau_a < \infty)$ is known and leads to the following equation after some calculations:

$$V_a(x) = \begin{cases} (K-a)\frac{x}{a}^{-2r/\sigma^2}, & if x \geq a \\ K-x & , if\ x \leq a \end{cases} \tag{32}$$

for every $a > 0$. For the optimal threshold of a, i.e., a^*, V_{a^*} should be differentiable at a^*, to follow the smooth fit principle. So,

$$\frac{d}{dx}\left[(K-a)(\frac{x}{a})^{2r/\sigma^2}\right]_{x=a^*} = -1 \tag{33}$$

By solving the above equation, following optimal condition can be obtained

$$a^* = \frac{2rK}{\sigma^2 + 2r} \tag{34}$$

Note that for $V^* \stackrel{\text{def}}{=} V_{a*}$, $V^*(x) \geq (K+x)$, as $[V^*(X_\tau)\ e^{-r(T-t)}]_{t\geq 0}$ is a super-martingale. Thus,

$$\mathbb{E}_x e^{-r\tau}(K+X_\tau) \leq \mathbb{E}_x e^{-r\tau}V^*(X_\tau) \leq \mathbb{E}_x V^*(X_0) = V^*(x) \tag{35}$$

for x > 0 and stopping times τ. Therefore, it can be stated that $V^* = V$ and the second-order condition also holds".

So, as shown in equations 34 and 35, the optimal time an IB takes to decide to finance a deal depends on: total capital investment (K), current interest rate (r), cost associated with remaining asymmetric information in the deal (X_t), expected risk associated with remaining asymmetric information (σ), and expected return (μ). In the empirical analysis section, proxy variables were used to explain asymmetric information and its role on the TTC that is associated with investment bank decision-making for financing.

2.3.3. Phase 3: Time for Approval: Regulator's Utility Maximization

In phase 3, the regulatory authority aims to ensure that antitrust/anti-competition laws are upheld, and the consumers are protected from high market concentration. The regulator's utility is the public utility or society's utility. Specifically, it wishes to ensure that the utility of the public is not diminished because of the M&A transaction while ensuring the economic efficiency benefits of an M&A. The regulators must also ensure that the deal does not result in excessive concentration, market power, market share consolidation, or price-setting power.

Consider a decision-making timeframe with initial period *t=0* and final period t=T (t = 0, 1, 2, ..., T). Denote the discount rate as r_t and the interest rate as ρ_t. By the time the deal is delivered to the regulator for approval, the acquirer would have already blessed the deal only if it is utility-maximizing from its end. However, the utility may be compromised if the regulator takes excessive time to bless the deal. The part of the acquirer's utility that depends on the time consumed by the regulator in decision-making can be defined as:

$$u^A(ms, mp, p) = (\alpha ms_t + \beta mp_t + \gamma p_t), \tag{36}$$

where *mp* is market power, *ms* is market share, and *p* is the monopoly pricing power of the acquirer after the acquisition. Thus, the present value of the acquirer's utility function is:

$$u^A = \sum_{t=0}^{T} \left(\frac{1}{1+r}\right)^t u^A(\mathrm{ms, mp, p}) = \sum_{t=0}^{T} \left(\frac{1}{1+r}\right)^t (\alpha ms_t + \beta mp_t + \gamma p_t), \tag{37}$$

Following (Thijssen, 2005), it is assumed that $\partial u^A/_{\partial ms} \geq 0$, $\partial u^A/_{\partial mp} \geq 0$, $\partial u^A/_{\partial p} \geq 0$

When a deal is already accepted by the acquirer and moved forward to the regulator for approval, it can be assumed that the target has also already blessed the deal as utility-maximizing. Thus, the present value of the utility function of the target is defined as:

$$u^T = \sum_{t=0}^{T} \left(\frac{1}{1+r}\right)^t u^T(\mathrm{DV}) = \sum_{t=0}^{T} \left(\frac{1}{1+r}\right)^t e^{-\rho^S t}\ \mathrm{DV} \tag{38}$$

where DV is the earning of the target from selling the company. It is also assumed that a deal presented to the regulator already satisfies the target's utility maximization condition. Hence, the regulator is concerned mainly about the general public, whose interests are to be protected along with the joint utility of the acquirer and target companies. Thus, the regulator wants to maximize the combined utility of the acquirer, target, and the public.

From the regulator's perspective, the general public's utility depends on the market power (*mp*) and market share (*ms*) of the acquirer after the acquisition and monopoly pricing power (*p*). The utility of the community is negatively related to all three factors. That is:

$$u^P = \sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^t u^P(\mathrm{I}) = \sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^t (I - \alpha ms_t - \beta mp_t - \gamma p_t), \tag{39}$$

Similarly, the general public's utility function is defined as: $u^P(ms, mp, p) = (I - \alpha ms_t - \beta mp_t - \gamma p_t)$. Following (Coates, 2014), it is assumed that

$$\partial u^P/\partial \mathrm{ms} \le 0, \qquad \partial u^P/\partial \mathrm{mp} \le 0, \text{ and } \partial u^P/\partial \mathrm{p} \le 0$$

The regulator's utility function is further defined as follows:

$$u^G = \alpha_0 \sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^t (\alpha ms_t + \beta mp_t + \gamma p_t) + \alpha_1 \sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^t e^{-\rho^S t}\,\mathrm{DV} + \alpha_2 \sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^t (I - \alpha ms_t - \beta mp_t - \gamma p_t) \tag{40}$$

where, $ms_t = ms_0\, exp\left(\sigma W_t(\mu_{ms} - \frac{\sigma_{ms}^2}{2})t\right)$, $mp_t = mp_0\, exp\left(\sigma U_t(\mu_{mp} - \frac{\sigma_{mp}^2}{2})t\right)$ and $p_t = p_0\, exp\left(\sigma Z_t(\mu_p - \frac{\sigma_p^2}{2})t\right)$ $\mathrm{T} \ge 0$ are expressions of a geometric Brownian motion. To determine the optimal utility level of the regulator, I have to solve the optimal stopping problem:

$$Q_s(x) = \sup_{\tau}\left[\begin{array}{c} \mathbb{E}_x\,[\alpha_0 \sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^t (\alpha ms_t + \beta mp_t + \gamma p_t) \\ +\alpha_1 \sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^t e^{-\rho^S t}\,\mathrm{DV} \\ +\alpha_2 \sum_{t=0}^{T}\left(\frac{1}{1+r}\right)^t (1 - \alpha ms_t - \beta mp_t - \gamma p_t)]_{\tau} \end{array}\right] \tag{41}$$

Please note that it is not necessarily the existing market power of the resulting entity from an M&A transaction that ultimately determines the regulator's time to approval, which is a portion of the longer TTC for the entire transaction, from negotiation to financing to regulatory conclusion.

In a similar process as the financing phase, solving $Q_s(x)$, I get s^*, which denotes the optimal time the regulator takes to maximize its utility. So, the optimal time for the regulator depends on the following: (a) market power (*mp*), (b) market share (*ms*), and (c) monopoly price power (p). In the empirical analysis section, the essay used the proxy variables for these variables also help to explain the regulatory aspect of TTC.

Based on the above hypotheses regarding the elements of Θ^S, Θ^B, $V(x)$ and $Q(x)$ are now presented, including hypotheses about deal-specific factors, financial ratios, market-specific variables, financing factors, and regulatory approval parameters. The hypothesized independent variables are explained in order of critical issues surrounding the M&A process.

In phase 1, I assume that the acquirer has a positive attitude and wants a shorter TTC. For company-specific variables, the acquirer's and target's measures of solvency, profitability, liquidity, leverage, and efficiency, as well as non-SPELL characteristics (e.g., tax implications, assets under management, and risk factors) are expected to affect TTC. The better the SPELL ratios of the acquirer, vis-à-vis the target, the greater the ability to expedite the process, thereby lowering TTC. The essay considers factors such as cash payments, advisory service firms, and deal size as critical determinants for deal-specific variables. Deal-specific factors describe the deal's complexity, and I assume that the higher the complexity of the deal, the longer the TTC. The market-specific variables such as GDP growth of the country, the presence of recession, etc. These variables could have both a positive and a negative relation with TTC.

In phase 2, the factors such as loan size, deal size, and length of the loan, the risk factors associated with the deal, the creditworthiness of the acquirer, along with the SPELL variables of the subject firm, determine TTC. In contrast, better values of the first three components delay financing, better SPELL ratios, and higher creditworthiness expedite the time for financing.

Finally, in phase 3, regulators consider the market share, market power, and price-setting power of the acquirer company after the M&A deal. The better the values of these parameters, the more time-consuming is the approval process.

2.4. Empirical Framework

2.4.1. Data

Measures are needed on variables on both sides of the equation to investigate the determinants of TTC and their impact. TTC itself can be measured in days, months, or even years. The independent variables can also be measured in numerous ways. For example, measures of profitability can range from return on assets (ROA), return on equity (ROE), return on investments (ROI), and return on sales (ROS). I utilize the Bloomberg M&A database (BMAD) as the primary data source due to its ready availability.

For all M&A activities involving publicly traded companies, BMAD provides data on financial and non-financial variables for both the target and the acquirer, as well as on several deal-specific indicators. It is important to note that because publicly available data sources such as BMAD cover only large companies, data is often weak on small companies. Specifically, a large percentage of M&A targets are small companies for which SPELL variables are not reported. Therefore, despite a large number of observations or deals, target financial information is available only for a limited number of firms. Given the asymmetry of negotiating power between large acquirers and small targets, a simplifying assumption is made that most target companies are too small to offer meaningful resistance during the negotiation process. Therefore, it is assumed that their financial characteristics have no bearing on TTC in Phase 1. This is not too far-fetched, as those financial characteristics are more nearly relevant in the pre-targeting phase. By the time a deal is announced, and negotiation commences, the acquirer is already known as most of what it needs to know financially about the target.

The BMAD is joined with other data sources such as Compustat (e.g., R&D data) and the World Bank (e.g., information on macroeconomic indicators). Note that many of the variables for which data were obtained needed to be transformed into more appropriate forms for the analysis. For example, a binary variable might be a more appropriate measure of the presence of a financial adviser in an M&A transaction, and TTC was measured as the number of days between the date of deal announcement and deal completion. Table 1 provides the summary statistics on a sample variable available through BMAD.

BMAD provides daily information on M&A activities from January 1987 to June 2018 for all segments of the global economy, including the global agri-businesses and food industries (GABFI). The GABFI components consist of 26,825 observations (transaction), out of which 89.87% were completed and 10.13% were terminated. About 50% involve disclosure about the nature of the bid (friendly or hostile), 99.34% of which were friendly bids. Note that un-friendly bids could either be hostile or unsolicited. About 69% of the transactions involved cross-sector deals (where two firms are not from the same sub-sector, i.e., the 4-digit SIC code of the acquirer and the target are different), while the rest were from within the same sub-sector. Regarding the mode of payment, 52.91% of the deals were settled only by cash, and 5.93% were settled only through a stock purchase. The remainder, about 41%, was through a mixture of cash, stock, and debt. Depending on the model estimated, the number of observations can drop significantly. For example, the presence of financial or legal advisory service firms is relatively rare in M&A transactions. Out of 26,825 transactions, only 6.25% employed a financial adviser on either the acquirer or the target side. Similarly, only 3.74% of the deals hired a legal advisory firm.

Based on the data, the average TTC is about 52 days, with a standard deviation of 127.31. Around 49% of the deals were announced and completed on the same day (TTC=0). Some 70% of the deals were completed within the first 60 days, but there are outliers. For example, the TTC was 6,731 days for the most extended transaction. In some cases, the deals got completed before the announcement, making the TTC negative (about 2.11% of the total observations). Thus, TTC values range from -731 to 6,731.

There were over 2,500 BMAD variables across the five categories of financial ratios ((Solvency, Profitability, Efficiency, Liquidity, Leverage) or (SPELL)) of the acquirers and targets, deal-specific variables, and other variables. Since there are multiple indicators for each SPELL variable, to avoid multi-collinearity in a given equation, only one measure within a SPELL category is included in a given regression.

Deal-specific variables available through BMAD include tax and market valuation variables. Examples include the nature of the bid, mode of payment, size of the deal, country of the acquirer and the target, percentage owned and sought in the acquisition, legal and financial adviser employed by the acquirer and the target, etc. Furthermore, the database provides data on non-SPELL variables for the acquirer and the target. Examples include assets under management, the risk factor of the target and the acquirer, expenses on R&D, etc. Details on the measurement of variables are provided below.

So far from the vast horizon of the databases, the specific variables to capture the parameters of the hypothesis were identified. In the following sub-section, the essay describes the methodology to calculate the particular variables that were finally used in the empirical model.

2.4.2. Empirical Model

Here I provide some detail on the measurement of the independent variables. Acquirer solvency is measured through the interest earned ratio (earnings before interest and taxes (EBIT) / interest payment obligations during the period). The profitability of the acquirer is measured through the return on invested capital (EBIT (1 – tax rate) / (value of debt + value of equity)) and the return on equity (income/shareholder’s equity). The liquidity of the acquirer is measured through the cash ratio (cash and cash equivalents / current liabilities). The leverage of the acquirer is measured through the debt service coverage ratio (operating income/total debt service). Finally, the efficiency of the acquirer is measured through the asset turnover ratio (net sales / total assets).

Deal complexity variables were measured as follows. Dummy variables were used to measure the presence of legal and financial advisers, the cross-country or cross-industry nature of a deal, the mode of payment, the payment currency, the nature of the deal, the friendliness of and the percentage of target’s share owned before the deal. In each case, the dummy variable assumes the value “1” if the issue is relevant and 0 otherwise. For capturing the share that the acquirer bought from the market before entering the deal, the variable “Percent Owned” was directly used from the database. As for currency, the dummy takes on the value of 1 if “Hard currency” (USD, EUR, GBP, CAD, JPY, AUD, or CNY) and 0 otherwise.

Large companies are usually more transparent as they can afford the costs of transparency (Ashbaugh, Johnstone, & Warfield, 1999; Buzby, 1975), and due to their large size, they are required to be transparent. Ali & Shaker (2017) identified four alternative measures, including the CIFAR index, Dipiazz and Eccles's transparency model, Bushman, Piotroski, and Smith's transparency model, and Standard and Poor's. Here I use the Standard & Poor (S&P) methodology due to its widespread acceptance. The transparency variable was thus calculated as follows. Every particular company in the sample that has reported the financial, non-financial, management, and ownership declaration receives a score of 1 so that the total score is equal to the number of disclosures. The average of the scores for each company is used as a proxy for transparency.

There are three primary sources of credit rating for the companies in the database - Moody, S&P, and Fitch. A new variable, "Rating," was calculated that assumes a value of 10 if the rating is anything more than or equal to "A-." For more than "B," a score of 9 was assigned. Above "BB-", 8 was assigned. Above "CCC", 7 was assigned. Above "D", 6 was assigned. Finally, for "D" and below, 5 was assigned. I, therefore, assume a continuous nature of the variable. To capture the potential of the deal resulting in monopoly power, current R&D investment by the acquirer is used, along with the size of the deal and repeated acquisition behavior by the acquirer.

Finally, to capture the global economic environment, I construct a dummy variable, "Recession", which assumes the value of 1 if the year of the announcement was during a recession year and 0 otherwise. The macro-economic literature indicates the following years as recession years for the global economy: 1990–93, 1998, 2001–02, and 2008–09.

The total number of observations for which data on all relevant variables exist is 2044. This represents about 8% of all M&A transactions in the GFABI. I use the following simple linear regression model to estimate the relationship between TTC and its determinants:

$$\text{TTC} = \alpha_0 + \alpha_1 \text{P} + \alpha_2 C + \alpha_3 F + \alpha_4 \text{R} + \varepsilon, \qquad (26)$$

where TTC is time to completion, and P is the vector of SPELL variables that capture the performance factors of the acquirer. C is the vector of dummy variables that capture the deal's complexity factor, including the hiring of a legal and/or financial advisory firm, deal-specific variables, transparency of the acquirer, and the presence of recession that captures the complexity from the economic environment. F is the vector of financing variables, including the acquirer's credit rating and the acquirer's risk factor. R is the vector of variables that includes repeated acquiring behavior of the acquirer, R&D investment of the acquirer, and the size of the deal.

2.5. Empirical Results

2.5.1. Basic Results

To show the causes of delay at each stage of the M&A process, Table 2 presents the OLS estimates of the impacts of hypothesized determinants on TTC by phase. The coefficients reflect the number of days, with negative numbers indicating deal acceleration and positive numbers indicating delays. As shown in Table 2, of the 5 SPELL variables used to capture company-specific characteristics of the acquirer, only the solvency and leverage indicators are statistically significant, but only at the 10% level. For an acquirer who would have completed a pre-targeting investigation before zeroing in on its target, it makes sense that its solvency is relevant. As an indicator of the ability to pay, it is appropriate to convince the target to complete the deal sooner. It is also applicable in motivating the acquirer itself to move faster. It is hard for a suitor who is broke to convince its target to sell quickly. The finding that greater leverage on the acquirer accelerates TTC is also consistent with the expectations. An efficiently leveraged company is better able to influence the target to accelerate the TTC.

The finding that acquirer liquidity, profitability, and efficiency do not matter in the negotiation and due diligence stage is not surprising. These are measures of operational performance of the buyer, which the seller may not pay much attention to as it is selling or giving up its independent identity.

Of the deal-specific characteristics, only deals involving the engagement of a financial adviser by the target and deals where both the acquirer, and the target are from the same country get completed faster. Both are statistically significant at the 5% level (the former is also significant at the 1%).

The coefficients of all advisory service firms' variables are positive and statistically significant at the 5% level, and two are significant at the 1% level. The presence of a financial adviser to the target delays a deal by 18 days. One would have expected that a financial adviser to the target brings its experience in moving the negotiation process along by helping its client fast understand the transaction's financial ramifications. But that is not the finding of this study. Due to data limitations (very few observations) regarding the involvement of legal advisory firms by the target, this variable was not included in the model.

The presence of a legal adviser to the acquirer is found to delay the TTC by 31 days. I expected a legal adviser to instill confidence in the acquirer by helping to flesh out key legal issues, including the regulatory issues that come later. However, I found otherwise. As I have explained in the latter part of the chapter, there are possible endogeneity issues related to the interaction between the engagement of a legal adviser and deal complexity. Complex deals may attract lawyers.

The presence of a financial adviser to the acquirer is found to delay the TTC by 24 days. Again, I expected a financial adviser to be able to make the financial arrangements easier and help the acquirer by helping to flesh out financial issues. But it appears that while investment bankers may bring other forms of value, such as better terms, accelerating the deal is not their contribution. Again, I re-examine this issue below due to the concerns about endogeneity problems.

I hypothesized that because firms in the same industry are more familiar with the conditions of their industry, deals involving the same sector would close faster than deals involving other sectors due to better knowledge and faster due diligence. The degree of asymmetric information is also expected to be reduced for the same industry deals. However, I found that same-industry deals are no faster than deals involving a different industry. Similarly, it is expected that same-country deals require fewer days to complete. They may require less due diligence, involve a singular time zone and fewer cultural or language barriers, and may allow greater familiarity. However, surprisingly, I find that same country deals are not concluded faster. I also find that friendly deals do not close more quickly. I attribute these to the fact that most acquirers have engaged in proper vetting before making a bid and commencing negotiation. So, country and industry advantage or less hostility may not pay off in terms of TTC.

Deal denominated in hard currency is expected to be easier for the target to understand and involve lower levels of cross-border currency risk exposure. Similarly, deals consummated with cash are expected to be easier and faster than stock deals or mixtures. The coefficients of currency of payment and cash as a mode of payment are statistically significant and negative at the 1% level. On average, cash deals close 37 days faster, and deals denominated in hard currency close 23 days faster.

Front-loading by the acquirer, which involves the early acquisition of the target’s stocks before bid offering and negotiation, does not seem to affect the TTC one way or the other. I see no statistically significant benefit of early attempts by the acquirer to load up on the company stocks of the target. In essence, front-loading reflects the acquirer’s determination and confidence. Its insignificance may suggest that while it may be relevant in shaping the deal's cost to the acquirer or squeezing the target, it may not be relevant to TTC. Deals initiated during a recession are slowed down by 15 days, probably reflecting the existence of limited resources and less desire to stage a takeover.

Two variables were used as proxies for factors that affect TTC through the financing phase. First, acquirer transparency is expected to accelerate TTC. Second, the Altman Z score was hypothesized to involve lower TTC. Note that a high Altman Z score (above 2.99) implies that the company is safe from bankruptcy, while a lower score (below 1.81) means that the company is exceptionally prone to default. The result suggests that neither of these variables has any bearing on TTC.

Finally, the theoretical expectation is that regulators favor deals that do not create monopoly power. Two proxies for factors that delay M&A deals in the regulatory approval process include repetitive acquisitions by an acquirer and a huge deal. A frequent acquirer may trigger greater SEC scrutiny. Similarly, large deals are more likely to lead to monopoly power than acquisitions involving small companies. Both repeat acquisition behavior and large deal size were found to be statistically insignificant.

In summary, in the negotiation and due-diligence phase, the factors that accelerate a deal include the acquirer's solvency and low leverage factor, as well as cash and hard currency as modes of payment. However, the engagement of transaction advisers tends to slow down the completion of deals in phase 1, be they financial or legal firms. Factors identified as relevant from the financing phase do not appear to delay or accelerate the completion of a deal effectively. Repeated acquisition behavior of the acquirer and larger deal size does not lead to delays in the regulatory approval process, thereby lengthening TTC.

2.5.2. Multi-Collinearity Check

Results presented in Table 2 involve many variables which reflect the financial health of the acquirer. These variables may be highly correlated. For example, a more solvent and profitable company is expected to be more efficient and liquid but less leveraged. Therefore, to check for and possibly address multi-collinearity, I conducted a Variance Inflation Factor (VIF) analysis and present the results in Table 3. A higher variance inflation factor (VIF) score implies a probable presence of multi-collinearity. Specifically, a VIF value of 5 is considered a moderate presence of multicollinearity (Yawson and Zhang, 2019). The result in Table 3 shows that the VIF is under 2 for all the variables, implying the absence of multicollinearity.

2.5.3. Endogeneity Test

In Table 2, I found the positive impact of the advisory service firms variables on the TTC. The finding that the engagement of a legal adviser and the financial adviser by the acquirer delays the TTC raises questions about an endogeneity problem. It is possible that acquirers only bring legal advisers into complex deals. The Wu-Hausman endogeneity test was used to prove the presence of endogeneity from the acquirer’s legal and financial adviser at a 1% level of significance.

Endogeneity could arise from the following: First, in a hostile deal, the acquirer needs legal and financial advisory firms because they are unwelcomed by the target and portends greater complexity. Second, domestic deals are less likely to attract an adviser (being less informed about the host country's environment, a foreign acquirer implies greater deal complexity). Third, compared with a horizontal deal where the buyer is more knowledgeable about the target, a vertical deal is more complex and more likely to attract a financial adviser. Fourth, Hard-currency deals may be less volatile than weak currencies deals, obviating the need for advisers. Fifth, with non-US deals, banks may need special approval from their central banks to borrow in hard currency. Therefore, it is conceivable that the financing process is more complex and may require a financial advisory firm. Sixth, in cash payments, to effectively access the risk and do due diligence beforehand, it may be necessary to bring in legal and financial advisers. Seventh, a recession makes the whole situation even worse in terms of negotiation, getting financed, and overall economic vulnerability to decide. In this situation, advisory service firms play a major role in the deal completion. Therefore, a higher deal complexity could be a probable reason for hiring financial and legal advisory firms. At the same time, the inherent complexity of the deal delays the deals, and often the presence of advisory firms explains the delay in the completion of the complex deals.

Therefore, considering advisory firms as the source of endogeneity, complexity variables are used as instrumental variables (IV) to examine if deal complexity leads to the presence of an advisory firm. A 2-stage least square model (2SLS) is applied. In the first stage of regression, it is tested if a financial adviser is required for a complex deal, where the characteristics of the deal capture deal complexity. In the second stage, the impact of the predicted advisory firm on the TTC is estimated. Econometrically, the objective is to estimate:

$$\text{TTC} = \alpha_0 + \alpha_1 \text{P} + \alpha_2 C + \alpha_3 F + \alpha_4 \text{R} + \varepsilon, \tag{26}$$

However, the C vector is broken into C_1 and C_2, where C_1 consists of the acquirer's financial, legal, and target's financial adviser and C_2 consists of the rest of the deal complexity variables in vector *C*. It is suspected that C_1 is determined by C_2 . That is,

$$C_1 = \rho_0 + \rho_1 C_2 + \nu \tag{27}$$

and

$$\text{TTC} = \alpha_0 + \alpha_1 \text{P} + \alpha_2 \hat{\text{C}}_1 + \alpha_3 F + \alpha_4 \text{R} + \varepsilon, \tag{28}$$

where $\hat{\text{C}}_1$ is the estimated value of the advisory firms from equation 27, estimated by deal-specific variables, transparency of the acquirer, and the presence of recession. TTC is time to completion, and P is the vector of SPELL variables that captures the performance factor. F is the vector of financing variables, including the acquirer's credit rating and the acquirer's risk factor. R is the vector of variables that includes the acquirer's repeated acquiring behavior and the deal's size.

The results of the IV-regression model estimation are presented in Table 4. The IV-regression in Table 4 considers the acquirer's financial and legal advisory firms as the sources of endogeneity and re-estimates Table 2. The results regarding transaction advisers change somewhat. Legal advisers to the acquirer now have no impact on TTC. However, the target's involvement or financial adviser now accelerates a deal by 56 days. The engagement of a financial adviser by an acquirer still lengthens TTC and does so by 259 days.

2.5.4. Survival Analysis

An important TTC-related issue is whether delays in completion matter? A fundamental premise of the analysis is that delayed deals are less desirable than promptly completed deals. Delayed TTC implies that it can result in higher expenditure and cause companies to miss out on valuable business opportunities (Luypaert and De Maeseneire, 2015). According to Irina De Bruyne Demidova (2014), the most relevant impact of TTC lies in the conditional likelihood of deal termination that depends on the negotiation times (hazard ratio).

In Figure 2, TTC (on the vertical axis) is plotted against the probability of deal completion. Specifically, the likelihood of a deal in existence for a given number of days to be brought to closure is plotted. Note that the plot is limited to 2000 days of TTC. Deals that last beyond that are likely to have unique deal-delaying characteristics and problems unrelated to TTC. Figure 2 shows that as TTC increases, the likelihood of completion decreases. The hazard rate (probability of the deal getting completed) goes down from 9% at time-period 150 to 4.5% at time-period 600 and further to 1% at time-period 1400 (see panel A). The Nelson-Aalen cumulative hazard estimate is non-decreasing (panel B). The Kaplan-Meier survival function shows that survival probabilities go down to 58% over 50 days and down to 32% over 100 days. This means that 32% of the M&As still have not got completed after 100 days of the announcement of the deal (panels C and D).

To further examine the relationship between TTC and the probability of deal failure, a regression of TTC on a dummy variable capturing deal completion (1= deal completed, 0 = not completed) is estimated. The results presented in Table 5 show that TTC has a statistically significant relationship with the odds of deal completion. The coefficient of TTC in the Probit model is -0.00088, which indicates that the odds of the deal getting completed as opposed to not getting completed decreases. Other coefficients in Table 5 further show how other control factors contribute to the probability of deal failure.

2.5.5. Further Study

In this essay, I use survival analysis as a tool to measure the relevance of time on deal completion, i.e., whether the deal got terminated and the timing of termination. I also include explanatory variables predicting negotiation, financing, and regulatory approval time. The central concept of these models is the conditional probability that a process end at some future time t, given its “survival” up to time t. The chapter measures the conditional likelihood of termination called the hazard rate and its shape, called time-dependence or duration-dependence. The dependent variable is the time duration (number of days to event or time a deal takes to get completed), and the event is the termination when it occurs. Therefore, the dependent variable considers of time and event. Therefore, (1) time variable = number of days an M&A deal takes to get completed/terminated, (2) the event variable = 1 if the deal is terminated, and 0 if the deal does not get terminated. Independent variables areas before the negotiation, financing, and regulatory approval variables.

The hazard rate can be defined as the probability that the M&A gets terminated at time t, given that the individual is at risk at time t. Hazard rates varies with time. The probability of termination of an M&A deal may be low in the beginning but increases with time as deal the exceeds more than 5 months.

2.6. Summary and Conclusion

TTC is an essential issue in the M&A process. While this issue has received some research attention in recent years, the literature is quite limited. Specifically, while individual studies have focused on specific TTC determinants, a comprehensive analysis of factors that determine TTC has never been attempted. This has a limited ability of these studies to explain what accelerates TTC and what does not. The previous studies also lack theoretical and conceptual rigor. These gaps in the literature motivated this present study on TTC.

A conceptual/theoretical model of TTC determination is presented, breaking TTC into 3-time dimensions: negotiation and due diligence, financing, and regulatory approval. Models to capture underlying buyer and seller behavior that ultimately shape optimal TTC for each of these are specified. These theoretical models also helped in identifying company-specific characteristics, complexity characteristics of the deal, financing characteristics, and regulatory characteristics that shape TTC. The empirical analysis further showed the relationship between TTC and its key determinants.

The key findings include the following: (1) due diligence/negotiation factors such as acquirer solvency and leverage, which imply acquirer execution ability, accelerate the TTC. Also, deals involving payment in cash and in hard currency conclude faster, while deals involving both an acquirer and target from the same country or the same industry do not. It was found that the presence of legal or financial advisers lengthens the TTC. Delays in financing are not caused by limited transparency or the degree of risk involved. Deals consumed during a recession take longer while regulatory phase factors such as deal size and acquirer history of repeated M&A activities neither accelerate nor delay TTC. To investigate whether longer TTC is detrimental to the companies involved in an M&A transaction, survival analysis is used to show that delayed TTC increases the likelihood of deal failure. This result is crucial as it underscores the value of expediated TTC.

To summarize the potential broader impacts of this chapter, the implications for major categories of stakeholders are summarized: targets, acquirers, M&A practitioners, investors, and regulators. With available information on the company, market, deal complexity, and other variables, targets may find the procedure, and results help to predict how long a given M&A process takes. For example, a target should expect a non-cash deal involving an efficient acquirer to take longer. Acquirers might also find the findings of this study helps to implement their strategy. For example, targeting an efficient company means that the deal does not take as long as other deals. M&A practitioners, especially financial advisory firms, may find this study helpful in communicating the added time it would take to complete a deal with their clients. Investors may use the results to manage their expectations about the deal completion timeframe. Finally, the results could be helpful to regulators such as the Securities Exchange Commission (SEC) in benchmarking a transaction’s TTC and optimally deploying their efforts based on the deal's characteristics.

Being the first of its nature, this study has some limitations. First, it is relied on publicly available data from Bloomberg and CompStat. It is recommended that future studies use richer databases. Specifically, data on financial condition of the target, acquirer’s credit rating, and R&D investment of the acquirer and target will shed more light on the determining of TTC. The availability of data on time to complete each phase of the M&A will allow a better analysis that sheds more light on the structure of TTC. Researchers will be better able to specifically point out which phase has most impact on delaying the deals. Second, the analysis focuses on the GFABI industry. It is recommended that future studies focus on different sectors of the economy, including IT, Pharmaceuticals, E-commerce, and other key industries. Third, more detailed studies on specific segments of GFABI are recommended. However, these studies may be complex due to limited data availability. Fourth, the issue of endogeneity in the roles of financial and legal advisor firms needs to be better investigated. Finally, the benefits of the faster TTC, particularly the implication for faster realization of post-M&A objectives, need to be further investigated.

APPENDIX

Appendix

Table 2.1: Summary Statistics

Variable Category			**Variable Description**	**No. of Obs.**	**Mean**	**Std.**
			Time to Completion	16963	52	127
			Deal Status (Completed =1)	26825	1	0.50
Phase 1: Negotiation and Due Diligence	Company Specific Performance Factors	Solvency	Acquirer Borrow to Lability	13637	164	13946
			Target Borrow to Equity	1711	133	1659
		Profitability	Acquirer ROA (from EPS)	15360	-895	64027
			Target Net Sales	3226	100	0
		Efficiency	Acquirer Asset Turnover	15275	1	1.01
			Target Asset Turnover	3144	1	1.24
		Leverage	Acquirer Assets Equity	15906	13	1319
			Target Total Liabilities	3262	4	2
		Liquidity	Acquirer Current Ratio	15546	2	31
			Target Quick Ratio	3247	3	49
Phases 1&2: Negotiation, Due Diligence & Financing*	Deal-Specific Complexity Factors		Acquirer Legal Adviser	26825	0.15	0.36
			Acquirer Financial Adviser	26825	0.19	0.39
			Target Financial Adviser	26825	0.08	0.27
			Same Industry	24569	0.34	0.47
			Same Country	25984	0.62	0.48
			Friendly Nature of the Deal	13851	0.99	0.08
			Payment Currency (Hard=1)	26825	0.72	0.44
			Payment Mode (Cash=1)	26825	0.52	0.49
			Percentage Owned	26825	5.42	17.88
	Macro-Economic Environment		Recession	26825	0.20	0.40
	Transparency Factors		Acquirer Transparency	17724	0.80	0.23
Phase 2: Financing	Credit Worthiness & Risk Measurement of Acquirer		Acquirer Credit Rating	6076	3.77	2
			Acquirer Altman's Z Score	13483	-29.1	840
Phase 3: Regulatory Approval	Monopoly Power Factors		Acq. Repeated Behavior	26819	10.94	35
			Acquirer R&D Expenditures	5306	210	735
			Total Value of Deal ($Mil)	13492	303	2563

Table 2.2: Effects of Hypothesized Factors on Time to Completion

M&A Phases	Category		Variables	Empirical Estimates
Phase 1: Negotiation and Due Diligence	Company Specific Performance Factors	Solvency	Acquirer Borrowing to Liability	-0.319* (0.19)
		Profitability	Acquirer ROA (from EPS)	-0.218 (0.16)
		Efficiency	Acquirer Asset Turnover Ratio	-4.325 (3.86)
		Leverage	Acquirer Assets Equity Ratio	-0.297* (0.16)
		Liquidity	Acquirer Current Ratio	-2.797 (1.94)
Phases 1&2: Negotiation, Due Diligence & Financing*	Deal-Specific Complexity Factors		Acquirer Legal Adviser	31.34*** (7.85)
			Acquirer Financial Adviser	23.97*** (7.21)
			Target Financial Adviser	18.15** (7.98)
			Same Industry	7.153 (6.75)
			Same Country	4.203 (6.72)
			Friendly Nature of the Deal	-22.25 (28.08)
			Payment Currency (Hard=1)	-22.66*** (7.04)
			Payment Mode (Cash=1)	-36.54*** (6.52)
			Percentage Owned	0.139 (0.14)
	Macro-Economic Environment		Recession	15.37* (8.41)
	Financing Factors		Acquirer Transparency	188.6 (124.40)
			Acquirer Credit Rating	-0.807 (0.71)
Phase 3: Regulatory Approval	Monopoly Power Factors		Acquirer Altman's Z Score	-0.127 (0.24)
			Acq. Repeated Behavior	0.00142(0.002)
Model Summary			Constant	-37.75 (116.90)
			Observations	2,044
			R-squared	0.071

Note: Standard errors in parentheses; Significance levels: *** p<0.01, ** p<0.05, * p<0.
**These variables are relevant in more than one phase.

Table 2.3: Multi-Collinearity Test Using Variance Inflation Factors (VIF)

M&A Phases	Category		Variables	VIF Coefficient
Phase 1: Negotiation and Due Diligence	Company Specific Performance Factors	Solvency	Acquirer Borrow to Liability	1.21
		Profitability	Acquirer ROA (from EPS)	1.74
		Efficiency	Acquirer Asset Turnover	1.08
		Leverage	Acquirer Assets Equity	1.04
		Liquidity	Acquirer Current Ratio	1.11
Phases 1 & 2: Negotiation, Due Diligence & Financing*	Deal-Specific Complexity Factors		Acquirer Legal Adviser	1.94
			Acquirer Financial Adviser	1.42
			Target Financial Adviser	1.34
			Same Industry	1.33
			Same Country	1.03
			Friendly Nature of the Deal	1.18
			Currency of Payment (Hard=1)	1.09
			Mode of Payment (Cash=1)	1.09
			Percentage Owned	1.07
	Macro-Economic Environment		Recession	1.04
	Financing Factors		Acquirer Transparency	1.21
			Acquirer Altman's Z Score	1.96
Phase 3: Regulatory Approval	Monopoly Power Factors		Acquirer Repeated Behavior	1.20
			Announced Value of Deal ($Mil)	1.21
			Mean VIF	1.24

**These variables are relevant in more than one phase

Table 2.4: IV Regression- Effects of Hypothesized Factors on Time to Completion

M&A Phases	Category		Variables	Endogeneity of Acq. Fin. Adviser & Legal Advisor
Phase 1: Negotiation and Due Diligence	Company Specific Performance Factors	Solvency	Acquirer Borrow to Liability	-0.352 (0.2)
		Profitability	Acquirer ROA (from EPS)	-0.238 (0.2)
		Efficiency	Acquirer Asset Turnover	-1.621 (4.2)
		Leverage	Acquirer Assets Equity	-0.198 (0.3)
		Liquidity	Acquirer Current Ratio	1.791 (3.1)
Phases 1&2: Negotiation, Due Diligence & Financing*	Endogeneity: Deal-Specific Complexity Factors		Acquirer Legal Adviser	-57.91 (67.5)
			Acquirer Financial Adviser	258.9*** (56.5)
			Target Financial Adviser	-55.94* (33.5)
Phase 2: Financing	Credit Worthiness & Risk Measurement of Acquirer		Acquirer Altman's Z Score	-1.502* (0.8)
Phase 3: Regulatory Approval	Monopoly Power Factors		Acquirer Repeated Behavior	-0.185 (0.5)
			Value of the Deal ($Mil)	0.00153* (0.0009)
Model Summary			Constant	53.83*** (18.8)
			Observations	2,044
			Wu-Hausman Score (p-Value)	**11.2411 *** **

Note: Standard errors in parentheses; Significance levels: *** p<0.01, ** p<0.05, * p<0.
**These variables are relevant in more than one phase.

Table 2.5: Impact of TTC on the Likelihood of Deal Completion

M&A Phases	Category		Variables	Model 2
	Time to Completion			-0.0009*** (0.0002)
Phase 1: Negotiation and Due Diligence	Company Specific Performance Factors	Solvency	Acquirer Borrow to Liability	0.005 (0.002)
		Profitability	Acquirer ROA (from EPS)	0.003* (0.001)
		Efficiency	Acquirer Asset Turnover	-0.02 (0.04)
		Leverage	Acquirer Assets Equity	-0.005 (0.003)
		Liquidity	Acquirer Current Ratio	-0.05* (0.02)
Phases 1&2: Negotiation, Due Diligence & Financing*	Deal-Specific Complexity Factors		Acquirer Legal Adviser	-0.05 (0.12)
			Acquirer Financial Adviser	0.2* (0.12)
			Target Financial Adviser	-0.1 (0.12)
			Same Industry	0.2** (0.093)
			Same Country	-0.2* (0.09)
			Friendly Nature of the Deal	1.3*** (0.3)
			Currency of Payment (Hard=1)	0.2** (0.09)
			Mode of Payment (Cash=1)	0.05 (0.092)
			Percentage Owned	0.004** (0.002)
	Macro-Economic Environment		Recession	0.4*** (0.14)
	Transparency Factors		Acquirer Transparency	0.4 (2.01)
Phase 2: Financing	Credit Worthiness & Risk Measurement of Acquirer		Acquirer Altman's Z Score	-0.003 (0.009)
Phase 3: Regulatory Approval	Monopoly Power Factors		Acquirer Repeated Behavior	-0.003 (0.004)
			Value of Deal ($M)	-1.71e-05** (0.0)
Model Summary			Observations	2,044

Note: Standard errors in parentheses; Significance levels: *** p<0.01, ** p<0.05, * p<0.
**These variables are relevant in more than one phase.

Figure 2.1: Defining Time to Completion

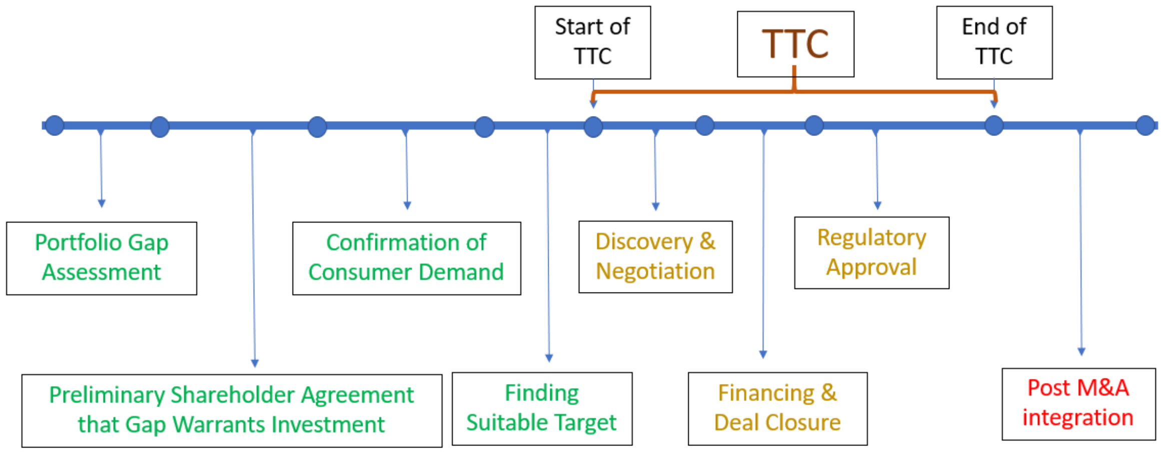
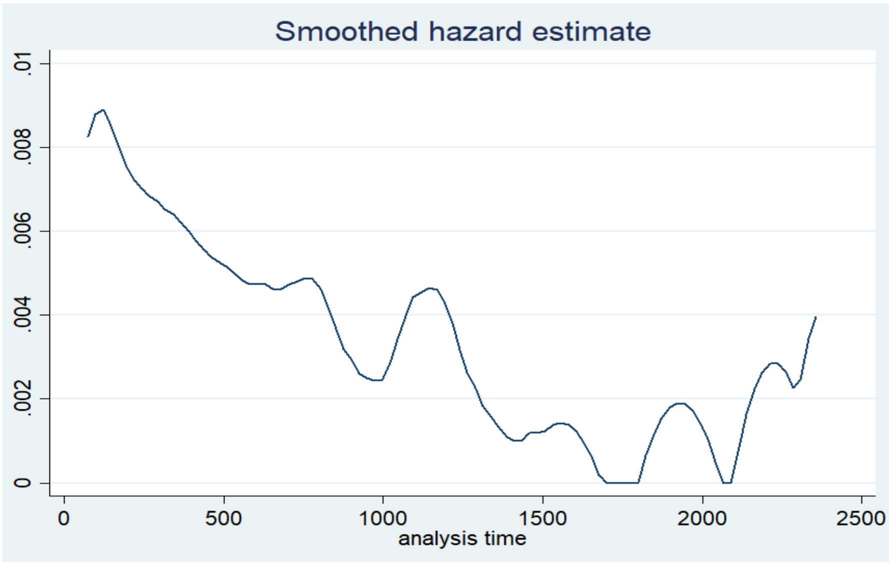


Figure 2.2: Survival Analysis Results – Relationship between TTC and the Probability of Deal Completion

A: Smoothed Hazard Estimate



B: Nelson Aalen Cumulative Hazard Estimate

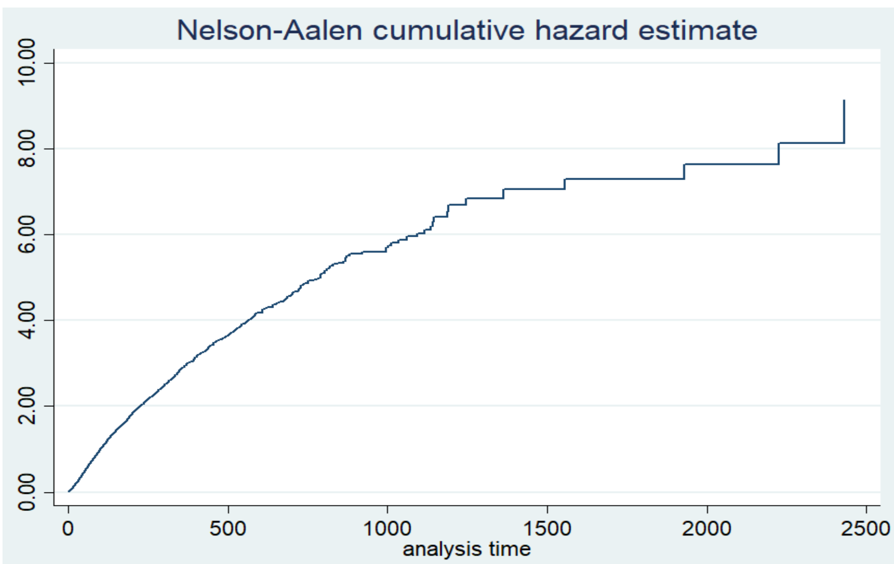
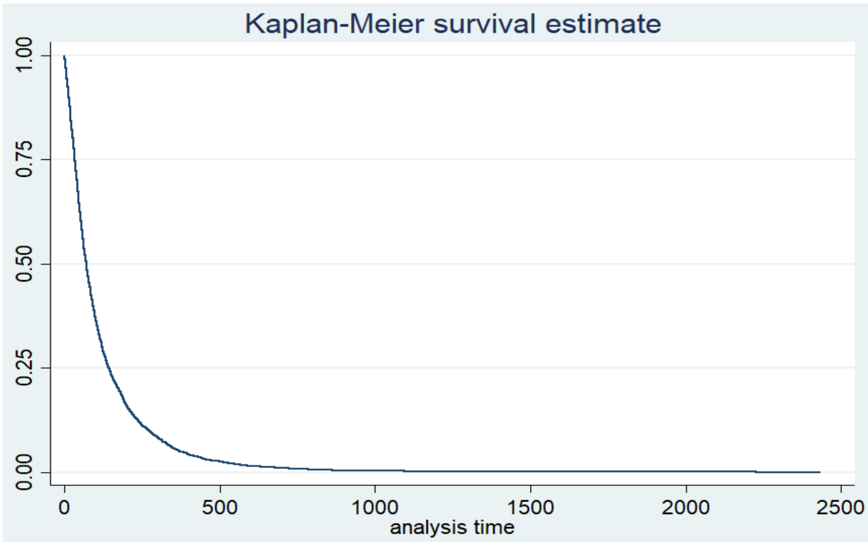
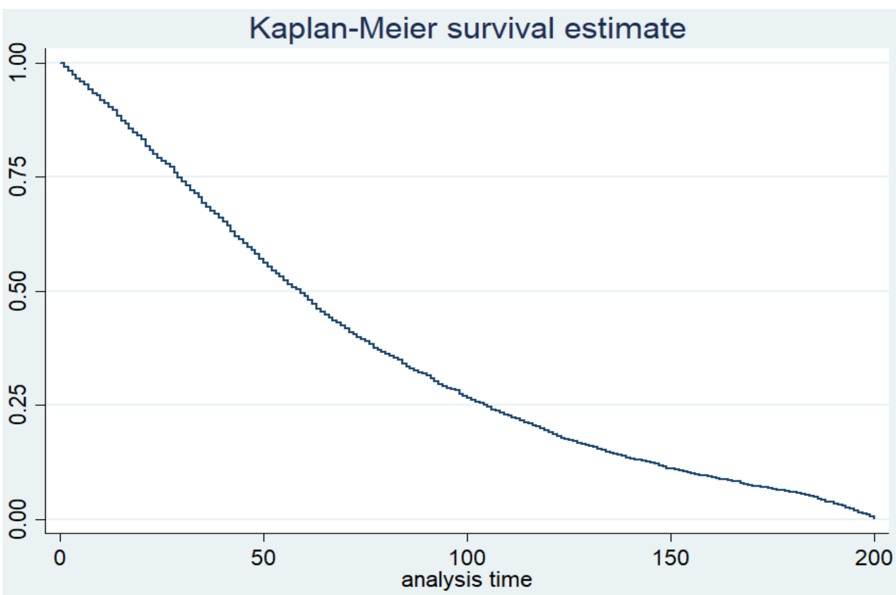


Figure 2.2 (cont'd)

C: Kaplan Meijer Survival Estimate (Full Sample)



D: Kaplan Meijer Survival Estimate (Truncated to Time Period 200)



CHAPTER 3: ESSAY 2: IMPACT OF ADVISORY SERVICES ON THE SUCCESS OF M&A IN THE FOOD AND AGRI-BUSINESS INDUSTRY

3.1. Introduction

The established literature on Agency Theory and the Theory of Transaction Cost defines asymmetric information (AI) and how it induces higher agency costs (Deshmukh, 2005). It also explains how AI makes it difficult for investors to navigate through the opaque M&A environment and assess a firm's actual value (Hughes, 1986). The AI phenomenon is evident in mergers and acquisitions, where the acquiring firm has limited knowledge about the target (and vice-e-versa). This creates a less transparent business environment for the acquirer. As AI is not observable, the literature has always attempted to capture it through proxy variables, an approach that is often discussed for its limitations.

Due to the presence of AI, the incentive of avoiding misconduct among both the buyers and sellers serve as a significant threat to the market. Therefore, a key step to reducing AI is promoting transparency in the market and among all stakeholders in M&As. The theory of adverse selection suggests signalling and screening as two key instruments to improve deal transparency (An, X., et al. 2011). Advisory firms play a key role in M&As (Teeffelen, L. V., 2014) as a screening mechanism by helping their clients (in this context, the acquirers) to navigate through the opaque business environment for M&A deals (Zhongyan, Z., 2014).

In the M&A process, the presence of two major types of advisory firms can be observed: legal and financial advisory firms. Through their expertise and industry knowledge, they help the acquirers in making better-informed decisions (Bilinski, P., & Yim, A., 2018). Therefore, in the presence of AI, acquirers are expected to hire advisory firms to improve profitability, market share, market power, and economies of scale (Alexandridis et al., 2010) so that they can better reap the benefit of synergetic gains (Bao & Edmans, 2011). The inherent asymmetric information in an M&A significantly influences the choice of payment method. A larger uncertainty leads to a higher ratio of stock payment by the acquirer (Klitzka et al., 2021; Adra, & Barbopoulos, 2018). Whereas target negotiates for a cash-heavy compensation.

Further, in stock compensation, the mechanism of using caps and collars in deciding the exchange ratio (ratio between acquirer shares to target share) helps the acquirer to share the risk of the acquisition with the target firm, since the "acquirer and target share prices can change between the signing of the definitive agreement and the closing date of a transaction" as per Wallstreetprep (Wallstreetprep, 2022).

Financial advisory firms also help the acquirer to incorporate a purchase price working capital adjustment clause in the deal to navigate through the financial opaqueness of the target company. The working capital that the target shows on its balance sheet at the time of deal announcement may differ from the amount it had a deal closing. To protect the acquirer from the risk of a reduced working capital of the target, "adjustment for working capital" clause is often advised to the acquirer to be included in the agreement (Wallstreetprep, 2022).

Finally, an earnout (a future payment, in addition to an upfront payment) is another mechanism used in M&A to bridge the valuation gap between a target's expectation of total compensation and what a buyer is willing to pay but compensating the target in the long run if the M&A turns out as a success. This mechanism further reveals the target's expectation about its own future performance through the choice that they make for upfront compensation and future compensation (Wallstreetprep, 2022).

Similarly, legal advisory companies help to take care of the due diligence process, the legal obligations related to the contract, patent handovers, anti-trust issues, and unpaid debt or borrowing coverage. It also advises the acquirer on certain tools to incorporate in the contract to ensure the risk-sharing between target and acquirer, post-M&A. For example, when Microsoft acquired Linkedin in 2016, there was a breakup fee in their agreement that is popularly known as "No Solicitation" or "No-shop" provision for the target that protects the acquirer from the termination of the deal by a seller accepting overbids from other potential buyers using the first buyer's offered bid (Wallstreetprep, 2022). At the same time breakup fee also protects the buyer in any of the following situations where the board of directors of the target company changes its mind to back off from selling their company or more than 50% of the company's shareholders don't approve the deal. Legal advisory firms also help the acquirer to incorporate the financial advice provided by financial advisory firms in their M&A contracts.

Therefore, financial and legal advisory firms help the acquirer to better understand the valuation of a target company, help in making a fair offer, advise on the optimal mode of payment, decide the optimal earnouts, termination fees, etc. and incorporate these mechanisms in the contract. The most prominent financial advisory companies are, Morgan Stanley, JP Morgan Chase & Co., Credit Suisse Group AG, Citigroup Inc, Barclays Plc, UBS Group AG, Goldman Sachs Group Inc., Bank of America Corporation, and Rothschild &Co. The most prominent legal advisory companies are Wachtell, Lipton, Rosen, and Katz; Davis, Polk & Wardwell LLP; Sullivan & Cromwell LLP; Latham & Watkins LLP; Clearly, Gottlieb, Steen & Hamilton LLP; Kirkland & Ellis LLP; Simpson, Thacher & Barlett LLP; Fried, Frank, Harris, Shriver & Jacobson LLP; Skadden, Arps, Slate, Meagher & Flom LLP and Affiliates; and Slaughter & May.

In this dissertation, chapter 3 (Essay 2) captures the sources of asymmetric information and measures it in an index. Furthermore, the essay finds the impact of advisory firms for a given asymmetric information level in the food and agri-business industry in a specific economic and industry environment.

3.2. Literature Review

The literature on transaction cost theory has pointed out the degree of difficulty involved in the measurement of AI. This is largely due to the unobservability of AI (Bergh et. al., 2018). Given these measurement problems, scholars have made repeated attempts to capture AI through proxy variables. The most commonly used proxies are the following. The first is the probability of the arrival of informed trades (PIN) in the stock market (Easley et al., 1996), which is defined as the proportion of the daily arrival rate of information-based trades to the daily arrival rate of all orders. The second is the bid-ask spread (BAS) that proxies for adverse selection (Lin et al., 1995), which is the temporary price effect induced by a trade. The third, the Illiquidity ratio (ILLIQ) (Amihud, 2002), quantifies the price to return response for a given trade size. The fourth is the Liquidity Ratio (LR) (Amihud et al., 1997), which calculates the trading volume for a unit change in the stock price. Generally, the higher the value of PIN and ILLIQ, the higher the degree of AI (Amihud, 2002; Easley et al., 1996). However, AI has a negative correlation with LR (Amihud et al., 1997).

Recent studies have tried to use more direct proxies for AI. Examples include the scaled accruals quality (SAQ) and the variance of accruals quality variables. Higher scaled accrual quality is inversely correlated with earnings quality but positively correlated with the degree of AI (Francis, 2005). Idiosyncratic stock volatility is also often used as a measure of AI with respect to the diversity of opinion. As per Karpoff, "High return volatility suggests a noisy information environment, making it more difficult for outside investors to assess the firm's performance", thus leading to larger AI (Karpoff et al., 2013). It can be concluded that the presence of firm-specific AI processes can be broadly divided into 4 categories: return-based measures, spread-based measures, liquidity-based measures, and others.

Return-based measurements of AI include (Yassin et. al., 2015) realized volatility, idiosyncratic volatility, variance of the earnings per share (EPS), and errors in forecasts (Chemmanur et al., 2009). Among the return-based measures, trading volume, and variance of stock returns have a significantly positive impact on AI (Abdul-Baki, 2013). Spread-based measures include daily spread, PQ spread, effective spread, and PE spread (Abdul-Baki, 2013). Turnover is a liquidity-based measurement (Duarte and Young, 2009). Higher illiquidity implies more AI. The number of analysts in a firm is also another proxy variable used to capture firm-specific AI (Chatterjee et al., 2012).

Among the studies from the extant literature that have established the existence of AI in an M&As transaction (Stultz, 1988; Fishman, 1989; Eckbo, Giammarino, and Heinkel, 1990; Hansen, 1987; and Rhodes-Kropf and Viswanathan, 2004), some have also presented index measurements of the AI. A few studies have shown how the presence of AI significantly impacts a deal through overpricing and high bid premiums (e.g., Chen, Hong, and Stein, 2002; Cheng, Li, and Tong, 2008; Diether, Malloy, and Scherbina, 2002; Chatterjee, John, and Yan, 2012; Miller, 1977). Overvaluation and overpayment are among the probable reasons for the high failure rate of M&A deals which lead to a significant diminution of shareholder wealth (Roh, 2011). To cope with M&A deal-related complexities and to improve the success rate, many acquiring firms hire M&A advisory firms (Sahyoun et al., 2017).

Existing research has suggested some primary reasons why firms hire an adviser in the context of an M&A transaction: (1) better deal performance and (2) faster deal completion (Sahyon et al., 2017). The "Superior Deal" (SD) hypothesis contends that M&A deals with advisory firms exhibit a superior post-merger performance than those without an adviser (Christopher, 2011). Measures of superior performance include higher post-announcement operating performance (Raghavendra Rau, 2000) in the short or long run, a better post-merger profitability, liquidity, or efficiency (Ertugrul & Krishnan, 2010). The Deal Completion (DC) hypothesis, on the other hand, also highlights the fact that advisory firms, as executors, were hired to negotiate and increase chances and speed of completion (Rau, 2000), with implications for transaction costs. However, existing studies are empirically inconclusive with respect to their support for these theories.

Evidence on the net effects of advisers is mixed. Some studies found evidence that advisers have a significantly positive impact on M&A performance. That is, companies with advisers perform better than those without advisers. Other studies found no significant difference in performance (Schiereck et al., 2009; Servaes & Zenner, 1996). Similarly, most studies found a positive association between advisory firms and faster completion (Bao & Edmans, 2011; Hunter & Jagtiani, 2003). However, Golubov et al. (2012) do not find a significant impact of advisory firms on TTC.

3.2.1. Gap in the Literature and Hypothesis Development

The extant literature has explored firm-specific AI but has tended to overlook deal-specific and country-specific AI. The economic environment at the time of a specific deal can contribute to the level of AI. For example, in cross-border M&As or cross-industry M&As, the acquirer might have less information regarding the economic environment of that country or industry. Similarly, in an M&A, the labor-market behaviour and the socio-political environment of the host country can create an environment of deal opaqueness. For example, a deal involving a developing country may create uncertainty and anxiety due to a strict labor market regulation. Therefore, AI could reduce the likelihood of deal success. This lack of information creates a certain level of opacity and, thus, a greater risk of failure in an M&A deal. This essay seeks to bridge that gap in the literature by considering a more detailed and broader picture of the sources of AI.

It is noteworthy that some studies have measured AI and addressed the impact of advisory firms on the likelihood of success of M&A deals. However, these studies have not controlled for the inherent level of AI in an M&A deal that could adversely impact the deal's success and therefore can neutralize the effect of advisory firms on the deal. This essay estimates the impact of the advisory services on the post-M&A deal performance for a given level of inherent AI.

3.3. Theoretical Framework

To explain the role of AI and advisory service firms in M&A transactions, I apply a simple adverse selection screening model. High incentives for misconduct (e.g., falsified information) and hiding pertinent information by target companies represent a considerable threat to the acquirer. This implies the presence of asymmetric information in M&A. Therefore, a key step in reducing AI is encouraging transparency amongst target companies.

Microeconomics theory suggests that signaling and screening are two ways to increase the level of transparency in a deal. In an environment where the target company has private information about its own financial health, it can either disclose it or not. Maintaining its reputation and its quality are key incentives that induce a seller to use signaling to reduce the degree of AI. On the other hand, unlike signaling, screening is more relevant at an earlier stage when an uninformed acquirer seeks to make the initial decision to participate in a contract (Kubler et. al, 2008). Therefore, implementing a screening mechanism helps the acquirer to analyze the risk of the M&A deal and to decide if the worst possible outcome of the M&A deal makes participation worth it. However, when gathering new information is too expensive, and a high risk of economic loss is involved from a contract, screening methodologies suggests the optimal strategy is not participating in the contract at all" (Wikipedia, 2021). Moreover, if the acquirer believes that there is a risk involved of poor returns and the cost of hiring a consulting service firm is very high and not worth it, they will not make the initial investment from the start.

Therefore, in M&As, the acquirer engages an advisory service firm in its negotiation with its target to help it gain better information about the target. Hence, the advisory services firm helps the acquirer to make better-informed decisions by providing them fairness opinion about the target and suggesting an offer price, bid premium, termination fee, purchase price adjustment, earnout negotiation, material adverse change, and due diligence. As a result, the likelihood of the acquirer's post-M&A performance is expected to be better.

Next, I develop a theoretical model to explain the adverse selection scenario where the screening strategy is used to reduce the degree of AI in a deal. I assume that the acquirer offers a price to its target from a pool of possible target options. Possible target companies are heterogeneous in nature and the probability of their M&A success varies with their quality. Further, I also assume k types of targets (k = H, L), a high-quality target (H), and a low-quality target (L). Here, for simplicity, I assume only two types of companies. The probability of a deal's financial success for a high-quality target is (θ_H) and the probability of a low-quality target is (θ_L). Note that the two types of companies only differ in their success probability, where $\theta_H > \theta_L$. Each M&A transaction has a random return of R where (R = 0) for a failed deal and ($R = \tilde{R}$) or for a successful deal. The proportion of type k target is given by α_k, k = H, L. Let's consider the reservation utility as U_H for type H target company and U_L for type L target company. Therefore, it can be assumed that

$$\frac{U_L}{1-\theta_L} > \frac{U_H}{1-\theta_H} \tag{29}$$

Recall that at the onset of an M&A transaction, the acquirer would often offer an earnout or penalty and the contract often involve such clauses as material adverse change, working capital adjustment, termination fee, or ratio reversal. These are meant to hold the feet of the target to accurate disclosure. Misrepresentation of the information could therefore cost the target company if the deal falls through at the end of the M&A transaction. Now assume that the acquirer is monopolistic, and it offers a contract to the *k*-th type target with an upfront payment *K* and a future earnout (E_k) or penalty (P_k). That is, the acquirer offers a contract $\{(E_k, P_k)\}_{k=H,L}$ to the target, where the target receives an earnout E_k in the future, if the M&A deal turns out a success and pays a penalty P_k if the deal fails due to misrepresentation of information. Upon the failure of the M&A, the misrepresentation of the information can be investigated, and the acquirer can charge the target company the penalty for the misinformation if any. The acquirer will receive the specified amount of penalty from the target δP_k with $\delta < 1$. (Thus $(1-\delta)P_k$ corresponds to a litigation and investigation cost to prove misinformation during M&A.)

Thus, the acquirer's payoff from acquiring a type *k* target company is $(\tilde{R} - K - E_k)$ if the deal is a success. Else it is $(\delta P_k - K)$ if the deal is a failure. Therefore, the expected payoff of the acquirer can be written as:

$$\sum_{k=H,L} \alpha_k [(1-\theta_k)(\tilde{R} - K - E_k) + \theta_k(\delta P_k - K)] \tag{30}$$

Therefore, the Individual Rationality (IR) constraint, which can be defined as a requirement that each type of target company weakly prefers to participate in an M&A over not participating, can be written as:

$$(1-\theta_k)(K+E_k)+\ \theta_k(K-P_k)\geq U_k. \quad (31)$$

Equation 31 can be broken down as follows:

For H-type: $(1-\theta_H)(K+E_H)+\ \theta_H(K-P_H)\geq U_H$ (31.A)

For L-type: $(1-\theta_L)(K+E_L)+\ \theta_L(K-P_L)\ \geq U_L$ (31.B)

An Incentive Compatibility constraint that prevents a low-quality company from mimicking a high-quality company and vice versa can be written as:

$$(1-\theta_k)(K+E_k)+\ \theta_k(K-P_k)\geq\ (1-\theta_k)(K+E_{k\prime})+\ \theta_k(K-P_{k\prime}) \quad (32)$$

Equation 32 can be broken down as:

$$(1-\theta_H)(K+E_H)+\ \theta_H(K-P_H)\geq\ (1-\theta_H)(K+E_L)+\ \theta_H(K-P_L) \quad (32.A)$$

and

$$(1-\theta_H)(K+E_H)+\ \theta_H(K-P_H)\geq\ (1-\theta_H)(K+E_L)+\ \theta_H(K-P_L) \quad (32.B)$$

Therefore, the acquirer's objective is to maximize its payoff that is derived in equation (30), subject to the pair of constraints in equations (31) and (32). Note that, to satisfy equation 32.B, when 31.A is binding, $P_H=0$ should hold when 31.B is satisfied and 32.A remains unchanged.

It can also be shown that if E_H is reduced by a small fraction of $\in$, where $\in > 0$, then E_L and P_L must be changed by $\frac{\theta_L(1-\theta_H)}{\theta_H-\theta_L}\in$ and $-\frac{(1-\theta_L)(1-\theta_H)}{\theta_H-\theta_L}\in$, respectively. Therefore, the corresponding change of the acquirer's payoff is $\in$ times of

$$(1-\ \theta_H)[-\beta_H\frac{\beta_L(1-\delta)(1-\theta_L)\theta_L}{\theta_H-\theta_L}] \quad (33)$$

Solving the above optimization problem, it can be shown that each type of target choses the contract $\{(E_k,P_k)\}_{k=H,L}$ that reveals its type and therefore reduce the AI in the M&A. Therefore, the acquirer will be able to make a better decision through the screening method that will maximize its performance in the acquisition. Therefore, it can be concluded that the help of advisory service firms in addressing the requirement of different screening mechanisms in the contract helps the acquirer to navigate through the AI environment and make a better decision by offering a competitive contract to each type of target company.

Recall that the goal of this essay is to capture the sources of asymmetric information. The acquirer is unaware of the type of the target (H, L), and therefore there exists AI in the M&A deal. The sources of the AI in an M&A deal are determined by the characteristics of the industry, economic environment, company characteristics, or deal characteristics. In this chapter, I have used an index that captures different dimensions of AI, and the index value represents the level of AI in an M&A deal. Further, being unaware of the type of the target, the acquirer wants to use a screening mechanism to make a better decision in choosing a target and making an appropriate compensation. Therefore, another goal of this chapter is to identify possible screening mechanisms (advisory service firms, non-cash payment, termination fee) and investigate the impact of these screening mechanisms on deal performance for a given level of asymmetric information in an M&A deal.

3.4. Empirical Framework

3.4.1. Data

As shown in Essay 1, for all M&A activities involving publicly traded companies, BMAD provides data on financial and non-financial variables for both the target and the acquirer, as well as on several deal-specific indicators. BMAD provides daily information on M&A activities from January 1988 to June 2018 for all segments of the global economy, including the global agri-businesses and food industries (GABFI). As is the case with Essay 1, the GABFI M&As consist of 26,825 observations (transactions). Out of these, 63.65% of the acquirers used a screening mechanism, which ranged from hiring a financial or legal adviser, not paying in cash, or incorporating a termination fee clause. Some 28.10% of the acquirers hired either a financial or legal advisory firms. Individually, 19.71% hired a legal adviser while 15.69% hired a financial advisory firm. Only 7.29% of the acquirers hired both a legal and a financial advisory firm.

Of the 26,825 transactions, 50% involved disclosure about the nature of the bid (friendly or unfriendly) 99.34% of which were friendly bids. In other words, unfriendly bids are very rare. Note that un-friendly bids could either be hostile or unsolicited. About 69% of the transactions involved cross-sector deals while 37.89% involved cross-country deals (see Essay 1).

As mentioned before, paying the target in stock, and including a termination fee clause work as screening mechanisms in M&A transactions. Out of the 26,825 M&A transactions, 47.37% of the acquirers did not pay cash to their targets. But only 0.51% of the acquirers included a termination fee in their contracts. Most importantly, 35.54% of the acquirers implemented a screening mechanism (not paying in cash and termination fee) without the help of an advisory service company. Some 15.92% of all acquirers did not include any screening mechanism (not paying in cash or termination fee), despite hiring an advisory service firm.

In this chapter, the country-specific AI in an M&A, arising from the economic environment of a country, is captured by the presence of recession in the host or target country at the time of the deal. I constructed a dummy variable, "Recession," which assumes the value of 1 if the year of the announcement was during a recession (0 otherwise). The macro-economic literature indicates the following years as recession years for the global economy: 1990–93, 1998, 2001–02, and 2008–09. However, government regulation in a specific industry, specific law related to a specific industry for a country, labor law of a country and the corruption score of a country are also country-specific AI that could not be captured in this dissertation due to data limitations.

To capture the deal-specific AI, the following variables are included in the regression: (1) deals involving companies from different countries, (2) deals involving companies from the different industries, (3) size of the deal, (4) percentage of target's stocks or equity previously owned by the acquirer, and (5) nature of the deal.

Firm-specific AI can be captured by the financial data of debt, liquidity and leverage ratios, credit rating score, supply chain information, and legal contracts of the target company. However, as mentioned in chapter 1, the target food firms are usually very small in size and are not listed on the NYSE. Therefore, reliable data is not readily available. The only information that is possible to extract is whether the company has reported its financial information and the count of the number of disclosures. The literature suggests that disclosure information may reflect AI when the real data on the financial variables are unavailable. Therefore, future researchers may be able to bridge the gap in this chapter by improving their information base on the firm-specific AI.

In this chapter, the firm-specific AI is captured through the reported financial variables of the target. Ali & Shaker (2017) identify four alternative measures to capture company transparency: (1) the CIFAR index, (2) the Dipiazz and Eccles's transparency model; (3) the Bushman, Piotroski, and Smith's transparency model; and (4) the Standard and Poor's transparency model. the S&P methodology is used here to capture AI. The calculation methodology is as follows: every company in the sample that made the financial, non-financial, management, and ownership declaration received a score of 1 so that the total possible score was equal to the number of disclosures. The principal component of the scores for each company is used as a proxy for AI. On average, 65% of the target firms did not report any parameter that reflect their (1) profitability (ROI, ROC, ROE, ROA, return on working capital (ROWC), profit margin, earning per share, and growth of profit margin), (2) efficiency (operating margin, and growth of operating margin), (3) liquidity (quick ratio, price to sales ratio, price to book ratio, price-earnings ratio, current ratio, and cash ratio), or (4) leverage ratio (debt to equity, debt to asset, and debt to capital). Also, 65.84%

of the targets did not report the ownership structure of their company (Chemmanur et al., 2009), 84.80% did not report their analyst's recommendation (Li et. al., 2019), and 80.01% did not report numbers related to their accrual variables (Thomson & Kim, 2020). In the following sub-section, the essay describes the methodology of the empirical model.

3.4.2. Empirical Model

In the data section, I identified the proxy variables that capture the presence of AI. In this section, I use principal component analysis (PCA) (Bharath et al., 2009) to measure the degree of AI in every M&A deal using the above-mentioned proxy variables. I then used propensity score matching (PSM) (Petrova and Shafer, 2010) to capture the effect of screening mechanisms (non-cash payment, and termination fee) and advisory services firms (financial and legal advisory service companies) on M&A deal performance for a given level of inherited AI in a deal and the characteristics of the acquiring firm.

A. Principal Component Analysis (PCA):

The lack of disclosure is tantamount to the presence of AI. AI exists when the target firm fails to disclose information. There are many target-specific AI variables to consider: (1) profitability (e.g., ROI, ROC, ROE, ROA, return on working capital (ROWC), profit margin, earning per share, or growth of profit margin); (2) efficiency (e.g., operating margin, or growth of operating margin). The third is its liquidity (e.g., quick ratio, price to sales ratio, price to book ratio, price-earnings ratio, current ratio, and cash ratio); (4) leverage ratio (e.g., debt to equity, debt to asset, and debt to capital); (5) Sixth is the ownership structure of the target; (6) analysts' recommendation about the target; and (7) information on target's accrual variable. An AI-related variable that is economy-related is the Presence of a recession. Deal specific AI variables include the size of the M&A deal, hostile nature of the deal, same industry, same country, and percentage of previously owned share in the target's company

Since many of the variables presented above probably are correlated, principal component analysis (PCA), can be used as an index of *p*-dimensional information (*p*-parameters) to reduce the dimension of the data, preserve the maximum variation of the data, and reduce multicollinearity. Hence, the proxy variables above are used (as there is no direct measurement of AI) to capture AI in M&As. It is denoted by an *n*p* matrix $\boldsymbol{X}_{n*p} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \dots \dots \dots . . \boldsymbol{x}_p]$.

The observed values of the proxy variables $(\boldsymbol{x}_i)$ are then transformed into the vector of weights $\boldsymbol{U} = [u_1, u_2, \dots \dots \dots . . u_p]$, which map each component of matrix $\boldsymbol{X}$ (i.e., each $\boldsymbol{x}_i$) to a new component $\boldsymbol{Z} = [\boldsymbol{z}_1, \boldsymbol{z}_2, \dots \dots \dots . . \boldsymbol{z}_p]$ such that

$$\boldsymbol{Z} = \boldsymbol{X}\boldsymbol{U}, \tag{34}$$

and

$$\boldsymbol{U}'\boldsymbol{U} = 1. \tag{35}$$

Therefore, the *i*th component $\boldsymbol{z}_i$ has an orthogonal relationship with is the first *i-1* components, accounting for a maximum possible variance of $\boldsymbol{X}$. The factor loading matrix, which is the correlations between the original variables $\boldsymbol{X}$ and the components/factors $\boldsymbol{Z}$, are then derived. These are denoted as $F = corr(X, Z)$" (Katchova, 2021). Finally, factor rotation, which involves the rotation of the factor loadings matrix, is conducted. This structure helps to interpret the clusters of variables that are highly correlated with a particular factor. Therefore, factor components are named after the set of variables they are most correlated with. For simplicity and completeness of the analysis, only a specific number of factors can be incorporated in the final analysis, known as "Factor Retention" (Braeken, & Van Assen, 2017). Therefore, with that, finally, this chapter finds the factors that capture different dimensions of AI in M&A deals, which will be used in the next section.

B. Propensity Score Matching (PSM):

Some acquirers opt for advisory service firms while others don't. Similarly, few acquirers choose to include screening mechanisms in their M&A contracts, and others don't. In this essay, to measure the impact of hiring advisory service firms on the profitability of the acquirer, screening mechanisms are included in the M&A contracts. However, since there might exist a structural difference between firms that do and firms that do not include such mechanisms, it is hard to compare the outcomes of these two groups directly. Therefore, an appropriate methodology is needed to select two samples from the pool of M&A observations such that the characteristics of these two samples match as much as possible. The only difference between these two samples is the application of the screening mechanism. When one sample has implemented any of the screening mechanisms, the other sample has not. Therefore, having two similar characterlike samples makes it easier to compare the impact of the advisory service firms (and screening mechanisms) on the performance of the acquirers from the M&As. Propensity score matching is a valuable technique to address such a scenario.

The M&A observations are assigned to two groups: the group which hired advisory service firms or implemented any of the screening mechanisms (non-cash payment, termination fee, advisory service firms) is called the treatment group, while the control group is comprised of firms that did not. Variable D is a binary variable (also called a treatment variable) that determines if the acquirer hired a screening mechanism (non-cash payment, termination fee, advisory service firms) or not. D assumes value 1 for treated observations (i.e., for the acquirers who used a screening mechanism) and D = 0 for control observations (i.e., for the acquirers who did not use any screening mechanism).

A logistic regression model is estimated for the propensity of observations to be assigned to the treated group. $\boldsymbol{X}$ is the vector of explanatory variables that explains the performance of the acquirer in an M&A. At the same time, $\boldsymbol{X}$ explains the condition of hiring an advisory service firm or implementing a screening mechanism. The $\boldsymbol{X}$ vector includes the financial condition of the acquirer, and the inherent AI in an M&A (captured through the principal components in the previous section). The top four principal components are included to incorporate intrinsic AI (from the previous section), and the pre-hiring characteristics of the acquirer that include solvency (long-term borrowing to total liability), efficiency (asset turnover ratio), leverage (assets to equity ratio) and liquidity (current ratio) of the acquirer.

Therefore, the predicted probability of implementing a screening mechanism or hiring an advisory service firms can be written as $\widehat{p(x)} = prob\ (D = 1|x)$. It can also be expressed as the odds ratio: $log[p/1 - p]$. The predicted probabilities ($\hat{p}$) or the conditional probabilities of hiring an advisory service firms given the pre-hiring characteristics (X), is then obtained. With $\hat{p}$ estimated for every observation, instead of matching on the pre-hiring characteristics X individually (inherent AI of the M&A deal, acquirer's solvency, efficiency, leverage, liquidity), the observations of the treated and the control group can be matched based on propensity score $\hat{p}$. The goal is to find the best possible match for each of the treated observations.

Various matching methods can be used to match the observations from the treated group to the control group based on their propensity scores. These include the kernel, nearest neighbor, and stratification methods. In this essay, the one-to-one nearest neighbor matching is used. It is the most intuitive matching approach used in the p-score literature. For each treated observation i, a control observation j is selected which has the closest X value. Therefore, the objective is to minimize the distance between treated observation and control observations, which can be defined as: $min\, ||p_i - p_j||$ (36)

However, alternatively, the Kernel matching approach is used. In this approach, each observation i from the treated group is matched with many observations from the control group, with weights that are inversely proportional to the distance between treated and control observations. This can be defined as:

$$w(i,j) = \frac{K(\frac{p_j - p_i}{h})}{\sum_{j=1}^{n_0} K(\frac{p_j - p_i}{h})} \quad (37)$$

where h is the parameter of the bandwidth. This procedure matches a treated firm to the single control firm with the similar propensity score. Hence, the absolute value of the difference between the treated and control's propensity is minimized. The objective of this procedure is "local minimization of the difference in propensity scores" (Petrova and Shafer, 2010).

C. Treatment effects:

Finally, the treatment effects are calculated. That is, the impact of hiring an advisory service firm or implementing screening mechanisms in an M&A contract is derived by comparing the post-M&A performance of the acquirer. Performance is measured as follows: Y = acquirer profit margin = (net sales $-$ cost of sold good)/ net sales)). Then this performance parameter is compared between the treated and control observations. Therefore, assuming y_1 as the post-M&A profit of an acquirer from the treatment group, and y_0 is the profit of a matched acquirer from the control group, mathematically, it can be expressed as:

$$y = \begin{cases} y_1 \; if \; D = 1 \\ y_0 \; if \; D = 0 \end{cases} \quad (38)$$

The average treatment effect (ATE) is the performance (profit of the acquirer) difference between the treated acquirers and control acquirers, which can be expressed as:

$$ATE = E(y_1 \mid p(x), D = 1) - E(y_0 \mid p(x), D = 0) \tag{39}$$

A simple t-test on the difference between the outcomes for the treated and control groups can be applied to find the significance of incorporating screening mechanisms or hiring advisory service firms. Empirically each treated observation i is matched to j control observations and their outcomes y_0 are weighed by w, which can be expressed as:

$$\frac{1}{n_1}\sum_{i\in\{D=1\}}[y_{1,i} - \sum_j w(i,j) y_{0,j}] \tag{40}$$

The methodology described above is used to generate the empirical result in the section that follows.

3.5. Empirical Result

This section is divided into two parts. The first part measures the degree of asymmetric information in a deal using principal component analysis. The second part estimates the impact of the screening mechanism (non-cash payment, termination fee) and advisory service firms on the performance (profitability) of the acquirer using propensity score matching.

3.5.1. Measurement of Asymmetric Information

There are different dimensions of asymmetric information, namely target-specific AI, deal-specific AI, and economy's AI (defined above). Each form of AI has its sub-measures (Table 3.1) that are represented by a collection of variables. A correlation matrix is developed (Table 3.2). A high correlation between the variables implies the appropriateness of using PCA. Further, the Kaiser-Meyer-Olkin (KMO) test is used. It reveals how much variation of the variables could be explained by underlying principal components. A high value (here it is 0.85; Table 3.6) implies the PCA is justified (Child, 1990). For the visual representation, a scree plot (Figure 3.1) is used to determine the number of relevant components for the analysis.

Following these checks, the principal components are calculated (Table 3.3). This is performed using the sub-measures of each type of AI. The derived components are rotated to introduce the orthogonality in the parameters that reduce the multicollinearity (Table 3.4). This procedure leads to a sequence of loadings (Issah and Antwi, 2017) (Figure 3.2). The principal components that capture the maximum variability (Table 3.5) of the underlined AI parameters are considered for the next phase of analysis. This methodology leads to filtering four principal components that I have used in the second part of the analysis for propensity score matching.

3.5.2. Impact of Advisory Services on Asymmetric Information

Table 3.7 presents the results of propensity score matching analysis, i.e., the difference between the performance (profitability) of an acquirer which incorporates a screening mechanism and those that do not. It is found that acquirer firms that use advisory service firms have a higher profit margin after one year of the M&A, compared with similar acquiring firms which did not use hire any advisory service firms. This is evidenced by the positive and statistically significant (at the 10%, 5%, and 1% level of confidence interval (C.I)) difference in the estimated means of acquirer's profit. The nearest neighborhood matching, kernel matching, and stratification matching were used in the analysis.

The results that were derived in this chapter are as follows. First, results show that treatment group acquirer firms have a profit margin that is on average 906 points higher (4564 points higher when using the nearest neighborhood matching, at a 10% level of C.I) than similar control group acquirers, using the kernel matching method. Second, it is also found that acquirer firms that use financial advisory service firms have a similar impact on their performance and have a profit margin that is on an average 657 points (using the kernel matching method) higher than the higher their counterpart (636 points, when using the stratification matching method). Third, though the above two findings hold at a 10% level of C.I, the impact of legal advisory service firms holds at a 1% level of C.I. Treatment group acquirer firms (using the kernel matching method) have a profit margin that is on average 77.94 points higher (74.37 points higher when using the stratification matching, and 120 points when using nearest neighborhood matching (at 5% C.I)) than similar control group acquirers. Hiring both financial and legal advisory service firms lead to on average a profit of 650 points higher (using kernel matching method, at 10% C.I) for the treatment group acquirers compared to the control group acquirers (596 points higher using stratification matching, at 10% C.I).

Finally, the result shows that implementing screening mechanisms in an M&A agreement (non-cash payment and termination fee) has no impact on the performance of the acquirer. Therefore, it can be concluded that advisory service firms not only help the acquirers to incorporate different screening mechanisms, but they add real value through different other dimensions (for example choosing a better target, price negotiation, and due diligence) that help acquirers to navigate through the AI in an M&A deal.

3.5.3. Further Study

This essay demonstrates a few interesting findings related to AI and advisory service firms and their impact on the acquirer's performance. However, due to the limitation in data, this essay falls short in presenting a holistic approach to measure the performance of the acquirer. The profitability of the acquirer as the performance measurement parameter is considered here. However, there are several other quantitative and qualitative measures of performance. For example, increased market share, higher price-power, better supply chain, and reduced competition are a few other dimensions of measuring performance. A holistic way to measure performance is considering both the long-term and short-term performance of the acquirer.

Therefore, an interesting extension of this research could be measuring the impact of advisory service firms on different dimensions of performance. Moreover, this chapter has considered the S&P methodology to measure the AI index. Country-specific AI using the transparency index and its impact on performance is also an interesting dimension to explore. This chapter only partially considered firm-specific AI, whereas the managerial information of the target, credit rating, and history of the target are a few other aspects of a company that might contribute towards the AI. It is challenging to capture those aspects of a company. However, having a good data source might help to improve the AI index. Finally, a better source of information regarding the screening mechanisms (earnout data, exchange ratio, purchase price working capital adjustment, no-shop clause) that the acquirer used in its M&A contract, gives a complete understanding of all types of screening mechanisms on the M&A performance.

3.6. Summary and Conclusion

This essay identifies three different dimensions of asymmetric information in M&A, namely, company-specific AI, deal-specific AI, and macro-economic-related AI. To navigate through a deal that involved AI, screening mechanisms are important to make better and more informed decisions. This essay identifies such screening mechanisms in M&As: hiring financial and legal advisory service firms, non-cash payment for the deal, and incorporating a clause of termination fee in the agreement. Therefore, to theoretically conceptualize the impact of the screening mechanisms on the performance of an M&A deal in the presence of AI, an adverse selection model is used. The model demonstrates that hiring advisory service firms improves the profitability (performance) of the acquirer. This conceptual model is also empirically tested using

Blomberg M&A data. Principal component analysis (PCA) is used to index the identified sources of AI. Propensity Score Matching (PSM) is then used to compare the impact of screening mechanisms on the profitability (performance) of the acquirer for a given level of AI.

It is found that employing advisory service firms has a significantly positive impact on the profitability (performance) of an acquirer. Treatment group acquirers (those that hired a financial and/or legal advisory service firms) have a profit that is 600 points higher, on average, compared to a control group acquirer (those that did not). Though, other screening mechanisms (non-cash payment and termination fee) do not have significant impacts on deal performance, when advisory service firms are not hired. Therefore, advisory service firms effectively improve the performance of the acquirer. Hitherto, the literature had not addressed this issue.

However, due to data limitations, this essay does not get into the granularity of the analysis and encourages future researchers to pay more attention to this topic. This essay fails to cover the impact of individual screening mechanisms to improve each type of AI. For example, how many cross-industry and cross-country M&As are financially successful if a financial or legal advisory service firm is hired as a screening mechanism viz-a-vis not hired. Data reveals that only 15% of the M&A involved either a legal or a financial advisor, out of which only 7% are cross-country M&A. Given the limited number of observations for each sub-category of AI and for each type of screening mechanism, it was difficult to generate reliable and consistent results to answer this question. Future researchers are encouraged to try to address this gap.

APPENDIX

APPENDIX

Figure 3.1: Scree Plot of the Eigenvalues of Factors or Principal Components

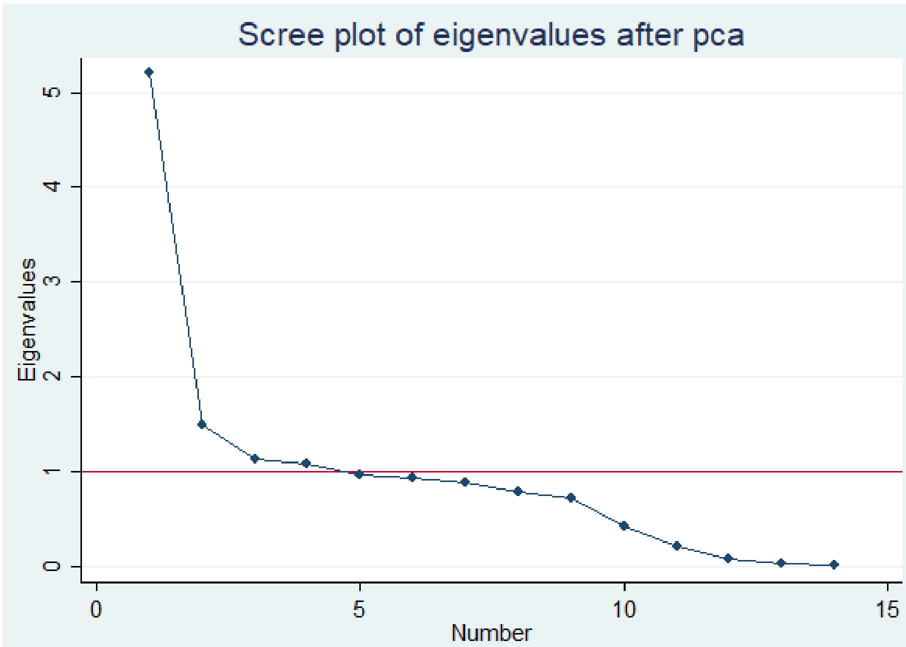


Figure 3.2: Scatter Plots of the Loadings and Score Variables

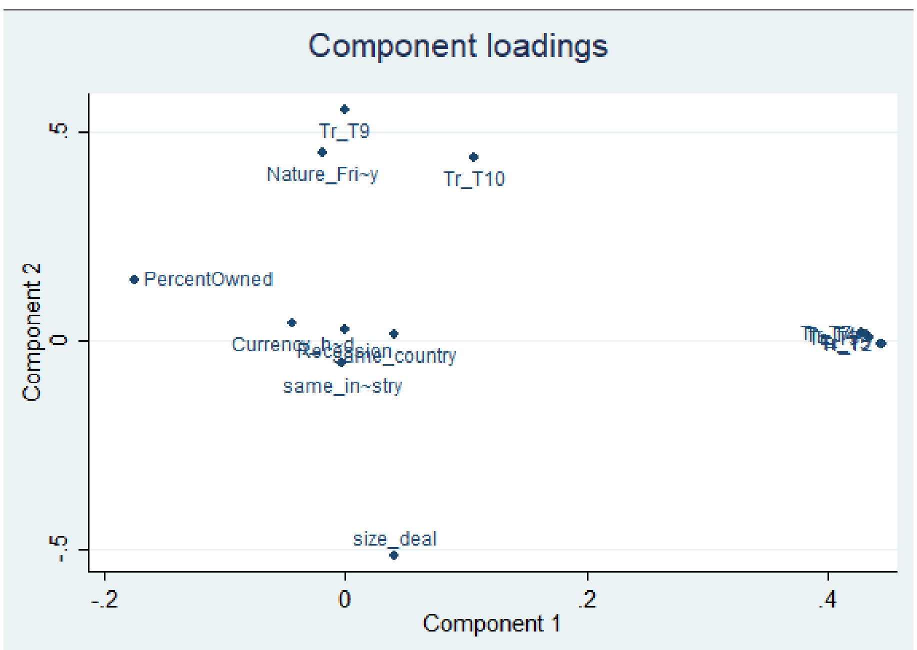


Table 3.1: Summary Statistics

Dimensions of AI	Proxy Variables to Capture AI	No. of Obs.	Mean	Std. Dev.
Economy Specific AI	Presence of Recession in Target's Country	26,825	0.21	0.41
Deal Specific AI	Size of the Deal (in Million $)	13,492	303	2560
	Type of Currency in Payment	26,825	0.72	0.45
	Nature of Deal (Friendly or Hostile)	13,851	0.99	0.08
	Shares of Target, Owned by Acquirer (in %)	26,825	5.42	17.88
	Same Industry	24,569	0.34	0.47
	Same Country	25,984	0.62	0.49
Target Specific AI	Target's Reporting of Solvency	26,825	0.75	0.43
	Target's Reporting of Profitability	26,825	0.60	0.49
	Target's Reporting of Efficiency	26,825	0.62	0.49
	Target's Reporting of Leverage	26,825	0.62	0.49
	Target's Reporting of Liquidity	26,825	0.67	0.47
	Target's Reporting of EPS	26,825	0.74	0.44
	Target's Reporting of Ownership Structure	26,825	0.66	0.47
	Target's Reporting of Assets Under Management	26,825	1.00	0.06
	Target's Reporting of Analyst Recommendation	26,825	0.85	0.36
	Target's Reporting of Accruals	26,825	0.80	0.40

Table 3.2: Correlation Matrix

Dimensions of AI	Proxy Variables to Capture AI	Presence of Recession in Target's Country	Size of the Deal (in Million $)	Type of Currency in Payment	Nature of Deal (Friendly or Hostile)	Shares of Target, Owned by Acquirer (in %)	Same Industry	Same Country
Economy Specific AI	Presence of Recession in Target's Country	1						
Deal Specific AI	Size of the Deal (in Million $)	-0.0184	1					
	Type of Currency in Payment	-0.0257	0.0511	1				
	Nature of Deal (Friendly or Hostile)	0.0188	-0.27	-0.0233	1			
	Shares of Target, Owned by Acquirer (in %)	0.0889	-0.0306	-0.1377	0.0081	1		
	Same Industry	0.0605	0.0212	0.0283	-0.0115	0.001	1	
	Same Country	0.0424	-0.0509	-0.0448	0.031	0.0285	0.0122	1

Table 3.2 (cont'd)

Dimensions of AI	Proxy Variables to Capture AI	Same Industry	Same Country	Target's Reporting of Profitability	Target's Reporting of Efficiency	Target's Reporting of Leverage
Target Specific AI	Target's Reporting of Profitability	0.0035	0.0226	1		
	Target's Reporting of Efficiency	0.0001	0.019	0.9322	1	
	Target's Reporting of Leverage	-0.0036	0.0378	0.8896	0.8794	1
	Target's Reporting of Ownership Structure	-0.0108	0.0309	0.8793	0.8645	0.967
	Target's Reporting of Analyst Recommendation	0.012	0.017	0.2632	0.278	0.2936
	Target's Reporting of Accruals	0.0255	0.0301	0.4198	0.4292	0.4585

Table 3.2 (cont'd)

Dimensions of AI	Proxy Variables to Capture AI	Presence of Recession in Target's Country	Size of the Deal (in Million $)	Type of Currency in Payment	Nature of Deal (Friendly or Hostile)	Shares of Target, Owned by Acquirer (in %)
Target Specific AI	Target's Reporting of Profitability	-0.0117	-0.1424	0.0277	0.1543	-0.3127
	Target's Reporting of Efficiency	-0.0116	-0.1389	0.0403	0.1666	-0.3138
	Target's Reporting of Leverage	-0.001	-0.1282	0.0552	0.1349	-0.2608
	Target's Reporting of Ownership Structure	-0.0011	-0.1287	0.0557	0.1378	-0.2701
	Target's Reporting of Analyst Recommendation	0.0265	-0.2416	0.0445	0.1907	-0.0659
	Target's Reporting of Accruals	0.058	-0.1987	0.096	0.1587	-0.0844

Table 3.3: Eigen Values of Principal Components (Unrotated)

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	5.20022	3.7011	0.3714	0.3714
Comp2	1.49912	0.362218	0.1071	0.4785
Comp3	1.1369	0.049379	0.0812	0.5597
Comp4	1.08752	0.124114	0.0777	0.6374
Comp5	0.963405	0.020355	0.0688	0.7062
Comp6	0.94305	0.054476	0.0674	0.7736
Comp7	0.888574	0.105323	0.0635	0.8371
Comp8	0.783251	0.066321	0.0559	0.893
Comp9	0.71693	0.29258	0.0512	0.9442
Comp10	0.42435	0.204778	0.0303	0.9745
Comp11	0.219573	0.138818	0.0157	0.9902
Comp12	0.080754	0.048509	0.0058	0.996
Comp13	0.032245	0.008127	0.0023	0.9983
Comp14	0.024118	.	0.0017	1

Table 3.4: E**igen Vectors of Principal Components**

Dimensions of AI	**Variable**	**Comp1**	**Comp2**	**Comp3**	**Comp4**	**Unexplained**
Economy Specific AI	Presence of Recession in Target's Country	-0.001	0.18	-0.17	0.62	0.48
Deal Specific AI	Size of the Deal (in Million $)	-0.09	-0.51	0.07	0.24	0.49
	Type of Currency in Payment	0.03	-0.11	0.69	0.09	0.41
	Nature of Deal (Friendly or Hostile)	0.09	0.43	-0.07	-0.25	0.59
	Shares of Target, Owned by Acquirer (in %)	-0.15	0.29	-0.29	0.13	0.62
	Same Industry	0.001	0.01	0.14	0.62	0.55
	Same Country	0.02	0.13	-0.35	0.22	0.77
Target Specific AI	Target's Reporting of Profitability	0.42	-0.12	-0.11	0.001	0.05
	Target's Reporting of Efficiency	0.41	-0.11	-0.08	-0.002	0.08
	Target's Reporting of Leverage	0.41	-0.09	-0.07	0.04	0.08
	Target's Reporting of Liquidity	0.42	-0.12	-0.10	0.001	0.06
	Target's Reporting of Ownership Structure	0.41	-0.09	-0.07	0.03	0.10
	Target's Reporting of Analyst Recommendation	0.18	0.47	0.33	0.03	0.36
	Target's Reporting of Accruals	0.25	0.35	0.29	0.12	0.36

Table 3.5: Rotation: Orthogonal Varimax (Kaiser off)

Component	**Variance**	**Difference**	**Proportion**	**Cumulative**
Comp1	4.84	3.05	0.34	0.34
Comp2	1.79	0.60	0.12	0.47
Comp3	1.18	0.08	0.08	0.55
Comp4	1.10	.	0.07	0.63

Table 3.6: Kaiser-Meyer-Olkin Measure of Sampling Adequacy

Dimensions of AI	Variable	KMO Estimate
Economy Specific AI	Presence of Recession in Target's Country	0.5603
Deal Specific AI	Size of the Deal (in Million $)	0.7738
	Type of Currency in Payment	0.5775
	Nature of Deal (Friendly or Hostile)	0.7961
	Shares of Target, Owned by Acquirer (in %)	0.9076
	Same Industry	0.4573
	Same Country	0.6103
Target Specific AI	Target's Reporting of Profitability	0.8521
	Target's Reporting of Efficiency	0.9626
	Target's Reporting of Leverage	0.8357
	Target's Reporting of Liquidity	0.8479
	Target's Reporting of Ownership Structure	0.8372
	Target's Reporting of Analyst Recommendation	0.7668
	Target's Reporting of Accruals	0.8504
	Overall	0.8567

Table 3.7: Impact of Advisory Services and Screening Mechanisms on the Performance of M&As

Type of Mechanism			Type of Matching Method		
			Nearest Neighborhood Matching	**Kernel Matching**	**Stratification Matching**
Mechanisms to reduce AI	Any Screening Mechanism (Legal Adviser/ Financial Adviser/ Non-cash payment / Termination fee)		34.04 (0.583)	26.04 (0.564)	29.43 (0.64)
	Advisory Service	Any Advisory Service - Legal / Financial	4564* (1.83)	*906** (1.74)	1458 (1.54)
		Legal	120** (2.00)	77.94*** (4.23)	74.37*** (4.66)
		Financial	1412 (1.09)	657* (1.727)	636* (1.73)
		Both of Financial and Legal Adviser	1252 (0.93)	650* (1.71)	596* (1.86)
	All other Screening Mechanism – (Non-cash Payment / Termination Fee) without any Advisor		-81 (-1.17)	-*63* (-1.17)	-45 (-0.77)

CHAPTER 4: ESSAY 3: PREDICTING ACQUIRERS IN FOOD AND AGRI-BUSINESS INDUSTRY MERGERS AND ACQUISITIONS

4.1. Introduction

Mergers and acquisitions (M&As) are a common strategy for achieving corporate growth and performance objectives, especially in the food and agribusiness industry (FABI). As discussed in earlier essays, most M&A deals involve two companies: (a) the acquire (or buyer), and (b) the target (or seller). Most acquisitions tend to be intra-industry, not inter-industry. However, the trend is increasingly shifting toward inter-industry transactions. Also, the incidence of cross-border and cross-industry M&As (versus single country or single industry) is steeply growing in the food sector, especially over the past decade (Food Processing, 2021). Industry trends show that food firms are taken over by other food firms seeking to strengthen themselves in specific production, supply chain, or marketing areas (Tan, et al., 2012). For example, in the first quarter of 2021, there were about 50 cross-border M&A deals in the global food and agribusiness industry (GFABI), 25 of which involved European firms or $100 million in value. Some 11 cross-border M&A deals involved North American firms, or ($16 million in value). The Asia-pacific region, as well as the Middle East & Africa, experienced 5 and 3 transactions, for a total of $210 million in value. (Figure 4.1).

Cross-industry M&A deals are also growing rapidly in the GFABI. Private equity (PE) and investment banks (IB) have invested nearly $20 billion in food companies since 2013 (Food Processing, 2021). The number of M&A deals implemented by private equity firms (PEs) in the food industry doubled from 223 deals in 2015 to 459 in 2017 (Fung, 2019). IT and technology firms are also increasingly acquiring food firms. Investments by tech companies in the GFABI increased from $60 million in 2008 to $1 billion in 2015 (Fung, 2019). Acquiring firms are not just acquiring food companies; they are also investing in brands, bringing funds, and introducing new ideas related to products, packaging, marketing, distribution, and retail assortment building (Fooddive, 2019). In 2017, of the total of 14196 GFABI M&As in the USA, 640 (4.5%) involved the food industry. Of the 640 M&As involving the FABI, 437 involved agricultural chemicals, 43 involved food services, 143 involved agriculture, and 123 involved beverages (Bloomberg, 2018). Similarly, investment banks acquired some 150 food firms from 2009 to 2017 and the growth rate is growing significantly.

The global market for seed, agri-chemicals, food manufacturing, retail and wholesale activities are already dominated by a handful of transnational corporations (TNCs). The most frequent acquirers in the food industry are Nestle (76 acquisitions in the last 30 years), Cargill (69 acquisitions), Anheuser-Busch (66 acquisitions), Koninklijke (66 acquisitions), Sysco (63 acquisitions), Archer-Daniels (61 acquisitions), Carrefour (56 acquisitions), Coca-Cola (56 acquisitions), Danone (53 acquisitions), Orkla (52 acquisitions), Compass group (50 acquisitions), Heineken (50 acquisitions), Kraft Heinz (50 acquisitions), Unilever (50 acquisitions), Kerry (49 acquisitions), Bunge (49 acquisitions), Hain Celestial (47 acquisitions), Abi Sab Group (46 acquisitions), Cadbury (46 acquisitions), PepsiCo (45 acquisitions). These dominant players often face competition in M&A by other leading players, for example, ConAgra Foods, Smithfield Foods, General Mills, Post Holdings, Michael Foods, Koch Foods, Lactalis American Group Inc., H. P. Hood Inc., Land O'Lakes, Dairy Farmers of America, Agropur Cooperative, Constellation Brands, Great Lakes Cheese Co., Tree House Foods and Maple Leave Foods. Selected recent mega M&A deals in the food industry by these leading acquirers and their approximate values are listed below.

Table 4.1: List of Mega M&A Deals in the Food Industry

Acquirer	Target	Value of the M&A	Year of Acquisition
H. J. Heinz Co.	Kraft Foods Group	$45 Billion	2015
Cutrale Group and Safra Group	Chiquita Brands International Inc.	$1.3 Billion	2014
Annie's Inc	General Mills Inc.	$820 Million	2014
Thai Union Frozen Products	Bumble Bee Seafoods	$1.5 Billion	2014
Post Holdings Inc.	MOM Brands Co.	$1.15 Billion	2015
Hershey Co.	Krave Jerky	$218.7 Million	2015
Hershey Co.	Allan Candy Co.	$28 Million	2014

Seed and agri-chemical industries also exhibit a similar trend. The prominent players in the seed and agri-chemical industry are Monsanto, Dow, Dupont, Bayer, Syngenta, and BASF. The agribusiness industry is also hitting the record of multi-billion-dollar acquisitions. Some of the large M&A deals that took place in the last decade are listed below in order to preliminarily illustrate the characteristics of the most frequent acquirers.

Table 4.2: List of Mega M&A Deals in the Agri-business Industry

Acquirer	Target	Value of the M&A	Year of Acquisition
China National Chemical Corporation	Syngenta	$43 Billion	2017
Dow Chemical Company	DuPont	$1.3 Billion	2017
Bayer	Monsanto	$63 Billion	2018

Looking at the above M&A trend, it might look like the big food companies have purchased other food companies. However, a closer observation reveals that relatively smaller companies have also purchased proportionately large companies (e.g., Bayer acquired Monsanto) as well.

Therefore, when the size of a company is one of the critical parameters that make a firm more likely to acquire a food company, it is not the only parameter. Inherent characteristics of a smaller company can make it a more probable acquirer than a big company. Furthermore, due to the increasingly global and inter-industry nature of M&A deals, it is becoming very difficult to predict which firms will be the next acquisition target or acquirer. More importantly, the literature on the prediction of firms that will be involved in M&A activities has mostly focused on predicting who the target firm will be, not the acquirer. Tunyi (2020) pointed out four major categories of this research from the perspective of historical development. He showed that the "common characteristics of the target captured by the financial ratios were the features of the M&A prediction in the first era (1968–1985). The second era investigated the hypotheses of target prediction (1986–2002). Studies in the third era (2003–2009) used alternative modeling techniques". These studies from the second and third eras "concluded that it was impossible to build a successful investment strategy around takeover target prediction". The "implication of M&A predictability on share valuation, governance and bond prices" was studied in the fourth era (2010–2018) exhibited that the "takeover prediction can lead to abnormal returns". For example, Adelaja, Nayga, and Faroog (1999) developed and estimated a model for predicting the likelihood that a firm will be targeted and the likelihood that a targeted firm would actually be taken over or merged with. Other research (Young et al., 2014; Wei et al., 2008) proposed a technology-driven M&A prediction where technological indicators of the acquirer and the target were used as independent variables, selected from the patent documents.

To date, the extant literature has not addressed the characteristics of firms that become acquirers. In an industry where M&As are becoming more complex (cross-industry and cross-border acquisition), it has become very important for industry players and experts to be able to better predict the likelihood of a firm becoming an acquirer. This information is valuable to investment banks as it would improve their ability to predict their clients. It is also important to target companies as the probability that the deal will go through depends on who the acquirer is. For intra-industry acquirers, this information is also useful in determining who the potential competitive acquirers would be. The question in this essay is, therefore "Do certain characteristics of a company make them more prone to acquire an existing food company?" Early identification of likely buyers and sellers has been an issue of interest to researchers for several decades.

In this chapter of the dissertation, I present my third essay, which seeks to explain which firms are likely to become acquirers in the global food & agri-business industry. M&As in GFABI has steadily increased in the last few decades (Kreiter, FoodInstitute, 2021). This essay attempts to find the key characteristics of these firms that are highly likely to take over a food company. If indeed M&A activities are predictable, information obtained from predictive models could be helpful to policymakers, academics, and most importantly, investment bankers, advisory service companies, and individual investors. Policymakers concerned about the degree of competition, industry concentration ratios, and prices paid by consumers, can proactively develop policies and strategies. At the same time, academicians can better understand M&A activities and provide independent advice to the private and public sectors and enrich the literature as well. Corporate leadership in vulnerable companies who prefer to remain independent and desire protection from becoming targets can use this information in predicting the probable acquirer and may use the information to prevent their actual takeover.

On the other hand, information uncovered by this research revealed that food start-ups need a better understanding of the characteristics of acquirers as they are often cash strutted and look forward to being acquired by a big firm. Investment bankers and lenders will find predictive models helpful in identifying possible acquiring firms and developing loans and other financial strategies to support their clients. Similarly, financial legal advisory companies involved in the M&A process can pitch their service to the most probable clients. Furthermore, individual investors can also minimize their expected risk from knowing in advance about probable acquirers. Identification of the acquiring firms' general characteristics will help to predict the probable acquirers interested in food firms. The literature will guide through this process in the following section.

4.2. Literature Review

An extensive review of academic literature conducted as part of this dissertation research provides some basis for several hypotheses for predicting which firms have a propensity to acquire another firm or be acquired. This literature also advanced ideas about key indicators and firm characteristics of acquirers and targets. These characteristics are useful in predicting future M&A prospects. For example, some scholars have suggested that differentials in financial characteristics between targets and non-targets are key drivers of M&A activity. Researchers have also suggested that a target and an acquirer are matched based on their characteristics.

For example, the extant literature showed that US acquirers have characteristically “higher financial leverage, lower profit margin, high liquidity, and slow growth” (Simkowitz and Monroe, 1971; Palepu, 1986; Adelaja, 1999) in comparison to their targeted firms. However, targets are characterized by high liquidity and capital widening (Li Shanmin, 2003). Other than the above firm-specific characteristics, the following non-firm forces also drive the merger process (Wasserstein, 1998): (1) technological change, (2) fluctuations in financial markets, (3) tax incentives, and (4) the tension between scale and focus. Many scholars also did non-experimental research where they found that (1) the operation of acquirers is far better than the target, (2) the average solvency level is higher for acquirers, and (3) the attractiveness of targets is higher than that of non-targets (Gao Jian and Chen Xinwei, 2000). “Managerial inefficiency resource richness, industry variations, and export orientation” are other possible motivations for M&As (Meador et al., 1996; Tsagkanos et al., 2007).

The variables that were frequently used in the M&A research to capture above mentioned parameters of a company are listed below. The asset-liability ratio variable is generally used to capture the solvency of a company. Profitability is measured by return on assets, return on equity, return on investment, and profit margin (Meador et al., 1996; Pasiouras & Gaganis, 2007; Barnes, 2000; Tsagkanos et al., 2007; Ali-Yrkko et al., 2005). Sales to assets, cost of goods sold divided by inventory, and cost-to-income ratio measures the efficiency of a firm (Tsagkanos, 2007; Pasiouras & Gaganis, 2007). Leverage is measured by debt-to-equity, debt-to-assets, Total Tangible Assets divided by Equity, and capital-expenditures-to-total asset ratios (Ragothaman et al., 2003; Barnes, 2000; Pasiouras & Gaganis, 2007; Ali-Yrkko et al., 2005). Liquidity is captured by cash flow, current ratio, and shares traded to shares outstanding (Ali-Yrkko et al., 2005; Meador et al., 1996; Barnes, 2000; Tsagkanos et al., 2007). The attractiveness of a company is often captured by the price-to-equity ratio, and market-to-book-value ratio (or Tobin’s Q) (Ragothaman et al., 2003). Growth and Scale parameters are captured by firm size, and growth (Meador et al., 1996; Ali-Yrkko¨ et al., 2005; Tsagkanos et al., 2007). Tax effects (Song & Chu, 2006) and other tax variables are used to capture the tax incentives for an acquirer in an M&A.

In terms of predictive analysis, researchers have applied different methods to develop M&A prediction models. Logistic regression (Barnes et al., 2000; Ragothaman, 2003; Pasiouras & Gaganis, 2007) is the commonly used prediction method. However, though discriminant analysis, rule induction (Ragothaman et al., 2003), and decision tree (Tsagkanos et al., 2007) models were also used in some recent studies. Ye Ouyang and M. Hosein Fallah (2011) have applied Neural Networks and Logistic regression models to predict M&As in the telecom industry. Self-organized mapping (SOM) and Hopfield neural network is rarely used (Hongjiu et al., 2007) to predict the target of mergers and acquisitions. Shao et al. (2018) have used K-means clustering to capture “acquirer features, target features, and their relationship features”.

4.2.1. Gap in the Literature

Despite the vast prediction literature in M&As, none of the literature has predicted the acquiring firms. More specifically, the characteristics of the acquirers in the food industry have never been studied. At the same time, the literature has not highlighted the necessity of the acquirer prediction exercise in the M&A process. The existence of a wide variety of acquirers is very evident from previous M&A examples. However, how the characteristics of one type of bidder (probable acquirer) possibly influence its decision and strategy in the M&A process has never been discussed before. For example, does the abundance and mobility of liquidity of a PE firm possibly make it a more probable food-industry acquirer? Or, in the era of food-tech, is the technological inclination of the IT firms a more desirable quality in an acquirer, compared to a traditional intra-industry acquirer? The essay discusses the changing dynamics of the food industry acquirers in the following sections.

4.3. Theoretical Framework

At any phase of the business life cycle, a company’s health is determined by five major parameters, namely: solvency, efficiency, liquidity, profitability, and leverage (Corporate Finance Institute, 2022). These parameters are distinct at different phases of the business life cycle. However, these parameters have a unique relationship with the health of a company. For example, higher solvency and efficiency imply a lower business risk (Corporate Finance Institute, 2022), which implies better company health. Similarly, greater liquidity and profitability imply a lower degree of business risk. They also imply that a company's products or services have shown a positive value in the market (Corporate Finance Institute, 2022), which implies better company health. Therefore, a company's health is always positively related to Solvency (S), Efficiency (E), Liquidity (C), and Profitability (*P*). Whereas a higher Leverage (L) is an indicator of the poor health of a firm (Investopedia, 2021). Therefore, a company's health function (*H*) can be expressed in the following form:

$$H = H\,(S, E, C, P, L) \tag{41}$$

where $\partial H/_{\partial S} > 0, \partial H/_{\partial E} > 0\ \partial H/_{\partial C} > 0, \partial H/_{\partial P} > 0, and\ \partial H/_{\partial L} < 0.$

In mergers and acquisitions, a company's efficiency, and long-term profit are expected to witness certain growth. Therefore, the health of the company induced by efficiency and profit gets better off. Whereas, to finance the M&A deal, an acquirer uses its cash to pay off the target company. This reduces the liquidity of the acquirer, leading to a deterioration of the company's health. To finance the M&A, a company borrows from an investment bank. That increases the debt balance (leverage) of the company. As mentioned above, the leverage of a company is negatively related to the health of the company. For the simplicity of the understanding, I consider the post-M&A expected efficiency (E^e), liquidity (C^e), profitability (P^e), and leverage (L^e) of the firm in a probable M&A. Finally, a company's solvency may go up or down depending on the situation. Therefore, a particular relationship between the company's health with solvency can't be stated. Therefore, taking a total differentiation of equation (1), one obtains the following:

$$\partial H = \frac{\partial H}{\partial (S^e)} d(S^e) + \frac{\partial H}{\partial (E^e)} d(E^e) + \frac{\partial H}{\partial (C^e)} d(C^e) + \frac{\partial H}{\partial (P^e)} d(P^e) + \frac{\partial H}{\partial (L^e)} d(L^e) \tag{42}$$

In equation (2), the first term ($\frac{\partial H}{\partial (S^e)} d(S^e)$) on the right side of the equation is ambiguous. $d(S^e)$ represents the change in the expected solvency, which could be either positive or negative. Though, a solvent firm implies a healthier company. Therefore, $\frac{\partial H}{\partial (S^e)} > 0$, but $\frac{\partial H}{\partial (S^e)} d(S^e) \lesseqgtr 0$. The level of efficiency is expected to increase following an M&A event. Therefore, in the second term, $\frac{\partial H}{\partial (E^e)} d(E^e)$ is positive, as $\frac{\partial H}{\partial (E^e)}$ is assumed to be positive. Similarly, the expected long-term profit $d(P^e)$ also increases in an M&A. Therefore, the fourth term of equation (2) is also positive, as $\frac{\partial H}{\partial (P^e)} d(P^e)$ is assumed to be positive. However, the expected cash reserve goes down in an M&A. Therefore, $d(C^e)$ is negative. Liquidity has a positive relationship with the company's health. Therefore, even though $\frac{\partial H}{\partial (C^e)}$ is positive, the third term of equation (2), i.e., $\frac{\partial H}{\partial (C^e)} d(C^e)$ is negative. Finally, the fifth term of equation (2) is $\frac{\partial H}{\partial (L^e)} d(L^e)$. An M&A leads to an increase in debt balance. Therefore, dL is positive. However, leverage has a negative relationship with the health of the company ($\frac{\partial H}{\partial (L^e)} < 0$). Therefore, the fourth term also gives a negative value. From the above, a company that is getting into an M&A if the following condition holds:

$$\frac{\partial H}{\partial (S^e)} d(S^e) + \frac{\partial H}{\partial (E^e)} d(E^e) + \frac{\partial H}{\partial (C^e)} d(C^e) + \frac{\partial H}{\partial (P^e)} d(P^e) + \frac{\partial H}{\partial (D^e)} d(D^e) \geq 0 \qquad (43)$$

$$\Rightarrow \frac{\partial H}{\partial (E^e)} d(E^e) + \frac{\partial H}{\partial (P^e)} d(P^e) \geq \left|\frac{\partial H}{\partial (C^e)} d(C^e)\right| + \left|\frac{\partial H}{\partial (S^e)} d(S^e)\right| + \left|\frac{\partial H}{\partial (L^e)} d(L^e)\right| \qquad (44)$$

$$\Rightarrow \frac{\partial H}{\partial (E^e)} d(E^e) + \frac{\partial H}{\partial (P^e)} d(P^e) > \left|\frac{\partial H}{\partial (C^e)} d(C^e)\right| + \left|\frac{\partial H}{\partial (S^e)} d(S^e)\right| \qquad (45)$$

Equation (5) is derived by transferring all positive values on the right-hand side and the modulus of all negative and ambiguous values on the left-hand side. From equation (4) it can be said that a company will acquire another company if the total improvement in its health from the M&A event, induced by an increase in expected efficiency and profit, is strictly greater than the deterioration due to decreased liquidity and increased leverage.

4.4. Hypotheses

In this section, I sketch out some hypotheses, based on the theoretical framework in the previous section.

The first hypothesis is the *efficiency hypothesis*. Efficiency implies greater business stability and lowers business risk. A highly efficient firm has more flexibility to make business decisions as it is more trusted by its shareholders. Therefore, a highly efficient company is more likely to acquire another company to further improve its efficiency.

The second hypothesis is the *profitability hypothesis*. Higher profitability reflects a low risk of the business. But it also implies a company's positive value in the market. A highly profitable firm will likely be willing to expand through acquisition and make the business even more efficient and profitable. Also, a highly profitable firm is more likely to possess sufficient creditworthiness to borrow money from an IB for acquisition and would be more capable of paying it off.

The third hypothesis is the *liquidity hypothesis*. Liquidity ratios reflect the short-term solvency of a firm and relative cash richness. High liquidity is desirable in an acquirer since it connotes greater ability to pay.

The Fourth is the *leverage hypothesis*. An acquiring firm is usually expected to be less leveraged before the acquisition, especially if it is looking to borrow money to expand its operations (Lintner, 1971). However, depending on the industry of the acquirer, an acquiring firm could be more leveraged as well. For example, Private Equity (PE) firms' capitalization structure mostly will depend on the high equity and assets compared to the percentage of the debt.

The fifth hypothesis is the *Power Hypothesis.* It suggests a positive relationship between a firm's power and the likelihood of being an acquirer. The power of a company is two-fold. The relative size of a company, compared to its competitors, reflects its monopoly power. The price to earnings and book value to market ratios determines the attractiveness of the firm and the trust of the shareholders. Based on these, it is hypothesized that affordability for an acquisition increase with the power of the acquiring firm (Goldberg, 1983, Bierman & Hass 1970; Simkowitz & Monroe, 1971; Sudarsanam, 1995; Taussig & Hayes, 1968).

Finally, the sixth and final hypothesis is the Recession Hypothesis. It suggests that the acquiring firms are less likely to invest in M&As when the economy is in a recession and invest more when the economy moves away from the recession. However, this characteristic is highly correlated with the acquirer's industry and its liquidity condition (Bernanke, 1981). For example, PE firms are more likely to invest in the food industry when the economy is in a recession. It is assumed that the food industry is less vulnerable to recession compared to all other sectors. Thus, PE firms want to park some of their money in safe investment, with a moderate return.

In the rest of this chapter, the characteristics of probable acquirers in the food industry are used to predict those that would likely be acquired. An empirical framework is presented in the following section to test the hypotheses above.

4.5. Empirical Framework

Recall that this chapter focuses on predicting future acquiring firms in the food and agribusiness industry using different empirical models. In past studies, panel data regression models have been predominantly used in predicting target companies. This chapter makes a significant contribution to the literature on M&A prediction by focusing on acquiring firms in the food and agribusiness industry and their characteristics. Improved ability and/or framework for predicting potential acquirers is useful to target companies, investment banks, regulators, and other potential acquirers for strategic reasons.

4.5.1. Data

As discussed in essays 1 (chapter 2) and essay 2 (chapter 3), for all M&A activities involving publicly traded companies, the Bloomberg Mergers and Acquisitions Database (BMAD) provides data on non-financial variables for the acquirer, as well as several deal-specific indicators. This includes the identities of the acquirer and seller, the bid price, the date of the transaction, the industries and countries of both the acquirer and the seller, as well as acquirer and seller financial data. For the purpose of this analysis, data is needed not only on acquirers that were involved in M&A activities but also on companies that were not involved. The counterfactual data on the companies that were not involved in GFABI M&A activities is not available from BMAD. BMAD provides daily information on M&A activities from January 1988 to June 2018 (31 years) for all segments of the global economy, including the global agri-businesses and food industries (GABFI). In order to keep the data source consistent for acquirers and non-acquirers, an alternative data source is required to supplement the BMAD, specifically on financial indicators. Therefore, data on financial indicators for non-acquirers and acquires were collected from the Thomson Reuters Database (TRD). This database provides historical data on companies, which allows for more dynamic or continuous analysis. This supplemented the BMAD. As is the case with Essay 1 (chapter 2), the GABFI M&A database consists of 26,825 observations (transactions). This means 26,825 acquisitions, but fewer acquirers since some acquirers were involved in several acquisitions. Out of these transactions, about 69% involved cross-sector deals while about 38% involved cross-country deals (see Essay 1).

Some 55% of the intra-industry GFABI acquisitions took place in the food manufacturing sector alone. Note the following in terms of frequency: agriculture (18%), beverage industry (13%), and brewery industry (5%). In terms of the nature of the acquirers, those acquirers from the private equity, retail, finance, and distribution sectors (those not from GFABI) were prominent acquirers of GFABI firms. Private equity and retail industry acquirers held 14% of the inter-industry GFABI acquisitions, followed by the distribution industry (9%) and the finance industry (9%). For example, the most frequent private equity acquirers in the GFABI are Swander Pace Capital, Blackstone Group, HM Capital Partners, and Sun Capital Partners Inc (Bloomberg, 2018). Each of these private equity firms has acquired on an average 15 foods firms since 2007.

Recall that acquirer-specific characteristics are important explanatory variables. To capture these characteristics, the following factors are included as the explanatory variables in the regression: (1) solvency, (2) profitability, (3) efficiency, (4) liquidity, (5) leverage, and (6) attractiveness of the acquirer. Solvency is specifically proxied by the asset to liability ratio. Profitability and efficiency of the acquirer are specifically proxied by return on equity and asset turnover ratio, respectively. Liquidity and leverage are proxied by the cash ratio and total debt to total asset ratio, respectively. The attractiveness of the company is reflected by the price to equity ratio, which is used as its proxy. The above-mentioned variables are hypothesized to determine the probability of being a food industry acquirer.

Now, in terms of the data structure, TRD provides quarterly data on financial variables. Since an acquisition date can be anywhere between January 1 to December 31, the quarterly financial data from TRD had to be transformed to fit a consistent data structure. To achieve this, the TRD data is used to create the values of the explanatory variables. Specifically, for every acquisition, the previous year's financial data of each acquirer is utilized (1 year prior to the M&A deal). In essence, it is assumed that the acquisition decision of a company in a particular year can be sufficiently proxied by its financial indicators from the previous year (for both acquirers and non-acquirers).

The dependent variable is a binary choice variable which measures if a firm was an acquirer in a given year. If a firm acquired another firm from the GFABI sector in a given year, the variable takes on the value of 1. That is, the dependent variable takes on the value of 0 if the firm did not take over any GFABI firm in that given year. In the following sub-section, the essay describes the methodology of the empirical model involving the described dependent and independent variables.

4.5.2. Empirical Model

Three types of panel data models were estimated to explain the acquisition behavior of acquirers across time and across firms. Note that there are N acquirer firms over T time periods. Of the 26,825 transactions available through BMAD, there were around 5000 acquirers. Of these 5000 acquirers across the globe and across industries that the BMAD provides information on, only 223 were listed on the New York Stock Exchange (NYSE), which TRD provides information on. Due to the complexity of modeling based on global data across several segments of the GFABI, this study focused only on US acquirers and there those whose stocks were traded on the NYSE. The total number of acquirers for which TRD information was available is 223 firms, out of which only 209 acquirers had an identifiable company ticker in both the databases (BMAD and TRD) which was used as a unique identifier to merge these databases. An additional 25,447 non-acquiring firms' observations were added, bringing the total number of firms in the combined database analyzed to 25,656 (25,447 non-acquirers and 209 acquirers). M&As are an occasional phenomenon. Therefore, the observed panel dataset is unbalanced, i.e., the data is not available for individual acquirers in all time periods ($T_i = T$). Due to the fact that the likelihood of a previous acquirer repeating acquisition behavior is high, the panel data exhibits correlation (clustering) over time for a given acquirer. So, it is assumed that there would be a correlation over time, but independence across acquirers. Therefore, to capture the rend across firm and across time, the panel data models used.

This essay used three types of panel data models used include: (1) pooled model (standard panel data with no fixed effect and random effect), (2) fixed effects model, and (3) random-effects model. The first one is relatively straightforward. The last two types of models are the individual-specific effects models. A pure fixed effects (FE) model is used if the individual-specific effects (α_i) are correlated with the regressors ($\boldsymbol{x}_{it}$). If not, a random-effects (RE) model is used.

The pooled data model specifies constant coefficients for the explanatory independent variables, consistent with the assumptions of the standard cross-sectional analysis. Therefore, the pooled data model can be written as:

$$y_{it} = \alpha_i + \boldsymbol{x}'_{it} + u_{it}\ ; for\ i = 1, 2, .. N, and\ t = 1, 2, \ldots . T \quad (46)$$

where y_{it} is the dependent variable (y_{it}=1 implies that the *i*-th firm has acquired a food company in the *t*-th time period, otherwise y_{it}=0). Regressor vector $\boldsymbol{x}$ consists of asset-to-liability ratio, return on equity ratio, asset turnover ratio, cash ratio, total debt-to-total asset ratio, and price-to-equity ratio.

In the fixed-effect (FE) model the acquirer-specific effects α_i are correlated with the regressors $\boldsymbol{x}$, where α_i are the intercepts. The intercept term will be different for each acquirer. Though the slope parameters will be same. Therefore, the FE model can be represented as follows:

$$y_{it} = \alpha_i + \boldsymbol{x}'_{it} + u_{it} \quad (47)$$

where the acquirer specific effects after estimation can be represented by the unexplained variation in the dependent variable:

$$\widehat{\alpha_i} = \overline{y_i} - \overline{\boldsymbol{x}}'_i\hat{\beta} \quad (48)$$

In the random-effect (RE) model it is assumed that the acquirer-specific effects α_i are independently distributed of the regressors and is included in the error term. Therefore, each acquirer has same slope parameters. A combined error term can be represented as: $\varepsilon_{it} = \alpha_i + e_{it}$. Therefore, the RE model can be written as follows:

$$y_{it} = \boldsymbol{x'}_{it} + (\alpha_i + e_{it}) \tag{49}$$

Several estimators can be used to estimate panel data models. Their properties (e.g., unbiasedness, efficiency and consistency) differ based on the appropriateness of the model. An estimator that is consistent and efficient is preferred. Usually, a "pooled OLS estimator", and a "random effects (RE) estimator" are consistent with a pooled model and random-effects model but inconsistent with a fixed-effects model. Whereas a "fixed effects (FE) estimator" is consistent in all three types of panel data models, though may not be the efficient estimator. A panel data obtained by stacking the data over individual firms (*i)* and over time periods (*t).* Then OLS regression is estimated on the panel data of *NT* observations, which can be written as follows:

$$y_{it} = \alpha + \boldsymbol{x'}_{it} + (\alpha_i - \alpha + e_{it}) \tag{50}$$

The estimators from OLS regression of the time-invariant dependent variable on the time-invariant regressors is called as "fixed-effect estimator", which can be written as follows:

$$y_{it} - \bar{y_l} = (\boldsymbol{x'}_{it} - \overline{\boldsymbol{x'}_\iota})\beta + (e_{it} - \bar{e_\iota}) \tag{51}$$

Where individual-specific effects, α_i gets eliminated.

RE estimator is an OLS estimation of the following transformed model:

$$y_{it} - \hat{\lambda}\bar{y_l} = (1 - \hat{\lambda})\,\mu + (\boldsymbol{x'}_{it} - \hat{\lambda}\,\overline{\boldsymbol{x'}_\iota})\beta + v_{it} \tag{52}$$

where $v_{it} = \left(1 - \hat{\lambda}\right)\alpha_i + (e_{it} - \hat{\lambda}\,\bar{e_\iota})$ and $\lambda = 1 - {\sigma_e}\Big/{\sqrt{\sigma_e^2 + \sigma_\alpha^2}}$

The individual-specific effects α_i are included in the error term.

It is noteworthy to recall that, here, y_{it} is a binary variable that assumes the value of 1 when a firm has acquired any firm from the GFABI sector in a given year, 0 otherwise. $\boldsymbol{x'}_{it}$ represents the vector of explanatory variables that determines the likelihood of being an acquirer in the GFABI, in a given year. The vector $\boldsymbol{x'}_{it}$ consists of the asset to liability ratio, return on equity, asset turnover ratio, cash ratio, total debt to total asset ratio, and price to equity ratio for the year 1988 till 2018. Therefore, the panel data prediction model can be expressed as follows:

$$P(Acquirer_{it}) = \alpha_i + \beta_1 Asset\ to\ Liability\ Ratio_{it} + \beta_2 Return\ on\ Equity\ Ratio_{it} + \beta_3\ Asset\ Turnover\ Ratio_{\boldsymbol{it}} + \beta_4\ Cash\ Ratio_{it} + \beta_5\ Total\ Debt\ to\ Total\ Asset\ Ratio_{it} + \beta_6\ Book\ to\ Price\ Ratio_{it} + \varepsilon_{it} \qquad (53)$$

where $Acquirer_{it}$ = 1 if *i-th* firm has acquired any food company in the time *t*, otherwise 0.

4.6. Empirical Result

This section presents results of the investigation into the characteristics of firms who become acquirers of food-industry firms. Before estimating the necessary regressions, it was necessary to first investigate whether the time series in the regression are non-stationary. So, unit root tests were conducted to ensure that the models are well-specified. Generally, regressions of non-stationary variables along with other unrelated non-stationary variables increases the possibility of a spurious regression, where estimated coefficients present themselves as significant when in fact they are not. Therefore, following the literature, a number of stationarity tests were conducted, including the Augmented Dickey-Fuller test (ADF), Phillips Perron test (PP), Kwiatkowski Phillips Schmidt Shin test (KPSS), and Dickey-Fuller-GLS unit-root test, to test the null hypothesis of stationarity against the alternative of a unit root.

Though the ADF test is widely used in the literature, it comes with certain limitations. This procedure is vulnerable to the inappropriate specification of lag length, and it also leads to a biased result when the series contains a time trend. Whereas the Philips-Peron test nonparametrically modifies the statistics of the ADF test and makes the test more robust to any serial correlation and heteroscedasticity. Results are also independent of the lag length of the series. However, the result of both the ADF and PP tests are biased in a small sample. In such scenarios, the KPSS test is more appropriate. Table 4.3 provides the results of the above-mentioned stationarity tests. A significant p-value of all variables implies that all the variables in the model are stationary in all the stationarity tests. So, the panel data regression is warranted.

The unique identifier of the panel data is the "gvkey", which is a unique six-digit number key assigned to each company in the Thomson Reuters database (Capital IQ Compustat database). The time of the panel dataset is identified by the "year" variable. The dependent variable is $Acquirer_{it}$ which assumes value 1 if firm i has acquired a company at t-th time. The independent explanatory variables are asset-to-liability ratio, return on equity ratio, asset turnover ratio, cash ratio, total debt-to-total asset ratio, and price-to-equity ratio capturing solvency, profitability, efficiency, leverage, liquidity, and attractiveness respectively. The distribution of these explanatory variables is represented in Table 4.4 (Appendix). This summary statistics table breaks down the not only reports the mean and standard deviation, but also the between and within variations of each explanatory variable. Between variation is the total variation between all company's mean at each time period and the overall mean of all companies across all time periods ($\sum \boldsymbol{n_t} \, (\boldsymbol{X_t} - \overline{\boldsymbol{X}})^2$) and the within variation is the total variation in the individual values of each company for every time period and its mean over all time periods ($\sum(\boldsymbol{X_{it}} - \overline{\boldsymbol{X_i}})^2$). As expected, all the explanatory variables follow certain distribution across firms and over time.

Next, all the estimators are explained. Table 4.5 presents the results of the pooled OLS estimator and the odds ratio(s). Note the odds ratio in table 4.5. An odds ratio of value 1 means that the result is not significant for an outcome happening. However, an odds ratio greater than 1 implies a positive association (higher chance of the outcome happening). So, one of the most important observations from the fixed effect estimator is the lower odds ratio for liquidity (odds ratio=0.72 <1). Therefore, it is observed that acquirer liquidity significantly influences its acquisition decision. Specifically, if the liquidity of an acquirer is low (not so low that it is not a viable acquirer), it is more likely to target another company, presumably to improve its liquidity. This may explain why cash cows are frequent and why vulnerable targets often need to protect themselves through strategies to disincentivize acquirers, especially the hostile ones. Often top executives feel insecure about their jobs during an M&A process, and they tend to sabotage the M&A. However, acquiring a highly liquid firm guarantees the financial solvency to the acquirer, and often they incentivize the top executives with the golden parachute agreement to engage in a hostile takeover. In such scenarios, if the executive gets terminated as a result of an M&A, he gets compensated by stock, cash, and severance pay in exchange of losing their job. "The chief executive officer (CEO) of Hewlett-Packard Enterprise, Meg Whitman, was offered $91 million if the company was acquired under her control and was promised $51 million in compensation if she was terminated" (Investopedia, 2022). Therefore, golden parachute mechanisms are often used as a poison pill to navigate through a hostile takeover of an attractive target company to improve the solvency of the acquirer.

Table-4.6 presents the fixed effect estimates and their odds ratios. Notice that the solvency, leverage, and attractiveness of an acquirer significantly influence its acquisition behaviour. Specifically, a less solvent company is more likely to become an acquirer (odds ratio = 0.60) while a more attractive company is less likely to be an acquirer (odds ratio = 0.73). Also, less leveraged companies are more likely to be an acquirer (odds ratio = 0.13). So, a company that is not so solvent or attractive, but is not badly leveraged, is in a better position to organize the support of investment banks to fund the acquisition to become an acquirer. This may explain the boldness of some firms in acquiring even more viable targets through leveraged buyouts (Investopedia, 2022). This result essentially sheds a deeper light on the relationship between leverage, attractiveness, and solvency in acquisition behaviour.

Table-4.7 presents the results of the random effect model and the associated odds ratios. The results are very similar to the results of the pooled OLS model (Table 4.5) in that liquidity is highly significant in determining acquisition behaviour. The odds ratio of liquidity is 0.72. This is consistent with the hypothesis that an acquirer gets into an acquisition to improve its financial condition. Therefore, one can assume that the acquirer’s pre-acquisition financial status is comparatively lower which the firm is attempting to improve through M&As. However, the acquirer needs to have lower leverage (odds ratio = 0.13 <1) to successfully complete the acquisition of a food and agribusiness firm, which is consistent with the hypothesis. A highly indebted firm will not be able to borrow money from the investment bank to pay for the acquisition.

Finally, Table 4.8 represents the result of the Hausman test. It is used to choose between the fixed effect and random effect models. The objective is to verify the similarity or the difference between the fixed effects estimates from random-effects estimates. The random-effects model is assumed to be appropriate under null hypothesis; and the alternate hypothesis is that the is the fixed effects model is a better choice of the given data. A highly significant p-value implies the rejection of the null hypothesis, i.e., the model is a fixed-effects model. Here p-value is 0.0016, which is significant at the 1% level. Therefore, the results of the fixed-effects model (Table 4.6) are more appropriate. The Wu-Hausman test verifies suggest no endogeneity in the model.

Therefore, the strict exogeneity condition holds. As discussed in chapter 1, the variable selection was conducted very judiciously to avoid the endogeneity problem.

4.7. Summary and Conclusion

The US Food and Agribusiness Industry is highly competitive. Due to a high degree of competition, firms in this industry typically exhibit low-profit margins. Therefore, to remain profitable, acquirers need to be well informed about their competitors. When industry knowledge is low, it is very difficult for an inter-industry acquirer to enter an industry and remain financially viable. At the same time, the increasing interest of cross-industry acquirers in foods firms makes the environment highly competitive for intra-industry acquirers. The earlier part of this chapter presents a theoretical framework to understand the characteristics of firms that make them frequent acquirers. Hypotheses were then developed in section 4.4 that were tested in section 4.5. It is found that M&A decisions are highly dependent on individual-specific characteristics. Therefore, using a fixed-effect model was the most appropriate choice to predict the acquirers. The results suggest that acquirers get into the acquisition to improve their low solvency, attractiveness, and liquidity. However, they need to be less leveraged in order to be eligible for a loan from the investment bank to pay for the acquisition.

This study and its findings are helpful to policymakers, academics, and most importantly, investment bankers, lawyers, and accountants involved in the M&A process. It is useful in better understanding concerns about the degree of competition, industry concentration ratios, and attractiveness as an acquirer. Investment bankers and lenders will particularly find predictive models useful in identifying probable acquiring firms and developing loans and other financial strategies to support such clients.

For this essay, the fact that the financial data on NYSE-listed food industry acquirers was used which limited the number of observations. Only data on 223 food industry acquirers was available. Therefore, panel data regression is the only tool used. Future research has the potential to use classification and clustering techniques, as well as a better database with more observations. It is strongly recommended that future researchers explore these improvements.

APPENDIX

Appendix

Figure 4.1: Cross Border M&A deals in the Food Industry - Q1 2021

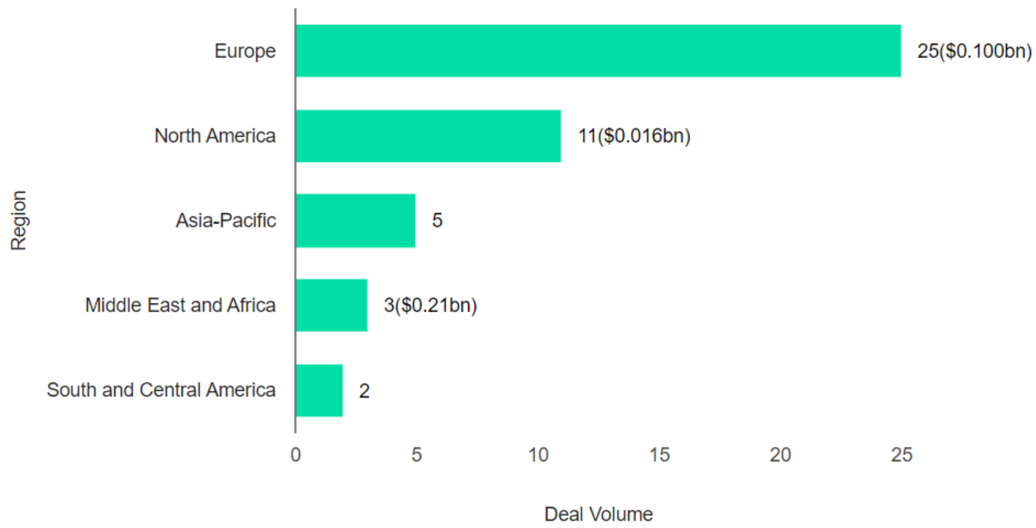


Table 4.3: Stationarity Check- Unit Root Test

Parameter	Variable	ADF Test	PP Test	KPSS Test
Solvency	Asset-to-Liability Ratio	0.60*	1.01*	1.01*
Profitability	Return-on-Equity	1.23***	1.00**	1.00**
Efficiency	Asset Turnover Ratio	0.80**	1.07***	1.07***
Leverage	Total Debt-to-Total Asset Ratio	0.13*	1.14*	1.14**
Liquidity	Cash Ratio	0.91**	0.72**	0.72*
Attractiveness	Book-to-Price Ratio	0.73*	1.01***	1.01*

In the ADF and PP test, ***, **, and * indicate that the null hypothesis, where the series has a unit root, was rejected at a significance of 1%, 5%, 10%, respectively. In the KPSS test, ***, **, and * indicate that the null hypothesis, where the series is stationary, was not rejected at the significance of 10%, 5%, 1%, respectively.

Table 4.4: Summary Statistics – Overall, Between, and Within Distribution of Variables

Parameter	Variable	Type of Variation	Mean	Std. Dev.	Observations
Solvency	Asset-to-Liability Ratio	overall	0.64	6.44	N = 167961
		between		11.28	n = 16870
		within		1.56	T-bar = 9.95
Profitability	Return-on-Equity	overall	2.91	1011.87	N = 160907
		between		2079.43	n = 16767
		within		338.25	T-bar = 9.59
Efficiency	Asset Turnover Ratio	overall	1.03	1.11	N = 165144
		between		0.94	n = 16610
		within		0.67	T-bar = 9.94
Leverage	Total Debt-to-Total Assets Ratio	overall	0.23	0.28	N = 170096
		between		0.25	n = 17185
		within		0.19	T-bar = 9.89
Liquidity	Cash Ratio	overall	1.82	16.08	N = 142782
		between		11.44	n = 14586
		within		13.88	T-bar = 9.78
Attractiveness	Book-to-Price Ratio	overall	0.76	0.90	N = 165627
		between		0.65	n = 17090
		within		0.73	T-bar = 9.69

Table 4.5: Pooled OLS Estimator – Odds Ratio

Parameter	Variable	Odds Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
Solvency	Asset-to-Liability Ratio	1.011	0.025	0.46	0.64	0.96	1.06
Profitability	Return-on-Equity	1.00	0.001	0.03	0.97	0.99	1.00
Efficiency	Asset Turnover Ratio	1.07	0.08	0.83	0.40	0.91	1.25
Leverage	Total Debt-to-Total Asset Ratio	1.14	0.57	0.28	0.78	0.42	3.08
Liquidity	Cash Ratio	0.72	0.07	-3.1	0.00	0.59	0.88
Attractiveness	Book-to-Price Ratio	0.80	0.10	-1.59	0.11	0.62	1.04
	Constant	0.001	0.00	-24.27	0	0.00	0.00
	/lnsig2u	1.61	0.12			1.36	1.86
	Standard Deviation of Error	2.24	0.14			1.98	2.53
	Rho	0.60	0.03			0.54	0.66

Table 4.6: Fixed Effects Estimator – Odds Ratio

Parameter	Variable	Odds Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
Solvency	Asset-to-Liability Ratio	0.60	0.136641	-2.23	0.025	0.386066	0.939515
Profitability	Return-on-Equity	1.234803	0.291684	0.89	0.372	0.777191	1.961858
Efficiency	Asset Turnover Ratio	0.801323	0.159697	-1.11	0.266	0.542214	1.184253
Leverage	Total Debt-to-Total Asset Ratio	0.133927	0.113335	-2.38	0.018	0.0255	0.703388
Liquidity	Cash Ratio	0.911111	0.083673	-1.01	0.311	0.761028	1.090792
Attractiveness	Book-to-Price Ratio	0.734598	0.119567	-1.89	0.058	0.533955	1.010637

Table 4.7: Random Effects Estimator - Odds Ratio

Parameter	Variable	Odds Ratio	Std. Err.	z	P>z	[95% Conf. Interval]	
Solvency	Asset-to-Liability Ratio	1.01	0.02	0.46	0.647	0.96	1.06
Profitability	Return-on-Equity	1.00	0.00	0.03	0.977	0.99	1.00
Efficiency	Asset Turnover Ratio	1.07	0.08	0.83	0.408	0.91	1.25
Leverage	Total Debt-to-Total Asset Ratio	1.14	0.57	0.28	0.782	0.42	3.08
Liquidity	Cash Ratio	0.72	0.07	-3.1	0.002	0.59	0.88
Attractiveness	Book-to-Price Ratio	0.80	0.10	-1.59	0.111	0.62	1.04
	Constant	0.001	0.00	-24.27	0	0.00	0.00
	/lnsig2u	1.61	0.12			1.36	1.86
	sigma_u	2.24	0.14			1.98	2.53
	Rho	0.60	0.03			0.54	0.66

Table 4.8: Breusch-Pagan LM Test for Random Effects versus OLS

Parameter	Variable	Fixed	Random	Difference	S.E = [sqrt(diag(V_b-V_B))]
Solvency	Asset-to-Liability Ratio	-6.1E-05	3.09E-05	-9.1E-05	5.14E-05
Profitability	Return-on-Equity	9.30E-09	4.68E-08	-3.75E-08	1.47E-06
Efficiency	Asset Turnover Ratio	-6.5E-05	0.000431	-0.0005	0.00021
Leverage	Total Debt-to-Total Asset Ratio	-0.00114	0.001556	-0.0027	0.000768
Liquidity	Cash Ratio	-4.72E-06	-1.9E-05	1.42E-05	0.000011
Attractiveness	Book-to-Price Ratio	-0.00022	-0.00027	4.42E-05	9.01E-05

chi2(6) = 21.33

Prob>chi2 = 0.0016

CHAPTER 5: CONCLUSION

Mergers and acquisitions (M&A) are a globally pursued business growth strategy aimed at improving the financial performance of a firm and reducing risk. If successful, it can also allow acquirers to reduce future competition, gain larger market share by expanding into new markets and territories, and achieve greater economies of scale. Ultimately, an important objective of participating firms is to optimize shareholders' value. The most commonly used measure of M&A performance is the improvement of a company's share price and profitability. A successful M&A strategy requires identifying the targeted acquisitions that can achieve these results.

However, M&A have a high failure rate as potential deals are fraught with many risk factors. Why do M&A fail to mature? Two important reasons are longer than appropriate TTC and AI. The first two essays of this dissertation address information gaps related to these two issues while the third essay focuses on a major gap in knowledge about who becomes an acquirer.

To analyze the risk associated with M&A, the process is broken down into three dimensions of potential delay: negotiation, financing, and regulatory approval. An acquirer faces greater risks in the negotiation phase. In this phase, the acquirer negotiates a deal with the target based upon the available information regarding the target. However, suppressed information by the target increases the risk of asymmetric information (AI). Therefore, an acquirer needs to thoroughly conduct due diligence before getting into an acquisition, which consumes time and delays the completion of the deal. The situation worsens when the acquirer faces competition from other bidders. The existence of AI not only increases the target's negotiation power but also further delays the deal. Overall, these three aspects intensify the contribution of each other towards deal failure. Longer TTC, AI, and competition increase the transaction cost and therefore lead to a higher probability of failure of the M&A deal.

Another key reason for the failure of an M&A deal is the presence of AI and lengthy time to completion. TTC is unobservable prior to deal completion. However, the characteristic observation of the M&A deal, and the characteristic of the target gives a better understanding of the deal complexity that helps in assessing the opportunity costs of a transaction. This is because transaction time (time invested in a failed deal) and therefore transaction cost (including the opportunity cost of funds tied up in a deal) are important determinants of deal failure. The findings reported in the first essay demonstrate the causal impact of TTC on deal termination. This result is crucial as it underscores the value of expediated TTC.

Longer TTC, due to suppressed information (AI), is more probable in an M&A deal when one party possesses private information, and the other party does not. It is one thing for the acquirer to know a priori that there will be complexities in a deal. It is another for the acquirer not to know what the unknowns are. The latter obviously involves a higher degree of risk. AI can occur when the acquirer fails to anticipate negative information about the actual financial position of the target. This results in an imbalance of power in a transaction that can culminate in deal failure. Therefore, extensive due diligence and proper use of screening mechanisms are required if an acquirer decides on the acquisition despite the presence of AI. Research, evaluation of information, and other due diligence measures are time consuming, which delays the deal. AI increases the transaction cost, which then rises further due to time consumed, leading to lower profitability of the deal for the acquirer.

Often an acquirer feels pressured to close a deal early without proper due diligence when several other bidders are willing to acquire the same target company. Therefore, knowing the characteristics of a potential acquirer is very important for the other bidders of an M&A in order to strategize the acquisition competition. The characteristics of a potential acquirer is also of great interest to regulators in order to optimally utilize the anti-trust law to protect the consumers' interest. High competition reduces the likelihood of the deal's success. Information obtained from predictive models could help acquiring firms more accurately identify probable competitors and make optimal strategic choices. As this dissertation establishes, an acquirer should become involved in an acquisition only if its increased wellbeing from expected enhanced profitability and efficiency is greater than reduced wellbeing from lower liquidity and higher leverage, induced by AI and longer TTC.

Again, this dissertation investigates the major reasons why M&A transactions fail and provides useful information on how to reduce the potential risks. One key finding is that hiring financial or legal advisory service companies is effective in providing a screening mechanism that helps to reduce the risk of an M&A deal. Advisory service firms help reduce AI and provide acquirers with better understanding of the unknown factors involved in an M&A deal. It is observed that acquirers seek the help of advisory service firms in complex M&A deals. The expected time consumption for the due diligence will be higher in complex deals. A further finding is that screening mechanisms such as hiring legal and financial advisors increases profitability for the acquirer, compared to other M&A deal where an advisory service firm was not hired. Moreover, advisory service firms help the acquirer understand the macro-economic environment, market competition, and regulatory requirements before and over the course of a deal, thereby better equipping the acquirer to successfully navigate the process.

This dissertation is potentially helpful to the major stakeholders of an M&A deal, namely targets, acquirers, M&A practitioners, investors, and regulators. With available information on the company, market, deal complexity, and other variables, targets may find the procedure and results useful in predicting how long a given M&A process would take. For example, a target should expect a non-cash deal involving an efficient acquirer to take longer. Targets can also use this data to anticipate probable acquirers. Acquirers might find this study helpful in implementing strategy, navigating AI, and anticipating the TTC of an M&A deal. For example, targeting an efficient company means that the deal will take a comparatively shorter amount of time. M&A practitioners, especially financial advisory firms, may find this study helpful in communicating the added time it would take to complete a deal with their clients and the associated value. Investors may use the results to manage their expectations about the deal completion time frame. Advisory service firms can refer to this study to inform their clients about the value-addition in M&A in a given level of AI. Finally, the results could be helpful to regulators such as the Securities Exchange Commission (SEC) in benchmarking a transaction's TTC and optimally deploying their efforts based on the deal's characteristics.

The high failure rate of M&A deals is a serious problem for every stakeholder. This has never been more true than in a post-COVID economy. In a market stressed by inflation and the continuing unknowns of a global pandemic, the findings of this dissertation provide valuable insight that could contribute to successful outcomes for both the target and the acquirer. The findings of this dissertation will help the acquirers to understand the underlying characteristics of an M&A deal that increases the complexity of the deal and therefore increasing the likelihood of deal failure or delay in the deal completion. The findings can also help the acquirers to navigate through the AI and increasing their profitability with the help of advisory service firms. Finally, bidders will better understand the characteristics of a successful acquirer and strategize the competition of the acquisition such that their profitability is optimized. Therefore, this dissertation will help the stakeholders to characteristically understand the requirements of a successful and profitable acquisition.

BIBLIOGRAPHY

BIBLIOGRAPHY

Adelaja, A., Rodolfo Nayga, Jr and Zafar Farooq. (1999). Predicting mergers and acquisitions in the food industry. Agribusiness, 15: 1-23.
Adra, S. & Barbopoulos, L. G. (2018). Liquidity and information asymmetry considerations in corporate takeovers. The European Journal of Finance. 25(7), 724-743.

Ahmed, N. (2015). Reinforcement of Good Governance in the International Financial Institutions. Law, Social Justice & Global Development Journal, pp. 105-135.

Alexandridis, G., Petmezas, D., Travlos, N. G. (2010). Gains from Mergers and Acquisitions Around the World: New Evidence. Financial Management. 39(4), 1671-1695.

Ali, M. N., & Shaker, A. S. (2017). The effect of accounting observation on the transparency of disclosing accounting information-an applied study in a sample of industrial companies listed in the Iraqi Stock Exchange. Al-Kout Journal of Economic and Administrative Sciences, (25).

Alsmeyer, G. & Jaeger, M. A useful extension of Itˆo's formula with applications to optimal stopping. Acta Math. Sin., 21(4), 779–786.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets. 5(1), 31-56.

Amihud, Y., Mendelson, H., & Lauterbach, Beni. (1997). Market microstructure and securities values: Evidence from the Tel Aviv Stock Exchange. Journal of Financial Economics. 45(3), 365-390.

An, X., Deng, Y., & Gabriel, S. A. (2011). Asymmetric information, adverse selection, and the pricing of CMBS. Journal of Financial Economics. 100(2), 304-325. ISSN 0304-405X,.

Andrew F. Weller, Anthony J. Harris and J. Andrew War. (2006). Artificial neural networks as potential classification tools for dinoflagellate cyst images: A case using the self-organizing map clustering algorithm. Review of Palaeobotany and Palynology, 141(3-4): 287-302.

Angwin, D. (2004). Speed in M&A Integration: The first 100 days. European Management Journal, 22(4), 418-430.

Arsov, S. & Bucevska, V. (2017). Determinants of transparency and disclosure – evidence from post-transition economies, Economic Research-Ekonomska Istraživanja, 30(1), pp. 745-760.

Bao, J., & Edmans, A. (2011). Do Investment Banks Matter for M&A Returns?, The Review of Financial Studies. 24(7), 2286–2315.

Bergh, D.D., Ketchen, D. J., Jr. Orlandi, I., Heugens, P. P. M. A. R., Boyd, B. K. (2018). Information Asymmetry in Management Research: Past Accomplishments and Future Opportunities. Journal of Management. 45(1), 122-158.

Bedwell, S. A., Billett E. E., Crofts, J. J., MacDonald, D. M., and Tinsley, C. J. (2015). The topology of connections between rat prefrontal and temporal cortices. Frontiers in Systems Neuroscience.

Berglöf, E. and Pajuste, A. (2005). What Do Firms Disclose and Why? Enforcing Corporate Governance and Transparency in Central and Eastern Europe. Oxford Review of Economic Policy, 21(2), pp. 178-197.

Bernanke, S. B. (1981). Bankruptcy, Liquidity, and Recession. The American Economic Review, 71(2), pp. 155-159.

Bharath, S. T., Jayaraman, S. & Nagar, V. (2013). Exit as Governance: An Empirical Analysis. The Journal of Finance, 68(6), 2515-2547.

Braeken, J., & van Assen, M. A. L. M. (2017). An empirical Kaiser criterion. Psychological Methods, 22(3), 450–466.

Bilinski, P., & Yim, A. (2018). Knowledge Spillover and Accounting Firms' Competitive Strength in the M&A Advisory Market. Working Paper.

Bodt, E.D., Cousin, J.G., & Demidova, I.D.B. (2014), M&A Outcomes and Willingness to Sell. Dans Finance, 35, pp. 7-49.

Bokpin, G.A. (2013). Ownership structure, corporate governance and bank efficiency: an empirical analysis of panel data from the banking industry in Ghana. Journal of Applied Accounting Research, 14(2), pp. 127-146.

Bugeja, M., Rosa, R. D. S., Duong, L., and Izan, I. 2012. CEO Compensation from M&As in Australia. Journal of Business Finance and Accounting. 39(9-10), 1298-1329.

Cai, Y., Tian, X. & Xia, H. (2016). Location, Proximity, and M&A Transactions. Journal of Economics & Management Strategy, 25(3), pp. 688-719.

Cain, M.D., Denis, D.J., & Denis, D.K. (2011). Earnouts: A study of financial contracting in acquisition agreements. Journal of Accounting and Economics, 51(1-2), pp. 151-170.

Chang, W. & Taylor, S.A. (2016). The Effectiveness of Customer Participation in New Product Development: A Meta-Analysis, Journal of Marketing, 80, pp. 47–64.

Chapman, B., Mehrotra, P. and Zima, H. (1997). A bank of Hopfield neural networks for the shortest path problem. Signal Processing, 61(2): 157-170.

Chemmanur, T., Paeglis, I., & Simonyan, K. (2009). Management Quality, Financial and Investment Policies, and Asymmetric Information. Journal of Financial and Quantitative Analysis, 44(5), 1045-1079.

Chow, C.W. and Wong-Boren, A. (1987) Voluntary Financial Disclosure by Mexican Corporations. Accounting Review, 62, pp. 533-541.

Christensen, C., R. Alton, C. Rising and A. Waldeck. 2011. The Big Idea: The New M&A Playbook. Harvard Business Review. Web. 139.

Coakley, J., and Iliopoulou, S. 2006. Bidder CEO and other executive compensation in UK M&As. European Financial Management, 12(4), 609-631.

Dai, Q. and Chen, S. (2006). Integrating the improved CBP model with kernel SOM, Neurocomputing, 69: 16-18.

Dauksts, R. (2018). M&A and due diligence. Price Waterhouse Coopers.

Davis, G., & Cairns, R.D. (2012). Good Timing: The Economics of Optimal Stopping. Journal of Economic Dynamics and Control, 362(2):255-65

Deshmukh, S. (2005). The Effect of Asymmetric Information on Dividend Policy. Quarterly Journal of Business and Economics, 44(1/2), 107–127.

Dhaliwal, D.S., Lamoreaux, P.T., Litov, L.P., & Neyland, J.B. (2015). Shared Auditors in Mergers and Acquisitions. SSRN Electronic Journal, 61(1).

Dietrich J. K. and E. Sorensen. (1984). An Application of Logit Analysis to Prediction of Merger Targets. Journal of Financial Economics, 12: 393-402.

Dikova, D., Sahib, P. R., & Witteloostuijn, A. V. (2006). The Effect of Acquisition Experience, Institutional Context and National Culture on Cross-Border Merger Abandonment and Completion. Academy of Management Proceedings, U1-U6.

Dory.J. P. (1978). The Domestic Diversifying Acquisition Decision (Research for Bushiness Decision, No.2). UMI Research Press, 82-85.

Duarte, J. & Young, L. (2009). Why is PIN priced?. Journal of Financial Economics. 91(2). 119-138.

Duncan, C. and Mtar, M. (2006). Determinants of International Acquisition Success: Lessons from First Group in North America. European Management Journal, 24: 96-41.

Easley, D., Kiefer, N., O'Hara, M., Paperman, J., 1996. Liquidity, information, and infrequently traded stocks. Journal of Finance 51, 1405–1436.

Fama, E. & Jensen, M. (1983). Agency Problems and Residual Claims. Journal of Law and Economics, 26: 327-350.

Fama, E.F. (1980). Agency Problems and the Theory of the Firm. Journal of Political Economy, 88(2): 288-289.

Francis, J., LaFond, R., Olsson, P., & Schipper, K. (2002). The market pricing of accruals quality. Journal of Accounting and Economics. 39(2), 295-327.

Gan, L.K., Shek, J. & Mueller, M. (2015). Hybrid wind-PV-diesel system sizing tool development using empirical approach, life-cycle cost and performance analysis: A case study in Scotland. Energy Conversion and Management, 106: 479-494.

Giroud, A., Huaman, JS. (2019). Investment in agriculture and gender equality in developing countries. Transnational Corporations.

Goedde, L., Horii, M., & Sanghvi, S. (2015). Pursuing the Global Opportunity in Food and Agribusiness. McKinsey & Company.

Gou, K. G. (2003). Demonstration of Prediction Model on Mergers and Acquisitions Prediction. 5: 31-32.

Grinstein, Y., & Hribar, P. (2003). CEO Compensation and Incentives - Evidence from M&A Bonuses. S&P Global Market Intelligence Research Paper Series.

Hagan, M.T., Demuth, H.B., Beale, M.H. (1996). Neural Network Design. PWS Publishing Company. 285-295, 399-413

Hanifa, M.H., & Rashid, Ab.H. (2005). The Determinants of Voluntary Disclosures in Malaysia. Case of Internet Financial Reporting, 2(1), pp. 22-42.

Harford, J. (2005). What Drives Merger Waves?. Journal of Financial Economics, 7: 529-560.

Hasbrouck. (1985). The Characteristics of Takeover Targets: q and other Measures. Journal of Banking and Finance, 9: 351-362.

Hughes, P. J. (1986). Signalling by direct disclosure under asymmetric information. Journal of Accounting and Economics, 8(2), 119-142. ISSN 0165-4101.

Jensen, M, Meckling, W. (1976). Theory of the Firm: Managerial Behavior, Agency Costs, and Ownership Structure. Journal of Financial Economics, 305-360.

Jian, G., Xinwei. C. (2000). Analysis of effect of mergers & acquisitions on Chinese security market. Economic Science, 21: 32-35.

Karpoff, J. M., Lee, G., & Masulis, R. W. (2013). Contracting under asymmetric information: Evidence from lockup agreements in seasoned equity offerings. Journal of Financial Economics. 110(3), 607-626.

Khudhair, A.N., Norwani, N.M. & Aljajawy, T.M. (2019). The relationship between transparency and financial performance in Iraqi corporations. Solid State Technology, 58E: 1-12.

Klitzka, M., He, J. & Schiereck, D. (2021). The rationality of M&A targets in the choice of payment methods. Review of Managerial Science.

Lange, O., Meyer-Baese, A., Hurdal, M., and Foo, S. (2006). A comparison between neural and fuzzy cluster analysis techniques for functional MRI. Biomedical Signal Processing and Control. 1(6): 243-252.

Kubler, D., Muller, W., & Normann, H. T. (2008). Job-market signaling and screening: An experimental comparison. Games and Economic Behavior. 64(1), pp. 219-236.

Lavelle, J. (2019). Gartner Says the Average Time to Close an M&A Deal Has Risen More Than 30 Percent in the Last Decade. Newsroom.

Li, Y., Lu, M. & Lo., Y.L. (2019). The impact of analyst coverage on partial acquisitions: Evidence from M&A premium and firm performance in China. International Review of Economics & Finance. 63, 37-60.

Lin, J. C., Sanger, G., & Booth, G. G. (1995). Trade size and components of the bid-ask spread. Review of Financial Studies. 8, 1153–1183.

Ludkovski, M. (2009). A simulation approach to optimal stopping under partial information. Stochastic Processes and their Applications, 119: 4061–4087.

Luypaert, M., & De Maeseneire, W. (2015). Antecedents of time to completion in mergers and acquisitions. Applied Economics Letters, 22: 299–304.

Mach, E. and Poncino, M. (1997). An application of hopfield networks to worst-case power analysis of RT-level VLSI systems. International Journal of Engineering Science, 35(8): 783-792.

Maqbool, S; & Zameer, M.N. (2018). Corporate social responsibility and financial performance: An empirical analysis of Indian banks, Future Business Journal, ISSN 2314-7210: 84-93.

Marquardt, C., & Zur, E. (2014). The Role of Accounting Quality in the M&A Market. Management Science, 61(3): 604-623.

Martinez, S. and Elitzak, H. (2019). Food Markets and Prices: Retailing & Wholesaling: Retail Trends. Washington DC: U.S. Department of Agriculture, ESCS for. Agr. Econ.

Monroe, R. J. and M. Simkowitz. (1971). A Discriminant Analysis Function for Conglomerate Targets. Southern Journal of Business, 6: 1-16.

Nash, J., Halewood, N., and Melhem, S. (2013). Unlocking Africa's Agricultural Potential: An Action Agenda for Transformation. World Bank, Africa Region Sustainable Development Series.

Olusola, O. A., & Olusola, O. J. (2012). Effect of Mergers and Acquisition on Returns to Shareholders of Conglomerates in Nigeria. Research Journal of Finance and Accounting, 3(7): 86-90.

Palepu. K. G. (1986). Predicting Takeover Targets: A Methodological and Empirical Analysis. Journal of Accounting and Economics, 8: 3-35.

Park, Y.S., Grenouillet, G., Esperance, B., and Lek, S. (2006). Stream fish assemblages and basin land cover in a river network. Science of The Total Environment, 365(1-3):140-153.

Petrova, M., & Shafer, M. T. (2010). Post-Acquisition Performance: A Propensity Score Matching Approach. Unpublished Working Paper.

Popli, M. & Kumar, V. (2015). Jumping from Springboard? The Role of Marginal Cultural Distance in Cross-Border M&A Deal Completion. Thunderbird International Business Review, 58: 527-536.

Rabobank. (2019). Slowdown in M&A activity within the Food & Agri market. Food and Agri Corporate Finance Update, H.Ramzi, A. B. (2013) Do information asymmetry proxies measure information asymmetry? Masters' thesis, Concordia University.

Reddy, K.S., Xie, E. & Huang, Y. (2016). Cross-border acquisitions by state-owned and private enterprises: A perspective from emerging economies. Journal of Policy Modeling, 38: 1147-1170.

Robert, J. H., & Mazzeo, M.A. (1993). Competing Bids, Target Management Resistance, and the Structure of Takeover Bids, The Review of Financial Studies, 6(4): 883-909.

Röller, L.H., Stennek, J. & Verboven, F. (2006). Efficiency Gains from Mergers. Efficiency Gains from Mergers, Chapter 3.

Rynkiewicz, J. (2006). Self-organizing map algorithm and distortion measure. Neural Networks, 19(6-7): 199-212.

Sanz, S. S. and Yao, X. (2007). Assignment of cells to switches in a cellular mobile network using a hybrid Hopfield network-genetic algorithm approach. Applied Soft Computing, In Press.

Seow, M.J., and Asari, V.K. (2004). Learning using distance-based training algorithm for pattern recognition. Pattern Recognition Letters, 25(12): 45-63.

Shanmin, L., Yugang, C., Shaozhao, Z., Hang, L., Caiping. W. (2003). Mergers and Acquistions and Recognization Demonstration of Chinese Listed Companies. Financial and Economic Press of China, 47-50.

Silva, F.D.F, Graff, G.D., & Zilberman, D. (2020). Venture Capital and the Transformation of Private R&D for Agriculture (Working Paper).

Singh, C. (2002). ASP -pricing: A Black -Scholes option pricing formulation. Unpublished doctoral dissertation, Louisiana Tech University, Louisiana.

Sorensen, D.E. (2000). Characteristics of Merging Firms. Journal of Economic and Business, 52: 423-433.

Stevens, D. L. (1973). Financial Characteristics of Merged Firms: A Multivariate Analysis. Journal of Financial and Quantitative Analysis, 20: 37-53.

Szmigiera, M. (2019). Mergers and Acquisitions – Statistics and Facts. Statista.

Teeffelen, L. V. (2014). The Added Value of Advisory Services in SME Mergers and Acquisitions. Working Paper.

Thijssen, J. (2005). Risk, Strategy, and Optimal Timing of M&A Activity. Trinity Economics Papers.

Thomson, E.K & Kim, C. (2020). Post-M&A Performance and Failure: Implications of Time Until Deal Completion. Sustainability, 12(7), 2999.

Thompson, E. K. & Kim, C. (2020). Information asymmetry, time until deal completion and post-M&A performance. Journal of Derivatives and Quantitative Studies. 28(3). 123-140.

Trabelsi, S., Labelle, R., and Dumontier, P. (2008). Incremental Voluntary Disclosure on Corporate Websites, Determinants and Consequences. Journal of Contemporary Accounting and Economics, 4(2): 120-155.

WallStreetPrep, 2022.

Walter, T.S., Yawson, A. & Yeung, C.P. (2008). The role of investment banks in M&A transactions: Fees and services. Pacific-Basin Finance Journal, 16(4): 341 – 369.

Wangerin, D. (2019). M&A Due Diligence, Post-Acquisition Performance, and Financial Reporting for Business Combinations. Contemporary Accounting Research, 36(4): 2344-2378.

Weller, A. F., Harris, A. J., and Ware, J. A. (2006). Artificial neural networks as potential classification tools for dinoflagellate cyst images: A case using the self-organizing map clustering algorithm. Review of Palaeobotany and Palynology, 141(3-4): 287- 302.

Yassin, M. M., Ali, H. Y., & Hamdallah, M. E. (2015). The Relationship between Information Asymmetry and Stock Return in the Presence of Accounting Conservatism. International Journal of Business and Management. 10(5).

Yawson, A. & Zhang, H. (2021). Central Hub M&A Advisors. Review of Finance,

Zavatta, G. (2014). Agriculture Remains Central to the World Economy. 60% of the population Depends on Agriculture for Survival. UN Expo.

Zhongyan, Z. (2014) The Source of Superior Information: M&A Advisors' Holdings of Call Options on Targets. *Working Paper*.