# Computational Modelling of Behavioural Mergers & Acquisitions Pricing Theory

A thesis submitted in fulfilment of the requirements for the degree of **Doctor of Philosophy**

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## Declaration

I certify that the substance of this thesis has not already been submitted for any degree and is not currently being submitted for any other degree or qualification.

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12th March 2019

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## Abstract

Merger & Acquisition (M&A) pricing has traditionally been performed using financial methods. Computational modelling techniques such as agent based modelling are challenging this status quo in the area of M&A pricing. This thesis uses an agent based modelling approach in combination with non-co-operative game theory and prospect theory to develop a model that incorporates psychological biases in M&A pricing. Traditional finance models cannot include these biases, even when the biases can have a significant impact on the final outcome. Computational modelling is a vast field of study, however the use of agent based modelling allows the research in this thesis to analyse individual and overall dynamics within the M&A transaction model. The agent based model in this thesis looks at two main models, a buyer-seller game between an acquirer and target company (company being purchased by the acquirer) and multiple acquirers bidding for a single target company. Then, there are numerous variations of these two models as prospect theory and cumulative prospect theory are applied to include psychological biases. The base models consider two main psychological traits: risk aversion (a continuum of risk averse to risk taking) for the acquirer and optimism (a continuum of optimistic to pessimistic) for the target company. The model shows that the change in the level of these traits (risk averse compared to risk taking, for example) will have a different outcome based on the type of game and psychological biases associated to them. The model shows, using real world examples of the Verizon and AOL as well as the Verizon and Yahoo mergers for verification, that risk averse acquirers and a pessimistic target company will result in a lower merger price. Further, real world M&A transactions for Sanofi and Ablynx (with Nova Nordisk as the secondary acquirer) and a potential merger between Bunge Limited and Archer Daniel Midlands (with Glencore as another potential acquirer) show that multiple acquirers and an optimistic target will usually result in the merger price being much higher than expected. This primarily occurs as the acquirers bid up the price in competition to meet the price required by the target company. In conclusion, this thesis has developed a computational agent-based model that is intended to provide significant insight into M&A transaction pricing and it is one of the initial studies in this research area.

# Journal Publications

The following chapters have been published in **peer-reviewed** journals:

**Chapters 3 and 4 are jointly published in the journal paper:**

Agarwal, N., Kwan, P. and Paul, D., 2018. Merger & Acquisition Pricing using Agent Based Modelling. Economics, Management and Financial Markets, 13(1), pp.84-99.

**Chapters 5 and 6 are jointly published in the journal paper:**

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# CHAPTER ONE

## Introduction

### 1.1 Introduction

Psychological pricing of mergers & acquisitions is an important field of study as companies grow mainly through organic and inorganic growth. Mergers & acquisitions (M&A) are the main forms of inorganic growth and allow organisations to expand quickly across sectors and geographic boundaries. As M&A activity is critical to the growth of the economy, it is important to make sure that such transactions are priced correctly. If we do not price M&A transactions correctly, it is possible that acquiring companies might pay a higher price for the transaction, which in turn will reduce the efficiency of the merged organization. Behavioural finance has also shown that human psychology has an impact on the way pricing of assets occurs. For example, Kahnemann and Tversky (1979) as part of their prospect theory and cumulative prospect theory stated that human beings value gains more than losses. This also occurs in the pricing of M&A transactions. Traditionally, M&A transactions have been priced using finance models like discount cash flow analysis or industry multiples. These models do not consider behavioural biases that can impact M&A transaction pricing. This can however be studied using a computational modelling approach. However, due to the lack of data available on behavioural biases in M&A transactions, it can be useful instead to simulate such M&A transaction pricing scenarios in silica by resorting to agent based modelling, which is a computational modelling technique that simulates the model's constituents and their interactions using software agents. This thesis attempts to analyse M&A transaction pricing in view of behavioral biases by applying an agent based modelling approach and analyze the simulation results to provide insights into the impact of behavioral biases on M&A transaction pricing.

### 1.2 Research questions and their significance

The main research problem that is answered in this thesis is to understand how behavioral factors impact the pricing of merger and acquisition transactions. Merger & acquisition (M&A) transactions are the main source of inorganic growth in companies and a significant part of the economic cycle, especially when merger waves result in industry consolidation that sets the industry up for cost rationalization, higher competition and growth. As a result, it is important to study M&A transaction pricing and understand how behavioral factors impact this pricing. This thesis analyses behavioral factors under the following contexts:

1. How does the acquirer and target firm's behavior impact M&A pricing at the different phases of a business cycle?

2. How does the acquirer's behavior impact M&A pricing in a hostile takeover?

3. Is there a difference in M&A pricing when the acquirer and target firm have a different analysis of the synergies to be obtained from the M&A transaction?

### 1.3 An original contribution to knowledge

In the real world, investment bankers currently use financial models that do not incorporate behavioural biases. However, behavioural finance literature (for example, Kahneman and Tversky 1979 and Baker, Pan and Wurgler 2009) shows that M&A transaction pricing is impacted by behavioural biases. This thesis exploits agent based modelling simulations to analyse the impact of behavior on M&A pricing that help incorporate these behavioural biases, which is a new area of research. As a result, *this thesis has an original contribution to knowledge primarily in the research area of M&A transaction pricing and secondarily in the area of computational modelling*.

1. Analyse the impact of the application of prospect theory and cumulative prospect theory in a single acquirer and target firm M&A transaction pricing model, and

2. Analyse the impact on M&A transaction pricing in a multiple acquirer and single target firm model.

Both these contributions are original contributions to knowledge in the application of leading behavioural theories to the area of M&A transaction pricing.

## 1.4 Outline of the thesis

Merger & acquisition (M&A) pricing is a critical activity that impacts global economic growth. As discussed earlier, computational modelling is useful in incorporating behavioural biases in M&A transaction pricing. This occurs as it provides a platform for individual behavior and system wide behavior to be simulated and analysed. This thesis implements a prisoner's dilemma game theoretic model in an agent based modelling simulation to understand the change in dynamics due to behavioural biases that can be introduced into this model using seminal contributions in behavioural finance (i.e. prospect theory and cumulative prospect theory, which were introduced by Kahneman and Tversky 1979 and Kahneman and Tversky 1992). In order to undertake this analysis and to answer the research questions, the thesis is set out in the following manner:

Chapter 1 – this chapter provides the motivation and introduction to this thesis.

Chapter 2 – reviews the literature and methodology that relates to M&A pricing.

Chapter 3 – develops the agent based simulation model for analyzing acquirer and target firm behavior when both have a different view of synergies from the M&A deal.

Chapter 4 – develops the agent based simulation model to analyse the impact of behavior on M&A pricing in a multiple acquirer scenario.

Chapter 5 – develops the agent based simulation model to analyse the impact of behavior on M&A pricing in a single acquirer scenario, while applying it to a commercial real world perspective.

Chapter 6 – develops the agent based simulation model to analyse the impact of behavior on M&A pricing in a multiple acquirer scenario, while applying it to a commercial real world perspective.

Chapter 7 – the final chapter of this thesis that provides a summary of the discussion, limitations and extensions of the research undertaken in this thesis.

## 1.5 Conclusion

In conclusion, this chapter has identified the motivation, potential research questions, the original contribution and the outline of this thesis. The intent of this chapter has been to set out the reasoning on why this thesis is valuable and the structure of the thesis to allow the reader to work through the research in order to analyse and answer the research questions. The next chapter will provide an insight into the literature review and methodology related to M&A pricing and agent based modelling, which are the main research areas of this thesis.

C H A P T E R   T W O

# Literature Review & Methodology

## 2.1 Introduction

Computational modelling can be defined as the development of computer simulations to analyse behavioural patterns in complex systems. Such a model comprises of several factors that characterise the complex system that is being analysed. Computer simulations are conducted by setting up a simulation model where a combination of variables is used to understand the underlying change in behavioural dynamics. Results of these simulations help researchers understand the dynamics and help make predictions of such phenomenon for real world systems. This type of modelling assists researchers to undertake millions of experiments computationally that can help identify the specific physical experiments that they need to perform. An important characteristic of computational modelling is that models can be used to analyse biological, financial, social and other complex systems at a molecular level, helping understand the dynamics at the individual level. Some examples of computational modelling are forecasting the weather, building better planes, studying earthquakes and forecasting future stock prices. (NIBIB 2017)

There are numerous types of computational models, for example, stochastic or deterministic models, process algebras, rule based models, petri nets, boolean/qualitative networks, state charts, hybrid systems, spatio temporal models, lattice based models and agent based models (Bartocci and Lio 2016). Out of these models, the agent based models are most appropriate for solving this psychological merger & acquisition problem (that relates to the pricing of mergers and acquisitions transactions based on behavioural traits of the acquiring and target companies) as it can be used to analyse behavioural dynamics at an individual/agent level. This helps in understanding agent-level interactions as well as the overall dynamics of the system. Agent based modelling has become a prevalent tool to simulate problems and to obtain significant insight. Mergers & Acquisitions (M&A) are an important part of the growth of a company and many companies undertake M&A activities when it is easier to buy a company rather than grow that expertise internally. When an acquiring company purchases another company in the M&A transaction, it is difficult to determine the specific price that the acquiring company should pay. This thesis intends to improve the understanding of the impact of psychological attributes on M&A pricing, and as a result, this chapter reviews the literature in the area of M&A pricing, agent based modelling in general and in the specific research area of finance and M&A. The next section starts by reviewing M&A pricing, leading to a review of the agent based modelling literature with the subsequent section analysing literature in the application of agent based modelling to finance and specifically M&A pricing. The final section of this chapter provides a conclusion and summary of the discussion.

## 2.2 Pricing in Merger & Acquisitions (M&A) Transactions

Behavioural finance has become a major stream of finance research, with agent based modelling becoming an important method to analyse behavioural finance problems. Behavioural finance research has had numerous proponents, but Kahneman and Tversky's (1979) paper has had a significant impact on this research area. They stated that humans value gains substantially more than losses and provided a loss aversion ratio to explain this difference. This means that acquiring companies in an M&A situation will be more greatly impacted by every additional amount they pay to acquire the target firm and vice versa. Baker and Wurgler (2009) undertook an empirical study and stated that if the acquirer paid an amount equal to the 52-week high of the target company's stock price, then it is likely that the target company's shareholders will be willing to sell. They say that the 52-week high stock price acts as an anchor for the shareholders of the target firm. Baker, Pan and Wurgler (2012) explain how the application of prospect theory can be applied to mergers and acquisition pricing. Frey et al (2017) also show how risk preferences can be treated similarly to human intelligence. In effect, this means that risk preferences can impact human behaviour and have implications for behavioural finance and M&A transaction pricing.

### M&A transactions and Market Dynamics

While behavioural finance tries to understand the implications of psychological biases on financial transactions. A question about misevaluation of target companies has also been raised by Shleifer and Vishny (2003). They state that misevaluation occurs when acquiring companies believe they can achieve higher synergies by taking over a target firm, when fewer synergies are actually realized after the merger occurs. Kiymaz and Baker (2004) add to this discussion by saying that mergers occur when there is a possibility to maximize synergies between companies, while divestments are a way to get rid of divisions or parts of a company that are misaligned to the firm's future strategy. Supporting this argument, Becher (2000) undertook a study to analyse 558 bank mergers that occurred between 1980 and 1997. He found that the target company's stock price increased on average by 22% compared to the stock price of the acquiring company, which only increased by an average of 3%. This represents the disproportionate increase in value noticed by shareholders of the acquiring and target companies.

While M&A activities occur throughout the business cycle, Shleifer and Vishny (2003) and Robinson and Viswanathan (2005) have found that most often these M&A activities come in what are called merger waves. This is usually dependent on market conditions, pricing of the target (if the market sees them at a discount, if the business cycle is at a bottom) and a combination of other factors impacting M&A activity. Krummer and Steger (2008) provide evidence to state that these merger waves occur over multiple decades, and these merger waves repeat over time in infrequent intervals as they depend on a combination of changing market conditions. Bouwman (2009) found that companies usually undertake herding behaviour that results in merger waves occurring. This could potentially occur if market conditions are supportive of such transactions. But he also states that overvaluation of target companies can occur when there is a market peak and this herding behaviour becomes very costly to acquiring companies in that instance. Eccels, Kersten and Wilson (1999), as a result, have warned acquiring companies to beware of overvaluing potential target companies.

Rhodes-Kropf, Robinson and Viswanathan (2005) undertook an empirical test to understand if valuation errors result in acquiring companies overvaluing target companies. As part of this test, the study dismantled the Market to Book value ratio into three parts (divergence of the stock price of the acquirer and target companies from the short-run industry valuation, long-run valuation of the sector against the short-run industry valuation and the company's long-term valuation to its book value). Their test results showed that a majority of the misevaluation related to the

Market to Book value for the companies existed in the short term, primarily due to the divergence of the company's valuation away from the short-run industry valuation. Their results also provided support stating high long-run Market to Book value companies are usually acquired by low Market to Book value companies.

**Emerging Market Factors in M&A Transaction Pricing**

Lebedev et al (2015) discuss M&A valuation in emerging economies and state that there are fewer empirical studies of M&A valuation in emerging economies compared to developed market economies. They say that substantial differences between institutional structures, corporate governance practices and market structures exist between emerging and developed countries. Gaur et al (2013) review the impact of M&A transaction announcements in China on the stock price of rival companies to the company that is undertaking the M&A transaction. They propose a hypothesis that an acquisition will signal the possibility of future growth in that industry, which will result in future growth and positive stock price returns for all companies in that industry on average. They test this growth hypothesis with a longitudinal study of Chinese domestic and cross border M&A transactions during the period of 1993 to 2008. Their results show strong support for their hypothesis, with the stock prices of rival companies increasing. They also undertook alternative tests in previous research that support this positive market reaction for rival companies to the company that is being acquired (the target company). So, their research shows that both the rivals of the acquiring company and the target company see positive stock price growth as M&A transactions seem to signal that the industry will likely grow in the future.

Reddy et al (2014) have also reviewed M&A valuations across 26 countries using the UNCTAD's dataset on worldwide cross border M&A activity. They noticed that several studies had been undertaken in relation to the 2007-08 global financial crisis to review stock market efficiency, corporate governance in relation to firm value and macroeconomic performance. However, they noticed that the impact on M&A transactions across multiple countries had not been undertaken. They analysed the pre financial crisis (2004-06) and post financial crisis (2008-10) timeframes to analyse the M&A deal volume, value and average M&A transaction value. Their results showed that the 2007-08 global financial crisis had negatively impacted M&A transactions across these countries. However, they found that M&A value in emerging markets increased as companies in these countries took advantage of lower asset prices in developed countries, which resulted in increased foreign acquisitions.

Earlier studies have reviewed M&A transaction pricing in emerging markets. McNichols and Stubben (2015) analyse if having higher quality accounting information from the target company results in higher profits for the acquiring company. This would occur mainly because higher quality accounting information would reduce the uncertainty in the accurate pricing of the target company. As a result, it is expected that it would reduce the possibility of the acquiring company overvaluing the target company. They utilised a large sample of M&A transaction data related to public companies from 1990 to 2010. Their results show that they found consistent evidence to support their hypothesis. This especially occurred when target companies provided high quality accounting information closer to the M&A transaction announcement. Acquiring firms were able to purchase target companies for a lower amount and were able to take a greater amount of the acquisition gain by paying a lower amount to purchase the target company. They state that their results are robust in view of a variety of controls and alternative measures of uncertainty in M&A pricing and accounting quality. In effect, they believe that better accounting quality leads to better decision making for the bidder (acquiring company).

**Accounting and Strategic Factors impacting M&A Pricing**

Custódio (2014) assesses the difference between the post-merger values of target firms from an accounting basis. She explains an accounting method related to the diversification discount between conglomerate and focused firms. Typically, as target companies are reported based on their transaction value, this exceeds the target's pre-merger book value, which results in the accounting value to be lower for merged firms. As conglomerates undertake more frequent mergers, their accounting value is lower than focused companies. However, Custódio (2014) removes goodwill out of the book value to eliminate the diversification discount. Nonetheless, Custódio (2014) states that it is better to use the Market to Sales measures to assess the value of pre-merger and post-merger values of merged conglomerates and focused firms. This reduces the diversification discount that comes through when using the accounting measure and, as a result, prices targets fairly for both conglomerate and focused firms. Using different valuation methods can add to the pricing impacts that different acquirers will have to account for and may have an impact on the price that they are willing to pay to acquire the target company.

While valuation methods and other factors may be important to M&A transaction pricing, researchers have found that the relationships between the management of the acquiring and target companies can also have an impact on transaction pricing. Further, according to Schmidt (2015), the independence of the board of directors is not always in the interest of the company's shareholders. In circumstances where the advice of the board has greater value than monitoring, the independence of the board decreases the value of the company. Schmidt (2015) tests this hypothesis by reviewing the linkage between the returns obtained by companies through M&A transactions and through social linkages of the board of directors with other companies. These social linkages are viewed as the social ties that the CEO and board of directors have as a proxy for the board of directors being less independent of the company's management. The results show that social linkages are related to higher returns for acquiring companies and the potential value received from the advice of the board of directors is highly valuable. However, the value of the advice of the board of directors will be low when monitoring costs are high. In essence, Schmidt (2015) states that evidence suggests that the value of a friendly board of directors can be both positive and negative depending on the specific needs of the company. This occurs as social inter-relationships between board and CEO may jeopardise the critical assessment of a potential merger, which a board would otherwise do.

While the social interlinkages between the CEO and board of directors of a company can have an impact on the value of potential M&A transactions, it is also seen that the potential credit rating of an acquiring company can have an impact on the method of payment for this transaction. Karampatsas et al (2014) state that acquiring companies with a high credit rating are more likely to pay cash to takeover another company, as they find that these acquiring companies have lower financial constraints and a higher credit rating allows them to access credit markets more easily. They also confirm that their results are financially significant and robust to deal and several firm-specific characteristics and are not sensitive to the technique used to measure the likelihood of the choice of payment method and not impacted by endogeneity bias. It is important to make it clear that the method of payment can have a significant impact on the M&A transaction price. There is a substantial amount of literature in merger and acquisition pricing that specifically focuses on the payment method for such transactions. See the following papers for example, Alshwer, Sibilkov and Zaiats (2011), Andre and Ben-Amar (2009), Dutta, Saadi, and Zhu (2013) and Boateng and Bi (2013). This has not specifically been discussed in this thesis as the research problem in this thesis does not intend to focus on the payment method for M&A transaction pricing.

In addition, Duchin and Schmidt (2013) find that, during periods of high merger activity (during periods that are exemplified as merger waves), these periods can be associated with low quality analyst forecasts, greater uncertainty and weaker CEO turnover performance sensitivity. In effect, these circumstances depict the lack of monitoring and lower penalties for undertaking inefficient M&A transactions. As a result, M&A transactions may nurture agency-driven behaviour, along with managerial herding that could lead to unproductive M&A transactions for the acquiring company. They also find that the average long run performance of M&A transactions undertaken during merger waves as a result is significantly worse, and corporate governance associated to such M&A transactions is weaker, suggesting that agency problems may exist in relation to these merger wave transactions.

Activist shareholders also impact the likelihood of M&A transactions occurring. Khorana et al (2017) state that hedge fund activism creates shareholder value by influencing bids for target companies. They say that activist interventions significantly increase the likelihood of M&A activity and notice that third party bids for target companies and completion rates of these M&A transactions are higher when activist shareholders are involved (influencing the target company to be taken over). But they see this trend reversing when the activist shareholders are bidders (are part of the acquiring company). Their study also noticed that failed bids for activism target companies led to enhancements in operating performance, financial policy and improved long run abnormal returns. Providing support that the activism shareholders have a positive impact on the company, this occurs as hedge fund activist shareholders monitor the management of the target company during M&A transactions rather than simply due to the undervaluation of target companies or the overvaluation by an acquiring company of a target company in a future transaction.

## 2.3 Behavioural factors impacting the Pricing in Merger & Acquisitions (M&A) Transactions

On the other hand, CEO overconfidence can play a significant role in cross border M&A transactions. Ferris et al (2013) used a sample of CEOs from the Global Fortune 500 companies during the period 2000 to 2006 in their study. They find that CEO overconfidence is correlated to numerous critical facets of international M&A transactions. Such overconfidence clarifies the numerous offers made by CEOs that relate to the frequency of diversifying and non-diversifying M&A transactions and the use of cash to pay for potential transactions. While CEO overconfidence is a global phenomenon, it is still more likely observed in companies headquartered in countries that encourage individualism, whilst de-emphasizing the value of long term orientation in these cultures.

Jenter and Lewellen (2015) also analyse the impact of retirement preferences of the target CEOs on potential M&A transactions. They use CEO retirement age as a proxy for CEO's private merger costs. They find strong evidence that the target CEO's preference can impact the success of an M&A transaction. The potential of undertaking a successful M&A transaction is usually higher when the target CEO's age is close to 65 years. However, takeover premiums and post-merger returns for target companies are similar for younger or retirement age CEOs. This shows that the CEO retirement age increases the likelihood of mergers without sacrificing target pricing. On the contrary, improved corporate governance is noticed with acquisitions led by younger CEOs, while a smaller increase in M&A transactions with CEOs at retirement age.

While CEO and board behaviours can impact the possibility of M&A transactions, there are also some early indicators based on the analysis of public and private companies in relation to future M&A transactions. Maksimovic et al (2013) find that public companies participate more in M&A transactions than private companies as this participation is dependent on credit spreads and aggregate market valuation. They find that public companies obtain higher productivity gains from M&A transactions, especially those done during merger waves as the acquiring company's stock has higher liquidity and is highly valued in such market conditions. They state that their results are not simply associated with better access to capital for public companies. They also find, by utilising productivity data related to the early stages of private company growth, that highly efficient private companies opt to become public companies as it provides them greater advantages. The initial size and productivity of the private company predicts the potential asset purchases and sales that these companies may undertake up to a decade later.

Further, Arikan and Stulz (2016) explain that agency theory proposes that more established companies undertake value destroying M&A transactions to benefit their management. This is in contrast to neoclassical economic theories that state that such companies would instead make value increasing acquisitions to exploit underutilised assets in smaller companies that they can leverage and improve through synergies. Their study shows that younger companies undertake related and diversifying acquisitions compared to mature companies where the acquisition rate traces a U-shaped path through a company's life cycle. They also find that, consistent with neoclassical economic theories, acquiring companies subsume growth opportunities and have higher performance by generating wealth through the acquisition of non-public companies throughout their life cycle. Additionally, consistent with agency theory, the research finds that older companies have negative stock price growth in a post-merger scenario when they acquire public companies.

In contrast, Fu et al (2013) state that overvalued companies can exploit their higher stock price and takeover undervalued companies. However, they challenge this idea and find that overvalued companies instead purchase even more overvalued targets. This primarily is related to CEO compensation and is value destroying for shareholders. Further, the acquisitions that these companies make seem to be concentrated among these acquiring companies and are related to the largest corporate governance issues. Further, Yim (2013) states that acquisitions are related to permanent large increases in CEO compensation that create incentives for them to pursue these M&A transactions earlier in their career. The study also finds that the firm's propensity to undertake M&A transaction decreases with the CEO's age. The study finds that a CEO that is 20 years older is approximately 30% less likely to announce an acquisition. The effectiveness of the CEO's age is strongest when they can impact post-merger compensation and is absent when there is no impact on the CEO's compensation. Further, this age effect cannot be explained by declining overconfidence with a decline in the CEO's age or by selecting young CEOs of acquisition prone companies. Insight into this CEO age effect has not been completely understood and needs to be analysed further, representing a gap in the current literature that is open for further research. This study explicitly underscores CEO personality-related characteristics and variations in agency problems for corporate decision making that may impact these results.

Numerous factors are important in pricing M&A transactions, and many of these factors are associated with the personalities and motivations of the management and board of directors running the acquiring and target companies. However, these M&A transaction opportunities are also dependent on market conditions. Levine (2017) develops an M&A transaction model in which these deals are utilised to reallocate investment opportunities between companies. In this model, the equilibrium state shows that acquiring companies lack internal growth opportunities and look to acquire target companies to improve their growth possibilities, primarily due to lack of organic growth options. The results show that profitability is highly predictive of the likelihood of potential acquisition of the target company. But the M&A transaction, while being value creating for the acquiring company, naturally leads to the decrease in profitability of the target company in the post-merger situation.

It is important to explicitly state that CEO and management behavior, as well as Agency Theory, are behavioural related factors that can impact the pricing of M&A transactions. Therefore, it was important to review this literature in this section.

To extend this discussion further, Aktas et al (2013) find that, while M&A transactions may provide additional benefits to acquiring companies, nonetheless, there are numerous acquisition costs that include the problem of incorporating diverse business units within a larger company. However, these costs and benefits are not directly observable from outside the company. This study establishes a simple model to conjecture the relative importance of these factors by using the time between successive deals. They look at more than 300,000 M&A transactions during the period of 1992 to 2009 and their results show that learning gains occur through repetitive acquisitions, especially when successive M&A transactions are similar in nature and when there is CEO continuity. The acquiring company, as a result, learns through each subsequent acquisition and can reduce post-merger integration costs, while improving the value of the acquisition for the company.

In this section, we reviewed literature related to the pricing of merger & acquisition transactions. Initially, the discussion analysed the psychological aspects that impact M&A pricing, for example, anchoring based on the 52-week high stock price of a target company. However, there are factors that can result in M&A transactions being incorrectly valued. Traditional finance models only consider theoretical factors; however psychological factors like fear, greed and risk aversion can have an impact on changing this valuation away from the valuation obtained from these traditional finance models. Additionally, macroeconomic or business cycles may impact valuation of such M&A transactions by creating merger waves, where, acquirers may end up paying more to purchase the target company, which may be due to the CEO's overconfidence or age, interlinkages between companies, hedge fund activism or CEO remuneration. Also, the pricing of M&A transactions can differ between developed and emerging markets, mainly as governance and institutional structures and cultures are different that result in different outcomes in terms of M&A pricing.

Whilst this section has reviewed literature from the research area of M&A transaction pricing, it is important to understand the other significant areas of interest to this thesis. This includes the research area of agent based modelling and the application of these methods to solve finance related problems, specifically reviewing the application of agent based modelling to price M&A transactions.

## 2.4 Agent Based Modelling

Agent based modelling allows us to model a system as a collection of autonomous decision-making entities called agents, where each agent will make its own decisions based on a set of rules, allowing agents to show behaviours that fit the system they represent. Examples of such behaviour are selling or producing. Agents undertake repetitive competitive interactions in an agent based model that relies on computing capabilities to explore dynamics that are out of the reach of simple mathematical models. In the simplest agent based model, we have a set of agents and a network of relationships between them. These agents can show complex behavioural patterns and these behaviours can evolve over time. Advanced agent based models can incorporate neural networks, evolutionary algorithms and other learning techniques that allow for realistic learning and adaptation (Bonabeau 2002).

Bandini et al (2014) describe an agent based model as a simplified and abstract representation of a reality. This could either be the existing or proposed reality, which may be defined as the 'target system'. Agent based models are setup to examine an observed or foreseeable phenomena. These models are programmed to analyse some type of behaviour in a common environment. Franklin and Graesser (1999) state that the idea of an agent is controversial even within the research area of the agent based community. In response, Wooldridge and Jennings (1995) provide the most common definition of an agent, stating that a specific set of properties characterise what it means to be defined as an agent: autonomy (ability to operate without interference from humans), social ability (ability of interacting using an agent based language), pro-activeness (ability to work based on internal goals compared to external stimulus) and reactivity (ability to perceive its environment and to react to it). This definition of agent based models is rather restrictive as the description of agent based models is broader than what is provided here, especially if you consider the application of these models in different fields of research.

Conte and Paloucci (2014) question the meaning of the term agent based modelling. They state that it can often be defined as the opposite of Equation base modelling (see Dyke Parunak et al 1998, Cecconi et al 2010). They state that agent based models are set at the intersection of agent theory, systems and architectures and social sciences. Conte (2009) defines agents as autonomous systems, which can replicate the transitions between the different states of the world, established on representations and mechanisms that incorporate these different states. Agents are seen to vary in dimensions, depending on how autonomous, self-interested, social and capable they are to learn from their experiences and observations. Agents also differ in their level of complexity; according to Wooldridge and Jennings (1995), agents have the sense to manipulate and reason based on mental representations. They are otherwise considered as agents in a weak sense. Another way of reviewing agents is the distinction in the mental representations; for example, symbolic representations permit agents to mentally manipulate these representations to reason, plan, formulate decisions and to communicate with each other. While, sub-symbolic representations are unaware and implicit and could be developed on a network structure that represents the relationship between neurons in the cerebral areas that may not be liable to purposive manipulation by agents. Antunes and Coelho (2004) say that agents also differ from a philosophical and meta-theoretical viewpoint. For example, researchers attempt to develop agent behaviour that has its basis as a personal utility function.

Agent based modelling in practice can have numerous and more complex applications than those that have currently been implemented, as many of the agent based models set up are based on simple ad-hoc rules (Epstein 2006), potentially developed in an arbitrary fashion that is implemented through the use of computer programs (Gilbert and Troitzsh 2005). Macroscopic effects of these agent based rules are reflected on the screen, which are stored, analysed and visualised for emergent phenomena. Gilbert and Troitzsh (2005) discuss that this type of modelling leads to the reflection of observations on multi-agent societies, where these experiments reflect real world phenomena. Examples of such models are provided by Axtell et al (2002) undertaking a simulation of the Anasazi culture and by Casti (1997) that develops a simulation of different physical environments. These models enable novel theories regarding abstract social phenomena to be developed and tested.

Phan and Amblard (2007) explain that the agent based modelling approach has allowed researchers to conceptualize and simulate a population of agents that interact with each other within the environment. In the field of social sciences, the agent based modelling approach allows the setup of complex models with multiple scales and heterogeneous agents engaged in social interaction. In this model, agents have developed capabilities from reactive agents constituting collective intelligence to cognitive agents with sophisticated patterns of rationality and logic.

Agent based modelling is seen as a mindset rather than just a technology to solve complex research problems. Numerous researchers consider agent based modelling an alternative to differential equation modelling, as if each agent is a set of differential equations. However, the synonym for agent based modelling is more microscopic modelling with the alternative being macroscopic modelling. Agent based modelling provides the complex framework with the microscopic interactions and behavioural dynamics between agents in the model. Bonabeau (2002) believes that it is time to re-define the use of agent based modelling as it has gained so much popularity. As a result, the paper reviews and classifies the benefits and use of agent based modelling. Agent based modelling may be seen as a simple technique, but it is conceptually quite deep and this unusual combination may result in improper use of agent based modelling.

It is also important to note that substantial research has been done in the agent based modelling area (see Chan, LeBaron et al (1999), Gilbert and Terna (2000), Duffy (2006), Cont (2007), Windrum, Fagiolo and Moneta (2007) and Famer and Foley (2009)) to solve complex problems in the social sciences. Agent based modelling has also been applied successfully to solve research problems in both industry and academia. Bonabeau (2002) discusses how agent based modelling is a powerful simulation technique that has been used to solve real world problems. Macy and Willer (2002) have utilised agent based modelling to analyse social interactions between human beings. Macal and North (2009) state that the application of agent based modelling ranges from modelling stock market behaviour, supply chains and consumer markets to estimating the spread of epidemics, analysing the threat of bio warfare or the factors responsible for the fall of an ancient civilization. Applications of agent based modelling have had far-reaching insights in the ways businesses use computers to support decision making, where agent based models substitute as laboratories for real world problem solving. Agent based models are developed using different computing environments. Gilbert and Bankes (2002) explain that agent based models have been built using Java, C++, Turbo Pascal, SOAR, Dynamo, SQPC, Z, Small Talk and numerous other languages. Specific agent based modelling environments have been ASCAPE, REPAST, Star Logo, Agent Sheets and NetLogo. Additionally, newer agent based modelling environments are available in Python, R, Mathematica and Matlab.

Pavón et al (2008) discuss that agent based modelling provides the implementation of tools to analyse social patterns, as agents allow the representation of behavioural and organizational capabilities of individuals in society with related interactions. Agents can behave as individuals that perceive and react to responses in the environment, taking into account beliefs and goals, while interacting with other agents in the social environment.  Agent based modelling tools and techniques exist that can be used to model complex problems. For example, simulations of stock price predictions, biological phenomenon (like the spread of bush fires), construction of buildings or simulations of complex physical or biological environments (Pavón et al (2008)). However, researchers need to have a programming background as some of these tools require them to program code in order to setup the model. Pavón et al (2008) state that researchers are more likely to use agent based graphical modelling languages that provide a more convenient way to solve these social simulations. Additionally, complimentary tools can be used to analyse emergent social behavioural patterns using existing simulation platforms, allowing the agent based framework to specify and analyse complex behavioural patterns that emerge in social systems.

Agent based modelling has also been utilised to solve economic problems through a specialized framework called Agent based Computational Economics (ACE). Arthur (2006) shows how ACE assists in the understanding of human behaviour, where neoclassical economics talks about an agent's actions, strategies and expectations that provide aggregate behavioural outcomes. However, agent based modelling explains how these actions, strategies and expectations might endogenously change, resulting in more complex patterns. In essence, agent based models can explain how an economic model behaves out of equilibrium rather than just in equilibrium.

Helbing and Balietti (2011) explain that computer simulations have helped us understand the interaction of physical particles, astronomical observations, chemical properties and allowed the design of energy efficient aircrafts and safer cars. They say that the use of computing devices are pervasive in our lives and agent based modelling provides us a better understanding of our social and economic systems. Khazaii (2016) provides further clarification saying that agent based modelling uses autonomous agents that live, move and interact in virtual environments. In addition to interacting with each other, they are capable of impacting and changing the environment around them. Agent based modelling provides researchers with a platform to define the initial properties of the agents and the environment as well as the rules of interaction. They can then observe the changes emerging from the interactions in the model over time as agents and interactions evolve.

Grignard et al (2013) state that, in the past few years, several agent based modelling platforms have been developed, where some are set up to develop simple models while others can be used to develop rich and complex models. The GAMA modelling and simulation platform is set up to design agent based models that provide multiple dimensions in both space and time to set up the research problem and to analyse the solution. Conte and Paolucci (2014) discuss that the field of agent based modelling focuses on the role of generative theories that aim to explain phenomena by evolving them. They say that the generative power of agent based modelling has been underutilized as simple solutions have been developed, while shadowing the application of complex cognitive models. They also talk about the use of Computational Social Science (CSS) and several variants like deductive, generative and complex CSS in relation to the use of agent based modelling.

Miller (2017) argues that the methods of agent based modelling do not reconcile with the work of other management and organizational researchers, raising fundamental philosophy of science issues. In consideration, agent based modelling has made modest contributions to the advancement of organizational theory and empirical research. As a result, Miller (2017) proposes a critical realism as a philosophical perspective to explain agent based modelling, where he clarifies the purpose of using agent based modelling techniques and approaches that help build and test management and organizational theory. Key requirements in critical realism are the development of specific models, clarifying ontology, evaluating and validating model outcomes, triangulating and providing limits of agent based models. This study provides key insight to agent based researchers (modellers and non-modellers) regarding the advancement of agent based modelling with an application to management and organizational theory.

Giabbanelli et al (2017) state that agent based modelling is a technique to capture human interactions in socio-ecological environments. They act as micro models that incorporate agents with heterogeneous decision making processes that are based on beliefs and experiences. These agents can anticipate socio-environmental effects of aggregate individual behaviour. They further state that fuzzy cognitive mapping takes a macro view compared to agent based modelling, and represents causal connections between concepts rather than individual agents. Giabbanelli et al (2017) also says that previously researchers have had an interest in reconciling these two areas by developing hybrid approaches and drawing strengths of each to more accurately model socio-ecological interactions. The idea is to use fuzzy cognitive maps rapidly and then use them to develop a virtual population of agents that have sophisticated decision making processes.

Agent based models have also been used for analysing the diffusion of electric vehicles, where diffusion of electric vehicles is considered a reasonable policy strategy to reduce greenhouse gases in the environment. Wolf et al (2015) analysed the large scale adoption of electric vehicles considering consumers' transport requirements, values and social norms. They used an agent based model called InnoMind (Innovation diffusion driven by changing minds) to simulate the effects of social implications and policy intervention. This agent based model includes agents that represent consumers which are expected to derive attributes from survey respondents. They model agent decision making using an artificial neural network that accounts for emotions within these consumers. They simulate four scenarios representing the diffusion of electric vehicles in the city of Berlin, Germany. Their results show varying effectiveness in the different market segments with policies that will need to be tailored to heterogeneous needs of these segments. This simulation proposed that setting up an exclusive zone for electric vehicles will accelerate the early diffusion of such vehicles rather than providing financial incentives to increase this early diffusion process.

Agent based modelling has also been utilised to simulate population health related factors in a developing region, including disease burden, estimate of resource investment for population health and health care costs, and health care infrastructure requirements. Kruzikas et al (2014) developed an agent based model where the primary agents are individual health care facilities that capture the population characteristics, facility catchment population and facility diagnostic capacity and strategies. In this model, health facility investment decisions are made by setting up new hospitals in selected jurisdictions. The model is run over a time horizon of as long as 20 years and multiple scenarios are developed to help inform public health planning, investment and policy outcomes.

Dehghanpour et al (2016) undertook a behavioural study of the retail energy market that analyses price based demand response from air conditioning loads. They use a multi-agent framework, which incorporates multiple input factors and a network of agents where the framework characterises the collective behaviour of these agents. In their framework, a retailer agent buys energy from a wholesale agent that is sold to the end consumer. The aim of the retailer agent is to maximize its profit by setting optimal retail prices considering the demand-supply balance in the electricity network. They utilise a Q-learning algorithm to optimize consumption patterns, while considering temperature setting points of devices, consumption costs and user comfort preferences. The retailer uses computational techniques to develop a reliable model of aggregate use of price sensitive loads to reduce model uncertainty. The multi-agent framework assists in decision making given incomplete information. In this model, they show that agents can optimize their behaviour and the proposed approach shows that consumers are able to reduce their consumption costs. Results show that power consumption costs are reduced as the system converges to equilibrium, optimizing the retailer's profit.

Agent based modelling has also been applied to solve other research problems, including a batch scheduling problem. Bonabeau (2002) developed a hybrid model integrating an agent based model with a heuristic tree search to solve such a problem. The agent based model provided the framework for the batch process and constraints for the batch schedule. However, to overcome a myopic decision process of agents in the model, it embedded a heuristic search algorithm. In effect, the heuristic algorithm searched the solution space used in the agent based simulation. As the objective function of the search algorithm utilised global information, the batch schedule provided better performance results. This helped the agent based model improve the search results as it utilised the advantages of agent based modelling and mixed integer programming, allowing it to attain solution efficiency and schedule performance. This performance was reflected in two case studies in this research paper, including a study on improving performance for the Dow Chemical Company.

Another example of the use of agent based models is where Huang et al (2014) have used it for modelling urban land use; in this paper a significant number of modelling techniques have been utilised in urban land use and have substantially improved over time. Agent based modelling is a relatively new technique to model urban land use, but is seen to resolve some of the challenges faced by traditional modelling techniques. Agent based model use has increased in urban land use modelling over the past two decades. In retrospect, approximately fifty-one agent based models have been developed to analyse urban residential choices in three specific categories, including urban land use utilizing classical theories, analysing the different stages in the urbanization process and integrated micro simulation and agent based models. This study reviews all fifty-one agent based models as a single consolidated category of models as well as focusing on the new features introduced by these models. They find that agent heterogeneity specifically related to attributes and behaviour has been important. Representation of land market processes related to preferences, resource constraints, competitive bidding and endogenous relocation have also been supported by agent based models. These agent based models have been quite useful in solving these problems that would have been hard to solve with other systems. This study also states that by utilizing heterogeneity of agents, land markets and by exploiting the broader dimensions of output variables, it will help them to improve model fitness and robustness resulting in an improved understanding of urban land use change.

Wang et al (2015) used agent based modelling to analyse a variety of cancer behaviours. They state that there have been numerous techniques used over the years to model cancer behaviours. Agent based models provide a discrete hybrid approach to simulate the diversity of the cancer cell population and the dynamics within each individual cell. This technique, as a result, provides powerful insights to computational cancer researchers. They state that numerous features of tumour morphology, which includes phenotype changing mutations, the angiogenesis process, influence of the extra cellular matrix, micro environment adaptation, reaction to chemotherapy and surgery, effect of oxygen and nutrients, metastasis and the treatment of health tissue, can be analysed using agent based models. This insight provides an explanation of cancer growth spanning multiple biological scales including varying time frames and space and can be used to analyse other experimental hypotheses using these agent based models.

Further, Chen and Zhan (2017) have undertaken a study to simulate staged evacuation strategies by applying agent based modelling techniques. In this simulation, they analysed an instance where all residents at a site are informed and evacuate at the same time compared to residents being informed in a staged approach, which resulted in a staged evacuation process across the different zones of the site within the affected area. This research used agent based modelling to understand traffic flow of individual vehicles and analyse the collective behaviour of evacuating vehicles. They utilised a microscopic simulation called Paramics that includes three forms of road network structure, taking into consideration different population densities. These three structures relate to a ring road structure, grid road structure and the road structure in the city of San Marcos (Texas, USA). The Paramics model incorporates default rules used for trip generation, destination choice and route choice. Results show that if the residents did not evacuate the premises, then that would have been the most optimal approach across the various gird road structures, while the performance strategies depend on the population density and network structure. They notice if the population density is high and the network structure is a grid, then a staged evacuation that includes non-adjacent zones in affected areas is the most suitable option to minimize the evacuation time.

Lee and Malkawi (2014) have also used agent based modelling to simulate multiple occupant behaviour in commercial buildings. The purpose of this simulation was to understand the dynamics of occupants in the real world in such an environment. Occupants were modelled as autonomous agents that interact with other agents in the simulation and the environment. This included the simulation of individual agent behaviour and the behavioural phenomena of the collective agents in the building. Further, by utilizing simulation coupling, the behavioural response of thermal conditions and energy use could be understood. The study tried to understand behaviours of how agents adjusted clothing levels, their activity levels, window and blind use and utilization of space heaters within this building to obtain their optimal level of comfort. They also tried to simulate how agents adapted to the dynamic thermal changes in the building, when the optimal level of comfort and energy savings had to be achieved.

Agent based models have also been used to validate environmental impact indicators. Environmental impact indicators have been validated as a pre-requisite for brokers to charge for eco-industrial parks. This task becomes more difficult as it is harder to obtain real world data where there are a small number of eco-industrial parks, but many companies wanting to use them. In such an instance, it is easier to utilise an agent based model to simulate such a scenario. Mantese and Amaral (2017) undertook a study using agent based modelling to validate and simulate eco-industrial parks that include the evaluation of the industrial symbiosis indicator, eco-connectance, by-product and waste recycling. This study was able to understand the use of these indicators and eco-industrial parks.

To summarize this discussion, agent based models allow us to model a collection of autonomous systems and understand their individual as well as collective behaviour. Here the agents make their own decisions and allows them to show behaviour that represents the overall system. As a result, agents are a simplified and abstract representation of reality. Agents differ in their level of complexity and vary in dimensions, depending on how autonomous, self-interested, social and capable they are to learn. Agent based models are used to solve complex problems that may be social, physical, biological or economic in nature. These models are written using different languages like C++, Java, Small Talk etc. While, there are specialised agent based modelling environments like ASCAPE, REPAST etc. that have also been developed to simulate real world problems. These models have been really useful for researchers to analyse complex problems of real world phenomenon and their use seems to be increasing over time.

In conclusion, in this section I have outlined the different uses and applications of agent based modelling. Agent based models have been applied to numerous fields of research, mainly as they can help simulate the complex behaviour of individuals and the overall environment. In the following section, I specifically look at the application of agent based models to finance and M&A transaction pricing.

## 2.5 Agent Based Modelling in Finance

Agent based modelling has been utilised to a great extent in finance. A summary of the application of agent based computation finance to financial markets can be reviewed in LeBaron (2000), where the paper has introduced the concept of Artificial Markets. In effect, the Artificial Markets framework has used agent based modelling to simulate the interaction between agents and to understand the complex dynamics of a stock market. LeBaron (2006) has used agent based models to subsequently delve further into understanding investor heterogeneity and its impact on changing asset prices in financial markets. Hommes (2002) states that agent based models can be developed to analyse rational agents in a financial markets framework with simple trading rules and stylized facts, including fat tails, volatility clustering, financial stress and long memory to understand price dynamics in a financial markets environment. Janssen and Ostrom (2006) discuss that there is an increased use of agent based models in combination with empirical methods in finance. They state that four types of empirical approaches including case studies, role playing games, lab experiments and stylized facts have been used, which allows agent based models to emulate real world scenarios to solve problems.

Hommes and Wagener (2009) perform a review of studies in the area of complex evolutionary systems with an application to behavioural finance. A study by Lux and Marchesi (2000) is one of the examples where agent based modelling has been used to analyse volatility clustering in asset prices. Lux (1998) analyses the socio-dynamics of speculation in markets, including the interaction between agents, chaos and fat tails in return distributions. Lux (2006) and Alfarano and Lux (2007) discuss how there are universal laws in financial models that impact them. Lux (2009) states that behavioural factors can be important to asset pricing and this paper analyses stochastic behavioural asset pricing models and the stylized facts that are associated to such models. Lux (2008) reviews the application of statistical physics in finance and economics, which aligns to the application of stochastic processes to solve finance problems. Chen, Lux and Marchesi (2001) test non-linear structures that relate to behavioural factors in artificial financial markets to understand the underlying dynamics.

Kim et al (2014) used agent based modelling to analyse the relationship between the dynamic interactions and behaviours of rational agents in the financial market with monetary policy. The agent based model analyses agent behaviour at different levels of irrationality, the dynamics of the group of investors that behave rather irrationally in the market and the unpredictability of the behaviour of both rational and irrational investors. Their results explain that a system that focuses on macro-level monetary policy tends to have steep fluctuations with the medium level irrational agents. But, when the same system utilises micro-level monetary policy as its base to manage interactions between the different types of investors, then it remains more stable than when macro-level monetary policy is used as the primary policy framework. As a result, a system that focuses on a combination of macro and micro-monetary policy also remains stable, which provides strong insight into the monetary policy in practice.

Further, one of the specific applications of agent based modelling to macroeconomic theory can also be seen in the paper by Lengnick (2013), where an agent based macroeconomic model was developed to compare it with a dynamic stochastic general equilibrium model. While this agent based model is simple, it has the insight of being able to provide numerous stylised facts regarding business cycles. The study supports the use of agent based models for macroeconomic analysis, as it is seen to provide more dynamic insight into agent behaviour than reproducing equilibrium microeconomic optimisation outcomes. On the other hand, it provides consistent micro structures and properties representing these markets. Agent based modelling also eliminates co-ordination failures and instability in the model that may be introduced due to assumptions in relation to equilibria. As a result, a general equilibrium condition in an agent based model can be shown to result from endogenous non-rational micro interaction.

Application of agent based modelling to the field of economics has been reasonably extensive. Ballot et al (2015) provide a survey that explains the growth and contribution of agent based models in extending research in the fields of economic analysis and experimental economics. This paper discusses how agent based modelling develops and improves the analysis of macroeconomic disequilibria, while understanding the likelihood of equilibrium in such real-world systems. Further, it reviews the application of agent based models in explaining phenomena in markets in practice. Additionally, this paper discussed the improvements made in these types of models that can act as alternate tools and techniques for solving harder research problems.

Bertella et al (2014) have used a behavioural finance approach using an agent based model to understand the effect of behavioural bias in financial markets. They developed an artificial financial market that included agents replicating the behaviour of fundamental financial analysts and technical chartists. These agents differ in the market strategies that they implement, as they focus on different factors that they consider important when analysing stock price and as they use a different decision making process to come up with their strategies. They also display differing confidence levels and memory spans through this decision process. They notice that excess volatility and kurtosis in stock prices in real-world markets replicates the concept of varying memory lengths in the decisions made by these agents. They also incorporate the concept of adaptive confidence that seems to positively correlate with the return rate obtained by these agents, which shows that stock price fluctuations can be significantly impacted by market sentiment. They also find that the inclusion of market confidence can escalate stock price volatility, as irrationality in agent behaviour increases.

While agent irrationality can have an impact on market prices, the way that orders are executed in financial markets can also have a significant impact on the volume and market price of these assets. Mastromatteo et al (2014) developed an agent based model to understand the impact of meta-orders on financial market order volume. They state that daily stock market liquidity is latent and reduces linearly around the current stock price, being a result of the diffusion of the stock price. Mastromatteo et al's (2014) model studies the deficiencies in the paper published by Tóth et al. (2011). They specifically analyse the intelligence around limit order execution, as well as the underlying logic around market order execution of orders. Mastromatteo et al (2014) have developed a way to allow limit orders to react to order flow and have changed the execution protocol. They discuss that the original square-root impact law that was developed in the original Tóth et al. (2012) paper is robust and they propose a framework to explain that even marginally small biases in order flow can have a non-linear impact on limit orders in the system.

Wah and Wellman (2013) further study the effect of latency arbitrage on liquidity and allocative efficiency of stocks in fragmented markets. They propose a simple discrete event agent based model that captures processing and information delays with a single stock that is traded across two different exchanges, where aggregate information about this stock is available to regular traders following a short delay. They find that an agent who undertakes an infinitely quick arbitrage between these two exchanges can make substantial profits when there is a divergence between the two markets. They simulate the interactions that include high frequency and zero intelligence trading agents at rapid transaction speeds at the millisecond level. Then, they assess market liquidity and allocative efficiency from the simulated order flow in the agent based model. Results show that market fragmentation and the existence of latency arbitragers negatively impact liquidity and total surplus within the system. When continuous time markets are replaced with periodic call markets, the opportunity to undertake latency arbitrage is eliminated, while additional efficiency gains are achieved through the aggregation of orders in the short time periods.

In financial markets, dynamics of human behaviour are critical to how market prices will move. In a financial market crisis, market prices will change rapidly and this impacts all humans across the globe, as it impacts the global economy. To understand the complex human behaviours that have led to financial crisis, Preis et al (2013) have suggested that researchers utilise the massive data sources that have been created through the interaction of humans on the Internet. Even by analysing Google trends that relate to query volumes regarding financial market search terms, researchers can obtain immense amounts of data that can be used for developing realistic agent based models. These models, combined with these extensive behavioural data sets, can provide insight into collective human behaviour and early warning signals for potential financial crises coming up on the horizon.

There is an abundance of financial information and other forms of complex information available to researchers, which can be used with agent based models to understand the functioning of financial markets further as well. Wiesinger et al (2013) have developed a virtual stock market using an agent based model framework that incorporated a large network of interacting bounded rational agents. In this study, they optimised the similarity between actual data and that reconstructed through their agent based model to identify strategies and parameters that reveal the functioning of stock markets in practice. They also test their findings using out of sample predictions that helps them find out if their prediction model is robust when analysing the NASDAQ Composite index.

Dimpfl and Jank (2016) study stock market volatility dynamics in relation to retail investor’s attention to the market, which is measured by Internet search queries related to leading market indexes. They find that strong co-movements of the Dow Jones Industrial Average index coincide with an increase in volume of search queries on the Internet for this index. Further, using Granger-cause volatility for search queries, they notice that a higher number of search queries on a day predict higher index volatility on the following day. They also find that including autoregressive models of realised volatility increases volatility forecasting both in and out of sample and across different forecast horizons, especially in high volatility phases. Such relationships can also be tested using agent based models, as they can incorporate the hybrid input from the Granger-causality and autoregressive models.

Hafezi et al (2015) state that developing an agent based model to accurately predict stock prices has been of significant interest to most investors. They develop a multi-agent framework called Bat Neural Network Multi-Agent System (BNNMAS) that would assist in predicting stock prices. This agent based model is a four-layer multi-agent model that is expected to predict the next eight years of DAX Stock prices on a quarterly basis. This BNNMAS system is evaluated by using fundamental and technical DAX stock price information and comparing the results with other Genetic Algorithm Neural Network (GANN) and Generalised Regression Neural Network (GRNN) models. Results show that BNNMAS provides reasonably accurate and reliable information and can potentially be utilised as a model for predicting stock market prices in the longer term for the DAX index.

Through this section, I have reviewed the application of agent based models to economics and financial markets. This thesis further reviews the application of agent based models to a specific area of finance called Mergers & Acquisition (M&A) transaction pricing. As a result, I further look to streamline this section to review literature that is related more to this specific research area of M&A pricing and agent based models. While there is limited research that has been conducted in this area to date, Agarwal and Zeephongsekul (2013) have discussed how psychological factors can impact the pricing of M&A transactions. They used the concept of incomplete information and real options to develop a model to find the optimal price (Nash equilibrium) that would be suitable to both the acquiring and target companies in an M&A transaction scenario. Such a model can also be simulated in an agent based modelling environment.

Further, Agarwal and Kwan (2017) have developed an agent based model that considers the risk aversion and optimistic behaviours of the acquiring and target companies respectively. This model tries to analyse if these behaviours will impact the pricing of M&A transactions. They also include a scenario to consider the case of a hostile takeover or changes in business cycles as part of this discussion, to help understand if such behaviours would impact these M&A transaction scenarios.

Results show that risk-taking acquirers will be willing to pay higher prices when the target company is optimistic and demands a higher price. The results also show that acquirers are more willing to pay higher prices when the business cycle is improving compared to when it is deteriorating. They also find that, as the hostile takeover characteristic of the acquirer increases, it pushes the final M&A price lower than if such a circumstance did not exist and this behaviour especially comes into effect when the target company is less optimistic in its behaviour.

While there are limited studies analysing M&A transaction pricing specifically, nonetheless there are other studies have been conducted that analyse aspects of M&A transactions using agent based modelling. Zedan, Bullock and Ianni (2013), for example, analyse merger waves and their dynamics using agent based modelling. Wiedlich and Veit (2008) analyse mergers among German electricity companies using these models, while Aid (2009) undertakes similar research considering European utility companies and measuring impacts on long term financial risk. Zedan (2013) develop agent based models to examine the merger of financial institutions and its impact on financial market stability and systemic risk compared to Schmidt (2010) who used agent based modelling to analyse mergers of Chinese banks that were investing outside China.

To summarise, agent based modelling has started being used extensively in finance, especially being utilised to simulate complex real world problems related to financial markets and macroeconomic situations. These models include such models as LeBaron’s (2000) Artificial Markets framework, Hommes (2002) agent based models using heterogeneous agents and Lengnick (2013) model that analyses macroeconomic equilibrium. These agent based models allow the researchers to understand the individual behaviour of each agent in the market or economy and the overall dynamics of the system, in this case the financial market or the macro economy. These models have also been used to understand specific problems like liquidity and limit order placement in stock markets, and how human behaviour may impact price moves in stock markets. Agent based models have also been developed to forecast potential financial crises and stock market volatility dynamics. Further, some researchers have also utilised agent based models to simulate the impact of behavioural factors in M&A transactions. This thesis extends on that research to develop a more realistic agent based model to simulate real world M&A transactions.

Finally, this section has shown that there are numerous applications of agent based modelling to economics, financial markets and to the specific research area of M&A transactions. However, there has been limited research in the M&A transaction pricing area from an agent based modelling perspective, especially when it comes to looking at behavioural and psychological factors that may impact such pricing (Agarwal and Kwan 2017). Agent based models provide an excellent framework to analyse the complex agent interaction due to the change in behavioural factors and the overall change in dynamics and optimal price that acquirer will be willing to pay and target companies will to receive in such M&A transactions.

## 2.6 Conclusion

In conclusion, the intent of this chapter has been to review the literature in the research areas related to Merger & Acquisitions (M&A), agent based modelling and the application of agent based modelling to finance and specifically to the pricing of M&A transactions. Through this chapter, there has been a discussion of factors that impact M&A transactions, agent based models and their application to different fields of application and, finally, the application of agent based models to economics, finance and M&A transactions. This chapter has also acknowledged that there is limited research that has taken place in the application of agent based models to M&A transaction pricing and that there is a gap in literature that can be utilised specifically to develop agent based models that analyse behavioural factors that impact the pricing of M&A transactions. This is expected to assist M&A practitioners to understand how behaviour can impact pricing of these transactions and for them to be able to better positions themselves when they undertake such negotiations.

Finally, it is critical to state that current merger and acquisition transaction models are specifically based on accounting models. While, we noticed the application of agent based modelling to finance and economic problems. Also, the application of these techniques to mergers and acquisition related problems. However, we have not seen an application of behavioural finance and agent based modelling to merger and acquisition transaction pricing. This is a clear gap in the literature based on the review undertaken in this chapter. As a result, this thesis will look to develop such a model in this thesis that will be analysed against real world merger and acquisition transaction (as no current model exist to compare the results). Additionally, risk aversion has been a basis for all economic models since the 1950s in the areas of finance and economics. However, risk aversion has not been utilized for merger and acquisition pricing, as merger and acquisition models are based on accounting methods. Further, the intent of this thesis is to utilize risk aversion as one of the behavioural traits to understand the changes in M&A transaction pricing. In traditional finance and economics literature, risk aversion is not treated in the same manner.

C H A P T E R   T H R E E

# Behavioural Mergers & Acquisitions Pricing using Prospect Theory[1]

## 3.1 Introduction

Merger & Acquisition (M&A) pricing is usually undertaken with traditional finance models like discount cash flow analysis and industry multiples. These models consider the future cash flows produced by the target and synergies that are obtained by merging two companies. Then, they discount these amounts to understand the current value of the target firm. However, such finance models do not consider the concept of behavioural finance, where psychological factors like risk aversion or optimism can impact that an acquirer is willing to pay to purchase the target company. In addition to these factors there are other factors such as loss aversion and human biases to gains and losses that are explained by cumulative prospect theory (Kahneman and Tversky 1992). Another example of behavioural finance is provided by Baker and Wurgler (2009), who undertook an empirical study and stated that if the acquirer paid an amount equal to the 52-week high of the target company’s stock price, then it is likely that the target company’s shareholders will be willing to sell. They say that the 52-week high stock price acts as an anchor for the shareholders of the target firm. Such behavioural finance studies provide suggestions that traditional finance models are potentially questionable when looking at real world M&A transactions. Nonetheless, these traditional finance models have been the mainstream tool of large investment banks, who undertake these transactions.

This chapter intends to provide a behavioural finance and agent based modelling perspective of pricing M&A transactions. The next section discusses the literature review related to the application of agent based models to behavioural finance and M&A pricing. Subsequently, this paper analyses the application of an agent based model to analyse M&A pricing using prospect theory (specifically loss aversion) and cumulative prospect theory (analysing differential biases to low and high probability

[1] This chapter is based on the paper published in the Economics, Management and Financial Markets journal.

gains and losses). Finally, the last section in this study concludes by summarizing the discussion in this study.

## 3.2 Methodology

The literature review related to mergers & acquisition and agent based modelling has been provided in chapter 2. The model in this chapter utilises MATLAB 2017 to develop a game theoretic agent based model to analyse a merger & acquisition pricing game. This model is based on a prisoner's dilemma game and includes factors like loss aversion (based on prospect theory), differential weights for low and high probability losses from cumulative prospect theory and a scenario where some outcomes can be certain (representing the certainty effect provided by prospect theory). As obtaining behavioural data in a merger & acquisition scenario is extremely difficult, all data that is used in this study has been obtained through the merger & acquisition simulation undertaken in the MATLAB 2017 environment. These games are run 1 million times to obtain the results for each experiment. The way this game is setup is that there is a pool of 1000 acquiring and target firms in total and, for each game, a single acquirer and target firm is selected to play this single round game. After the game is finished both the acquirer and target firm are returned to the pool and may be selected to play another game with another player. The acquirer has a behavioural trait continuum from risk averse to risk taking and the target firm has a behavioural trait continuum from optimistic to pessimistic. These are assigned to them using a random number in MATLAB 2017. For each game, an acquirer and target firm are picked to play and a prisoner's dilemma game theory model is utilized to analyse their utility based on the type of game (there are numerous types of games: co-operative, non-copoerative and zero sum games; however in this thesis we only consider a specific game called the prisoner's dilemma game) that they are playing. Code for these games is provided in Appendix A. The next section provides the results of the M&A transaction game, where there is a single acquirer and single target company. In effect, the M&A transaction is analysed in the following three ways to provide the results in figures 1 – 12 in section 3.3 below:

1. A base M&A transaction game is setup to analyse how the transaction pricing changes when there is an acquirer (with risk aversion – risk taking characteristics) and target company (with optimistic – pessimistic

characteristics). This base model has a loss aversion co-efficient from Prospect theory that is implemented by adding a loss aversion ratio to the M&A transaction pricing equation in the model (Kahneman and Tversky 1979). It is implemented as a percent in the pay-off equation of the game theoretic model. That states that humans value losses more than gains. See MATLAB code for this model in Appendix A – Model 1.

2. The base model is then extended to include Cumulative Prospect Theory (Kahneman and Tversky 1992) and the loss aversion co-efficient is increased to 50 percent (meaning that gains are only half as valuable as losses). See MATLAB code for this model in Appendix A – Model 2.

3. The base model is extended to include Cumulative Prospect Theory (Kahneman and Tversky 1992) and certainty effect (where the outcome can be nearly certain instead of being probable). The certainty effect is important as humans support different outcomes when outcomes are certain, when viewing losses and gains. See MATLAB code for this model in Appendix A – Model 3.

Further, prior to moving forward it is critical that we define the terms 'risk taking and risk aversion' and 'optimism and pessimism'. Risk taking and risk aversion is a continuum, where the acquirer is considered as risk taking if it is willing to pay more to purchase the target than would be logical and vice versa. Similarly, optimism and pessimism is a continuum, where a target expects to obtain a higher price than would be logical and vice versa. As these are behavioural continuums, they are assessed on a scale of 0.00 to 1.00 (i.e. there are no units associated to this scale). This terminology will be used through the rest of this thesis.

### 3.3 Merger & Acquisition Pricing using Prospect Theory

M&A transactions can be explained using Decision Tree structures (also called Classification and Regression Tree Structures in the area of Computational Modelling); these decision tree structures portray the algorithm that explains the figures obtained below (as well as in chapters 4-6). The decision tree structure that depicts the algorithm utilised in this M&A transaction model (and variation of this model in chapters 4-6) can be explained as follows:

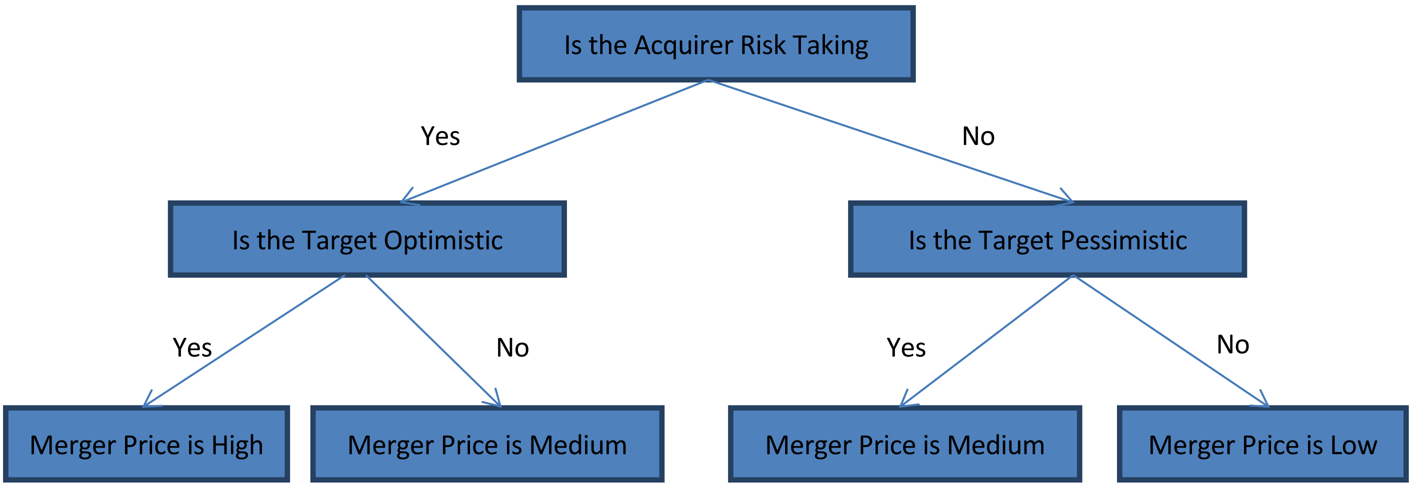


**Diagram 3.1 Generic CART Decision Tree for M&A Transaction Pricing**

This decision tree structure intends to explain how the acquirer and Target Company will make a decision. In effect, it shows the decision path and the inter-dependency of the decisions that both these companies will make. Also, as the behavioural traits are continuums (risk taking – risk aversion and optimism – pessimism), the game, when simulated numerous times in this thesis, tends to provide a more dynamic outcome than just a 0 or 1 decision. The results of agent based simulations undertaken in this thesis are represented as figures and show this change in dynamics due to the change in the behavioural traits and decision behaviour.

To help understand the figures provided in chapters 3 – 6, we provide the following explanation. These figures are 3-dimensional figures, where the x-axis provides behavioural traits for the target company, y-axis provides the behavioural traits for the acquirer and z-axis shows the price for the combination of the behavioural traits of the target and acquirer. So, as the values of the behavioural traits change on x-axis and y-axis, the price of the M&A transaction will change. The figures as a result show the change in price for different values of the behavioural traits of the target and acquirer.

The agent based modelling game in this thesis is based on a game theoretic concept called the two-person Prisoner's Dilemma. McCain (2004) and Rasmusen (2006) explain the Prisoner's Dilemma game with the following example: There is sufficient evidence to convict two people for criminal charges, each of them is interrogated separately and each is advised that "if they confess then they will be released and their accomplice will serve 15 years in prison and vice versa". However, if both of them confess, then both will serve 7 years in prison. The way it is applied in this thesis to solve the merger and acquisition problem is that the behaviours of the acquirer and target companies are considered. Then, a Prisoner's Dilemma game is played with each acquirer and target that helps simulate what the different transaction prices will be based on the changes in the behavioural traits of both the acquirer and target companies. In this thesis, the Prisoner's Dilemma game picks an acquirer and a target company at random. The acquirers are assigned at random a behavioural trait rating on the risk aversion – risk taking continuum on a 0.00 – 1.00 scale. Similarly, the target companies are assigned a behavioural trait rating on the optimism – pessimism continuum on a 0.00 – 1.00 scale. Then, approx. a million games are played to obtain the overall dynamics across the two continuums (that constitutes a single graph). The model is reset for each new graph and the set of games are played again. These graphs/figures are provided in chapters 3 – 6 covering the different factors that are analysed in this thesis.

The Prisoner's Dilemma model in this thesis in essence considers the following equation, it accounts for the selfishness of both the acquirer and target companies and negates the co-operative behavior of both of them. This occurs as the more selfish that each person is in the Prisoner's Dilemma model (i.e. they confess), then it is more likely that they will receive a lower jail term. The more co-operative they are (i.e. they do not confess), the more likely that they will receive a higher jail term. So, if the acquirer is selfish, they are more likely to obtain a lower price, if the acquirer is co-operative, they may agree to a higher price. But, a lower price is of greater importance to the acquirer. Similarly, if the target company is selfish they will demand a higher price and the target company will work with a lower price if it was co-operative. However, a higher price is much more meaningful for the target company. As a result, the Prisoner's Dilemma model works in a way that selfishness will support the outcome, while co-operation will reduce the outcome. However, being completely selfish is not good, as both will end up getting a jail term. So, the idea is to deceive the opponent and confess, which will result in a higher return. The way this thesis adds value is that it connects the behavioural factors of the acquirer and target companies to the Prisoner's Dilemma model and the concepts of selfishness and co-operation. This dynamic change in these behavioural traits for the acquirer and target effect the change in the merger and acquisition transaction price.

In this thesis, I setup an agent based model that incorporates the risk aversion and optimistic behaviour of the acquirer and target company respectively, we find the results provided in figure 1. That supports that the price would increase when the acquirer is risk taking and target company is optimistic. However, if I extend this model and include the concept of Loss Aversion from Prospect theory (Kahneman and Tversky 1979) and include the loss aversion co-efficient, where gains are only seen to be 28 percent as psychologically valuable as losses, then, I get the result as provided in figure 2.

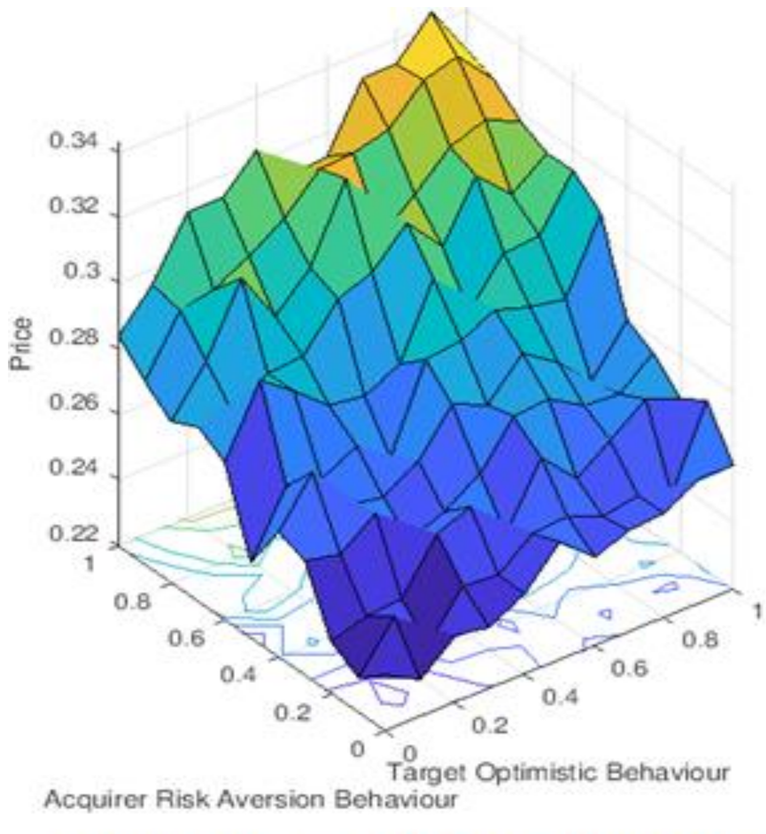


**Figure 1 Prospect Theory Loss aversion 0%**

Interestingly, gains in figure 2 are greater than those in figure 1, due to the requirement for people to make higher gains to compensate for losses. The same occurs in figure 3, where the loss aversion co-efficient is raised to 50 percent, where gains are seen to be seen as half as valuable as losses. Results in figure 3 however differ from figure 2, where target companies with more optimistic behaviour can obtain a higher price, probably as acquirers find it less confronting to pay more due to the lower ratio of psychological impact of gains and losses. This contrasts further to figure 4, where I increase loss aversion to 100 percent. In this case, losses and gains have the same weight. Nonetheless, figure 4 shows that the optimal outcome is still the same: where the acquirer is less risk averse and the target is more optimistic than the base case model.

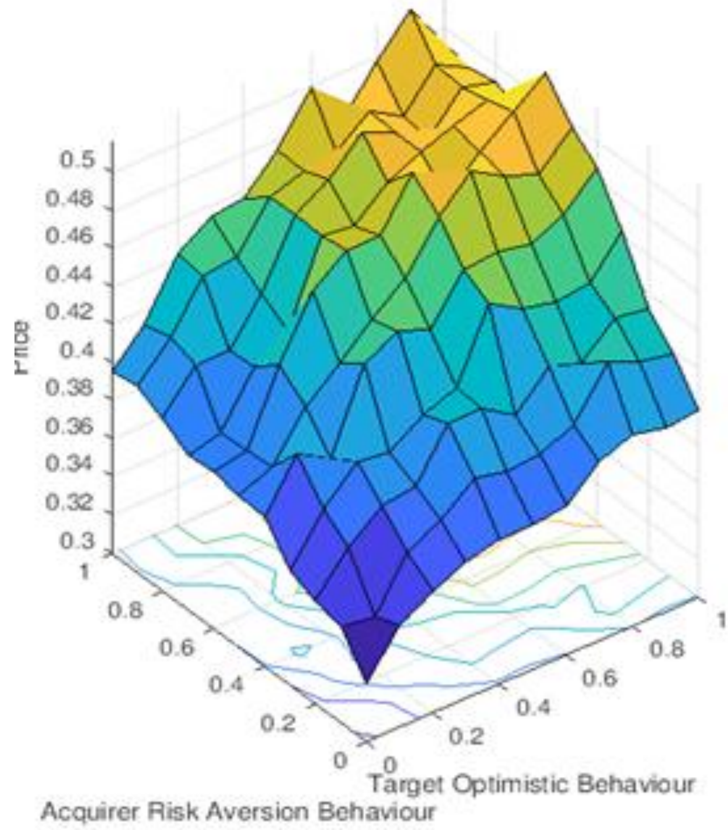


**Figure 2 Prospect Theory Loss Aversion 28%**

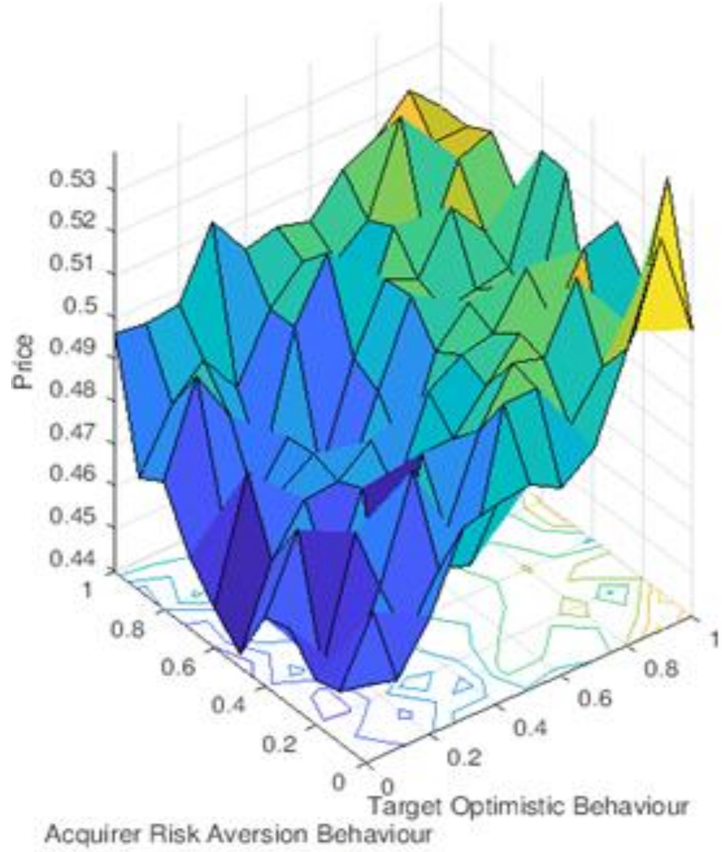


**Figure 3 Prospect Theory Loss Aversion 50%**

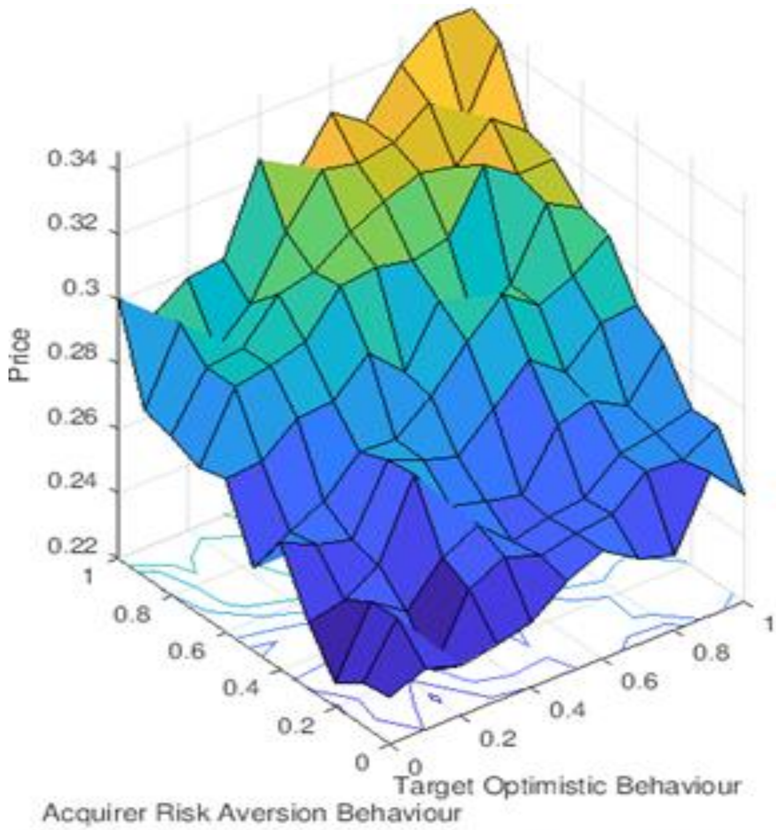


**Figure 4 Prospect Theory Loss Aversion 100%**

## 3.4 Applying Cumulative Prospect Theory to M&A Pricing

On the other hand, figure 5 – 8 represent the construct of cumulative prospect theory, where humans show risk aversion for gains and risk seeking for losses of high probability, in contrast to risk seeking for gains and risk aversion for losses of low probability. Figure 5 shows us that gains are higher when compared to figure 1, when only loss aversion was applied and cumulative prospect theory was not applied. However, in figure 5, both the risk aversion of the acquirer and the optimism of the target company highlight the most optimal results. But the result in figure 5 is lower than that obtained in figure 1. This mainly occurs as the risk dynamics for gains and losses change with the application of cumulative prospect theory. Weights of gains and losses between prospect theory and cumulative prospect theory differ, as prospect theory considers proportional weights, while, the weights in cumulative prospect theory are cumulative in nature.

In figure 6, the cumulative prospect theory weight for loss aversion is increased to 28 percent for gains and losses. This shows that when the risk aversion is nearly 3 times higher than the outcome in figure 5, as a result the outcome is more positive than that seen in figure 5. This is similar for figure 7, where I notice the results become even more positive.

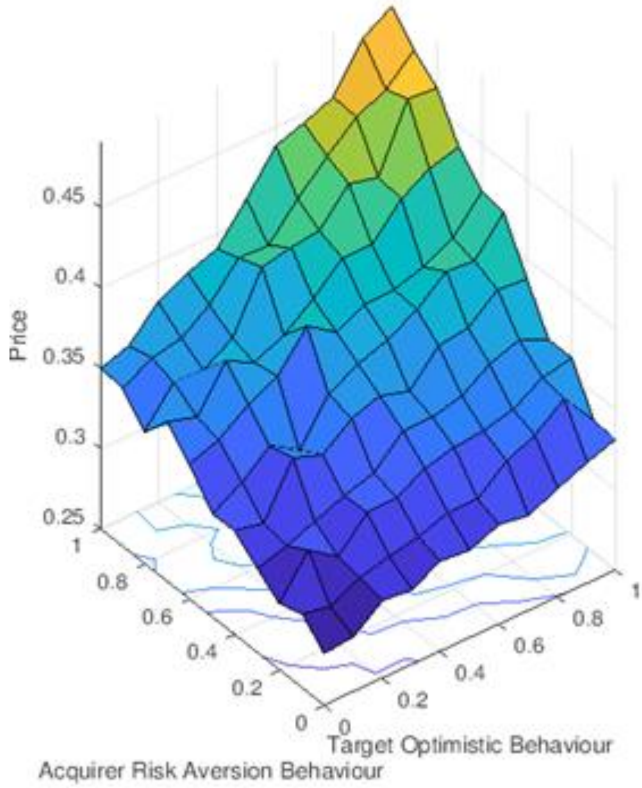


**Figure 5 Cumulative Prospect Theory and Loss Aversion 0%**

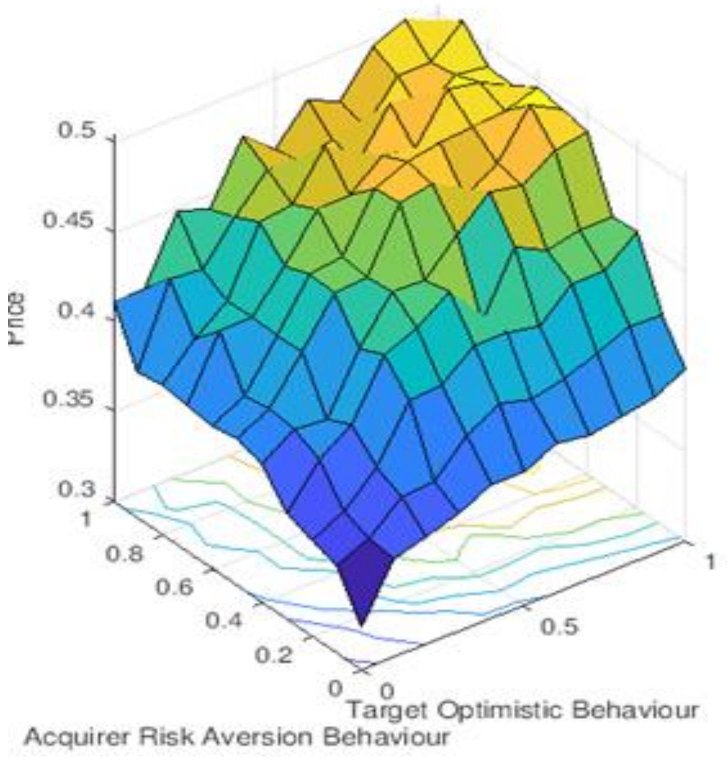


**Figure 6 Cumulative Prospect Theory and Loss Aversion 28%**

Especially, when the target company is optimistic, the results in figure 7 are much higher than those in figures 5 and 6. In figure 7, the loss aversion between losses and gains is increased from 28 to 50 percent, making it more valuable to be favourable to gains. In this circumstance, the target company's optimistic behaviour also has a significant positive impact on increasing the price of the M&A transaction. This mainly occurs as greater loss aversion encourages the target company to demand a better outcome as the perception of gains and losses are more even. On the contrary, figure 8 shows that when gains and losses have the same weight, even when preference for them may differ due to cumulative prospect theory, the most optimal outcome is still when the acquirer is risk taking and target is optimistic. However, as gains and losses are more evenly balanced in perception, the overall price of the M&A transaction reduces compared to figures 5 – 7.

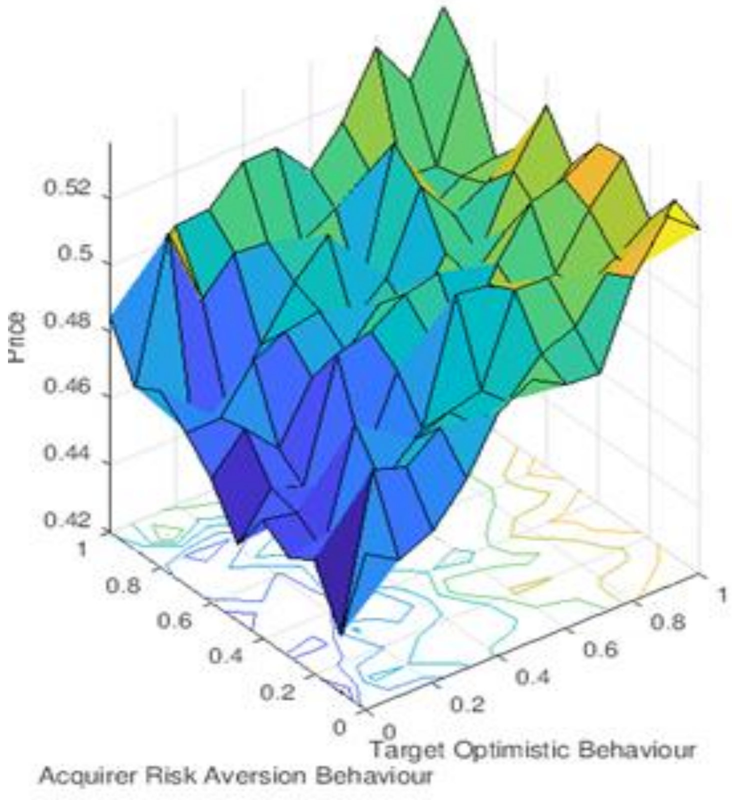


**Figure 7 Cumulative Prospect Theory and Loss Aversion 50%**

Figure 8 looks very similar to the outcomes in figure 1 and the overall utility in figure 8 is also the same for the acquirer and target company seen in figure 1. This occurs due to the fact that the probabilistic nature of gains and losses (cumulative prospect theory) negate the difference between the loss aversion co-efficient. In effect, this tells us that the outcome of cumulative prospect theory should be equal to that of prospect theory when loss aversion is 0 percent rather than 28 percent. This is a significant finding as the loss aversion co-efficient (difference in perception of gains and losses) has a greater impact than the probabilistic nature of gains and losses. This means that the acquirer and target company will be more concerned about the difference in gains and losses rather than if the gain or loss can be ascertained with a low or high probability.

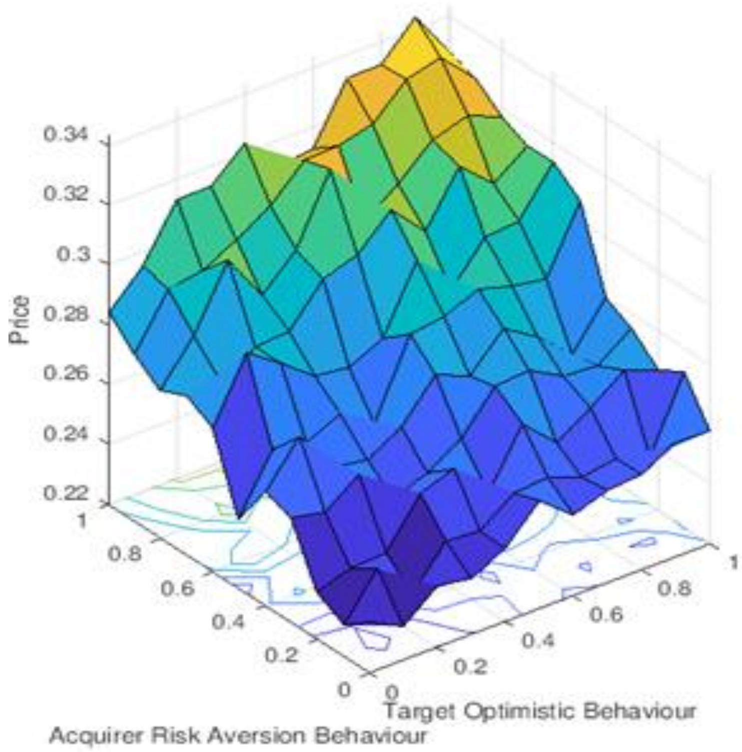


**Figure 8 Cumulative Prospect Theory and Loss Aversion 100%**

In comparison, figures 9 – 12 analyse the certainty effect explained in prospect theory. In figures 5 – 8, I analysed the concept of cumulative prospect theory, where humans deal differently with gains and losses with low or high probability. But prospect theory talks about the preference of humans to consider an outcome with certainty (100 percent certain) higher than a probabilistic outcome (probability of an event occurring is between 0 – 99 percent; this thesis assumed discrete values ). For example, if there is a possibility of gaining $1 compared to a 20 percent chance of winning $5. It is more likely that people will choose the certain outcome of gaining $1. In this context, figure 9 shows that when the certainty effect is considered, the results can be similar (in figure 5) to what can be seen under cumulative prospect theory, however this occurs only when loss aversion is low (loss aversion co-efficient is 0 percent) in both figures 5 and 9. This is a significant finding as it says that in circumstances where loss aversion is low, outcomes with high probability are considered the same as certain outcomes.

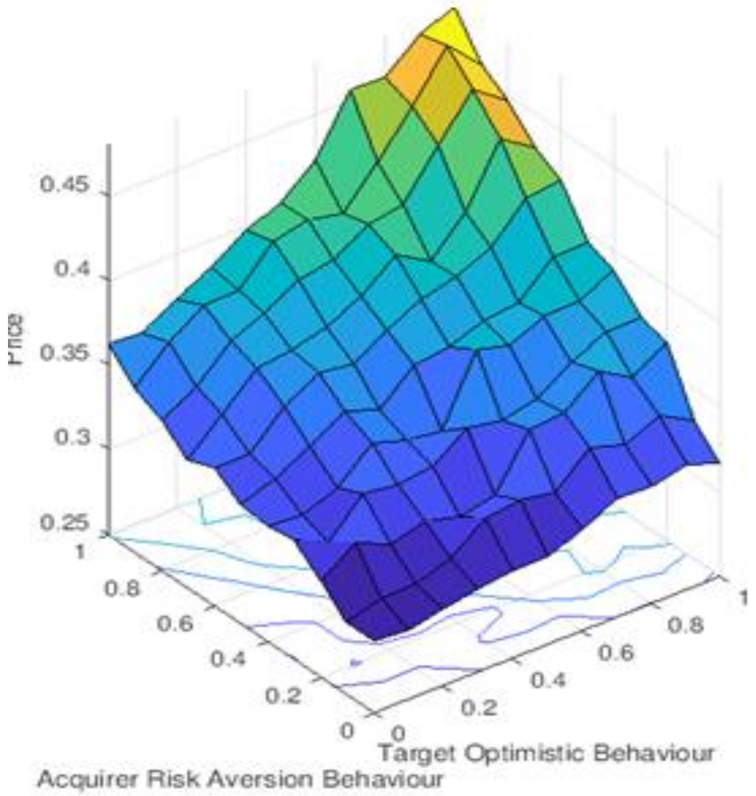


**Figure 9 Certainty Effect and Loss Aversion 0%**

However, figures 10 – 12 show that as loss aversion increases, the concept of certainty has a stronger impact on the acquirer and target company's results compared to when high probability outcomes (see figures 6 – 8) are present. This aligns with the concept of prospect theory's certainty effect that states that humans prefer outcomes that are certain compared to those that are probabilistic. But this provides us some further insight that the results in this model tend to increase from just the application of loss aversion in figures 2 – 4, but improve further with the application of the certainty effect in figures 10 – 12. Further, the utility reduces when the loss aversion increases (see figures 9 – 12). In effect, reduced loss aversion and increased certainty provide the best outcome. I can also see the differences in figure 9 – 12: as the loss aversion co-efficient increases, the overall price of the M&A transaction reduces as I have discussed earlier. In figure 9, the optimal outcome is still when the acquirer is risk taking and target is optimistic. However, the dynamics of the outcomes seem to change as the overall price falls from figure 9 to 12 and risk taking behaviour of the acquirer starts to also become important as the model transitions from figure 9 to 12.

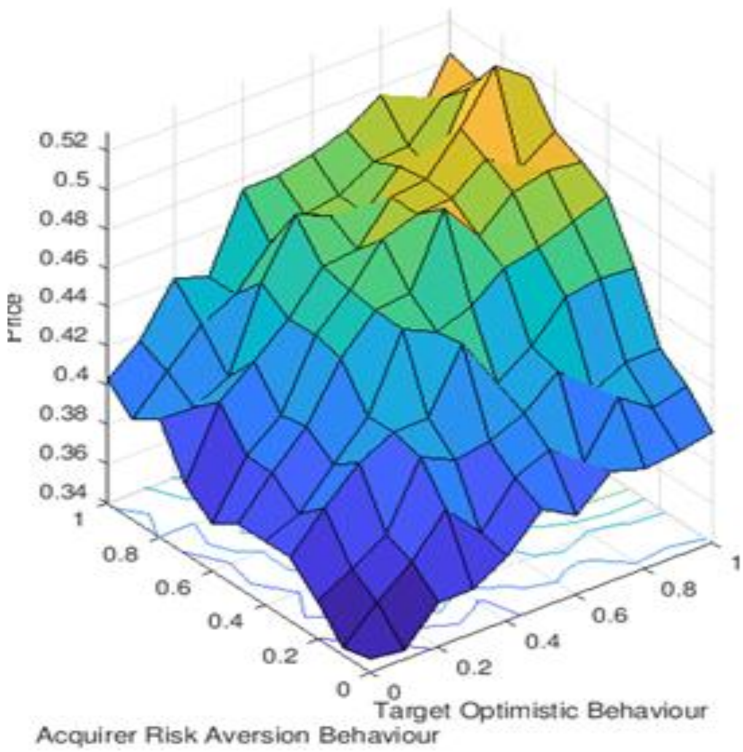


**Figure 10 Certainty Effect and Loss Aversion 28%**

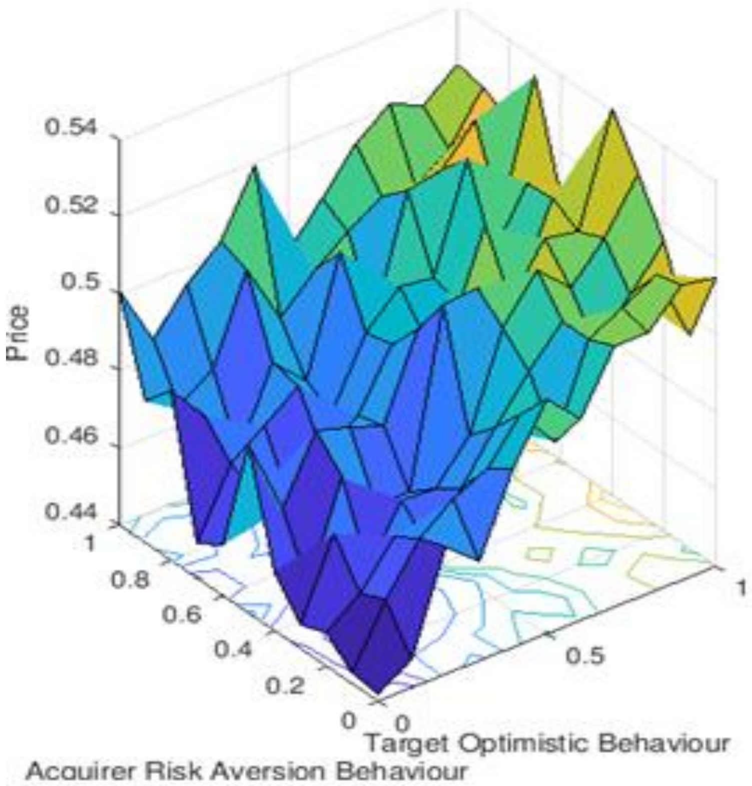


**Figure 11 Certainty Effect and Loss Aversion 50%**

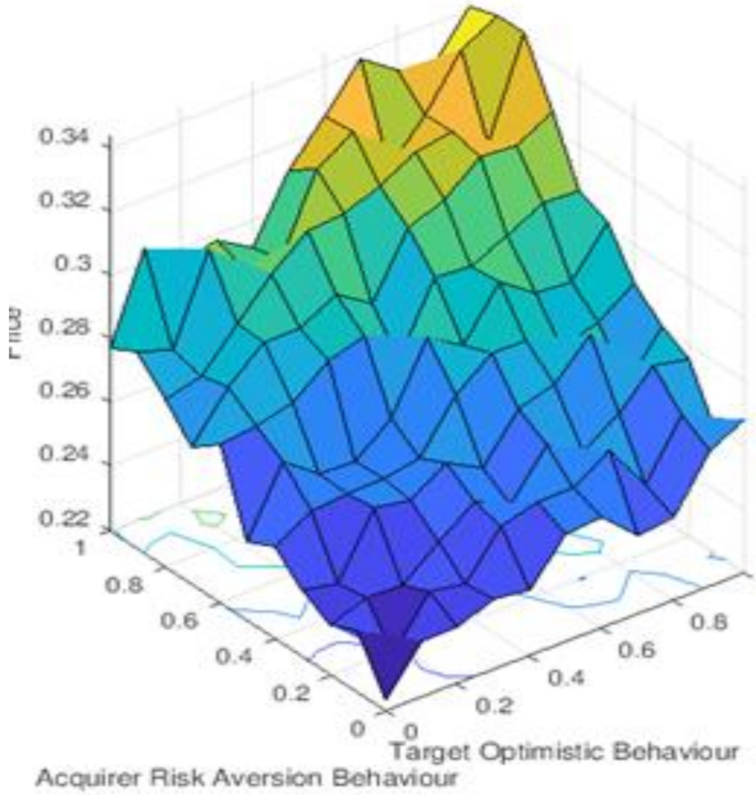


**Figure 12 Certainty Effect and Loss Aversion 100%**

In simplistic terms, the above figures 1 – 12, can be shown in the decision tree (CART) provided below. The results show that the optimal outcome for the acquirer and target company occurs when the acquirer is risk taking and target is optimistic, with returns reducing as the loss aversion co-efficient increases (as gains and losses have the same weight), but increasing as certainty increases in the outcome. This result aligns with the results of the AOL – Verizon and Yahoo! – Verizon mergers that we analyse in Chapter 5. These real world examples show that while the target companies were optimistic uncertainty decreased as additional issues adversely impacted the final transaction price of the merger. As we can see from the model, M&A transaction price will drop when uncertainty increases. Real world examples are provided in chapters 5. As, uncertainty in relation to the data breach issues relates to Yahoo! decreased, the valuation became more certain.

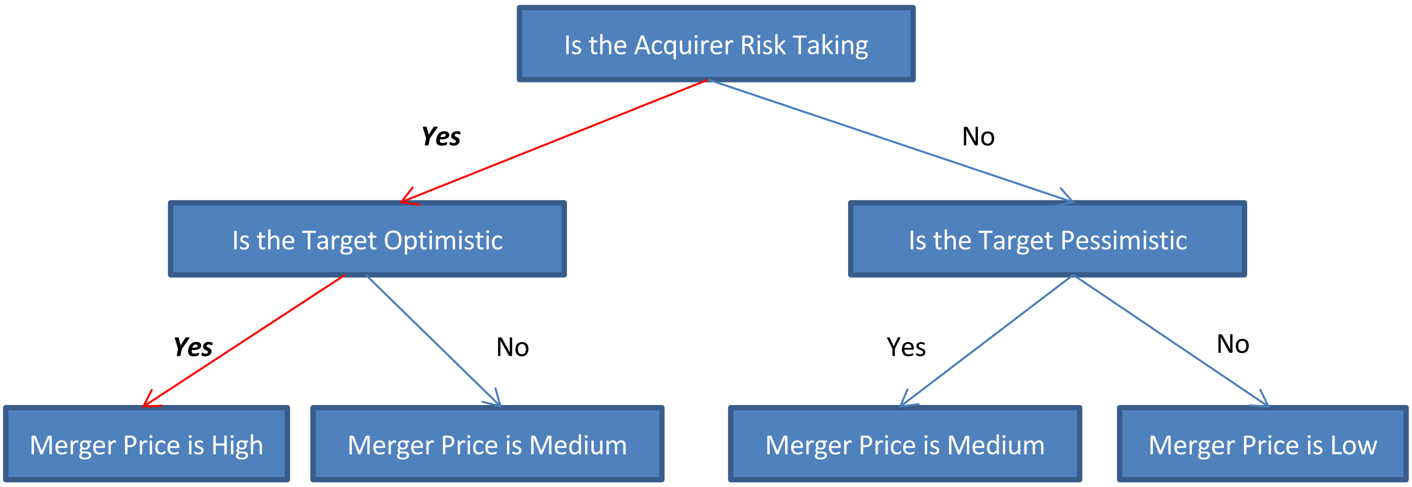


**Diagram 3.2 CART Decision Tree for Single Acquirer and Target Firm**

## 3.5 Conclusion

In this chapter, the computational modelling problem of finding the psychological price for a merger and acquisition (M&A) transaction for a single acquirer and target firm was undertaken. This agent based model was developed in MATLAB 2017 and implemented the concepts of game theory and prospect theory. The behavioural traits of risk aversion and risk taking for the acquirer and optimism and pessimism for the target firm were simulated to see what impact they have on the M&A

transaction price. The key factors that could impact the M&A transaction price on top of the behavioural traits of the acquirer and target firm are the loss aversion co-efficient obtained from the application of prospect theory. Results from these experiments showed that returns (M&A transaction price) increased when the loss aversion co-efficient was low and the opposite occurred as this loss aversion co-efficient was increased. The loss aversion co-efficient in prospect theory primarily reflects the ratio of the perception between losses and gains. When this co-efficient is low, say 28 percent, then the losses are approximately 2.5 times perceptively more important that gains. So, for every dollar that a person loses, they will need to gain approximately 2.5 dollars to feel that they have gained as much as they have lost. However, when the loss aversion co-efficient is 100 percent, the perception between gains and losses is reduced, so for each dollar that a person loses, they only need one dollar to make them feel that their loss has been covered. So, when the loss aversion co-efficient is low, the target firm requires a higher price when it is optimistic and the acquirer is willing to pay more. These outcomes are seen in figures 1 – 8 in this chapter.

Further, there is a concept of the certainty effect in prospect theory. In this instance, humans are happy to accept a lower price when they are given certainty and a higher price when the outcome is probabilistic. So, as the certainty in the game increases, the M&A transaction price starts to fall. Both increasing loss aversion co-efficient and certainty effect lower the M&A transaction price. These outcomes are seen in figures 9 – 12 in this chapter.

CHAPTER FOUR

# Behavioural Mergers & Acquisitions Pricing with Multiple Acquirers[2]

## 4.1 Introduction

This chapter incorporates behavioural finance theories using an agent based modelling framework to analyse M&A pricing. To develop this argument, the literature related to behavioural finance, M&A pricing and agent based modelling has been discussed in Chapter 2. The next section will analyse the methodology and the subsequent section will provide the results of this experiment. The final section will provide a conclusion for this chapter summarising the results.

## 4.2 Methodology

The model in this chapter has been developed using MATLAB 2017b. This model is based on the prisoner's dilemma game in combination with prospect theory and cumulative prospect theory. The intent of the model is to understand how the population of acquirers and target company's changes based on the behavioural traits of risk aversion, loss aversion and optimism. The individual population in this game gets optimised as the less fit individuals are removed at the end of each game. The code in Appendix A shows how the bottom 10 percent of players in the game is removed and a new 10 percent are added at the end of each game with randomized behavioural traits. This allows for mutation and dispersion in the game. This model is run for 1 million games in order to obtain the results that are shown in figures 1 – 12 below. The way this game is setup is that there is a pool of 1000 acquiring and target firms in total and for each game a single acquirer and target firm is selected to play this single round game. The acquirer has a behavioural trait continuum from risk averse to risk taking and the target firm has a behavioural trait continuum from optimistic to pessimistic. These are assigned to them using a random number in MATLAB 2017. For each game, an acquirer and target firm is picked to play and a prisoner's dilemma model is utilized to analyse their utility based on the type of game that they are playing. Code for these games is provided

[2] Parts of this chapter are published in the Economics, Management and Financial Markets journal.

in Appendix A. In effect, the M&A transaction model in this chapter analyses the M&A transaction problem in the following ways providing the results in figures 1 – 12 in section 4.3 below:

1. A base M&A transaction game is setup to analyse how the transaction pricing changes when there are multiple acquirers (with risk aversion – risk taking characteristics) and target company (with optimistic – pessimistic characteristics). This base model has a loss aversion co-efficient from Prospect theory (Kahneman and Tversky 1979) included in the model. That states that humans value losses more than gains. See MATLAB code for this model in Appendix A – Model 5.

2. The base model is then extended to include Cumulative Prospect Theory (Kahneman and Tversky 1992) and the loss aversion co-efficient is increased to 50 percent (meaning that gains are only half as valuable as losses). See MATLAB code for this model in Appendix A – Model 6.

3. The base model is extended to include Cumulative Prospect Theory (Kahneman and Tversky 1992) and certainty effect (where the outcome can be nearly certain instead of being probable). The certainty effect is important as humans support different outcomes when outcomes are certain, when viewing losses and gains. See MATLAB code for this model in Appendix A – Model 7.

## 4.3 Behavioural Merger & Acquisition (M&A) Pricing

The results in this chapter show that loss aversion has an impact on the utility of the acquirer and target company as seen from figures 1 – 4. The average utility tends to drop as the loss aversion increases from 0% (where gains are seen to be four times as valuable as losses) in figure 1 compared to loss aversion being 100% (where gains are perceived to be one time as valuable as losses) in figure 4. Though utility does not decrease between figures 1 and 2 significantly.

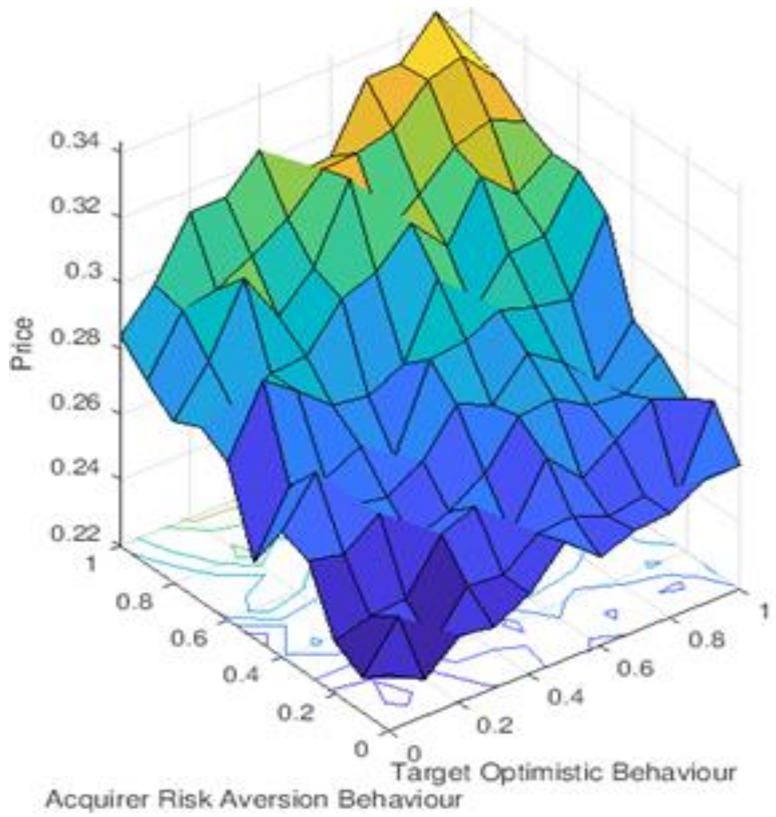


**Figure 1 Prospect Theory Loss aversion 0%**

However, I notice that the reaction to risk aversion and optimism traits has changed significantly. This occurs as an increase in loss aversion supports an outcome where the acquirer and target company becomes more risk averse or optimistic. Further, an increase in loss aversion has a significant effect on reducing the utility due to optimism in figures 3 and 4 compared to figure 1. This mainly occurs as the increase in loss aversion does not provide the target company any more utility that then would obtain by being less optimistic in this situation.

The model is further extended to include cumulative prospect theory and to obtain results when the probability of gains is high, and the results seem to be quite close to those when only prospect theory has been applied (see figures 1 – 4). The utility does not change with the application of cumulative prospect theory, as the utility averages out between the different types of acquirers and target companies that exist with each level of risk aversion and optimism behavioural trait. Figures 5 – 8 also show similar dynamics as figures 1 – 4 as utility decreases as the loss aversion co-efficient increases from figure 5 to figure 8. However, the overall utility tends to decrease as the loss aversion co-efficient increases. These results show that the loss aversion co-efficient has a greater impact on the utility in an M&A Transaction than the risk aversion and optimism factors.

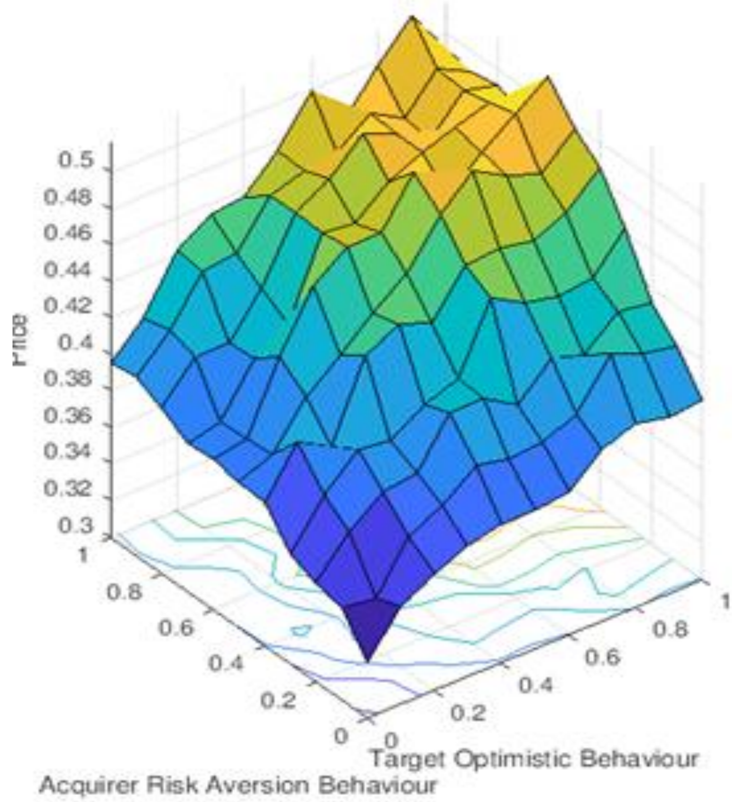


**Figure 2 Prospect Theory Loss Aversion 28%**

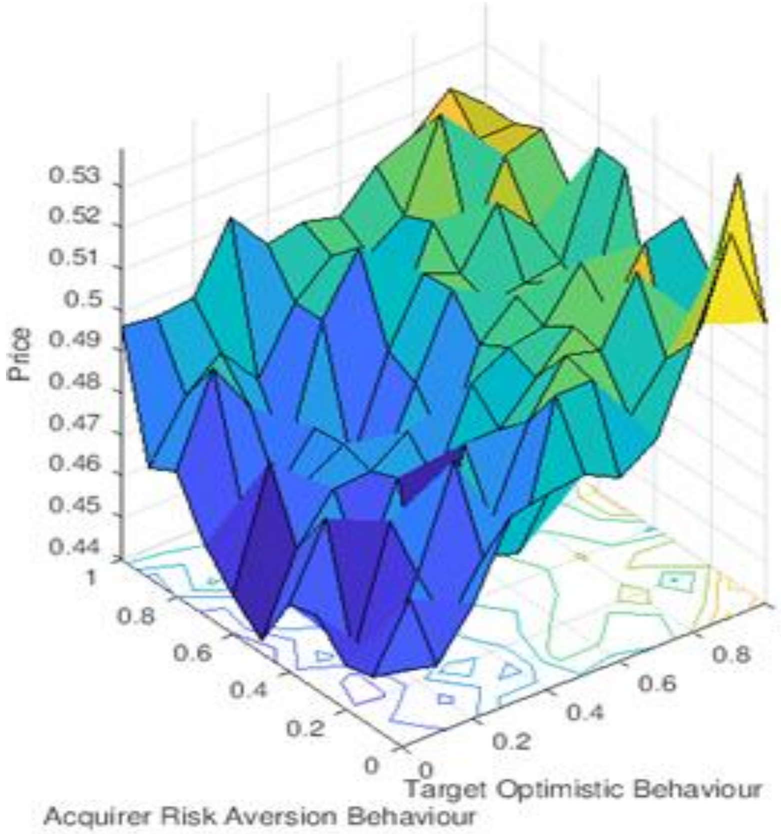


**Figure 3 Prospect Theory Loss Aversion 50%**

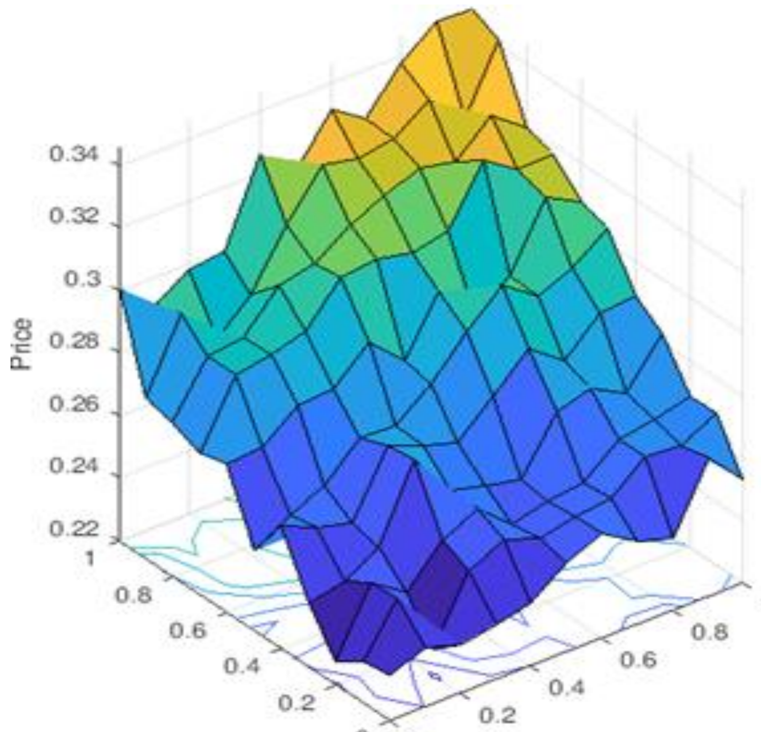


**Figure 4 Prospect Theory Loss Aversion 100%**

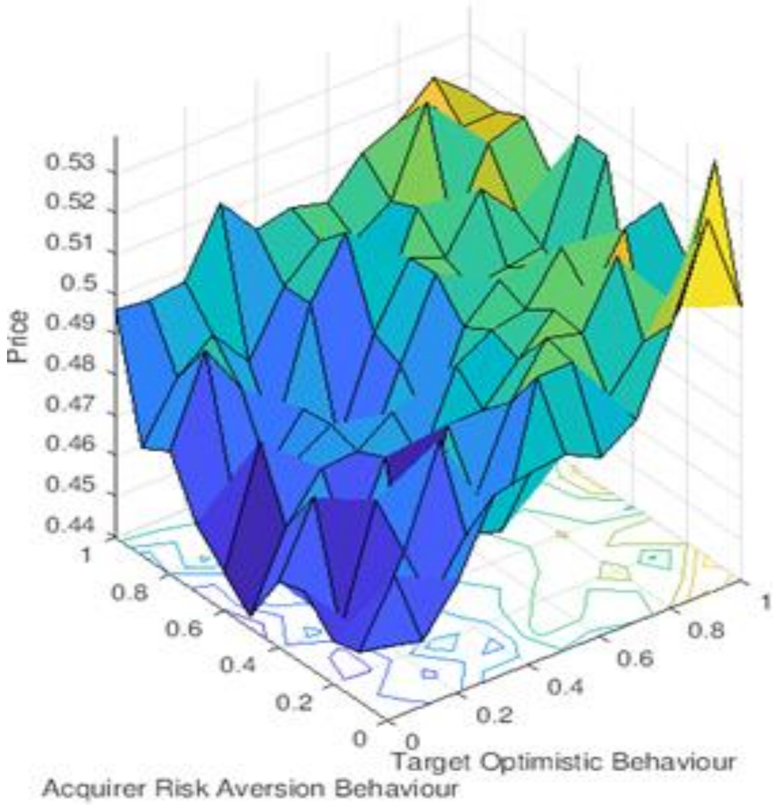


**Figure 5 C. Prospect Theory Loss Aversion = 0%**

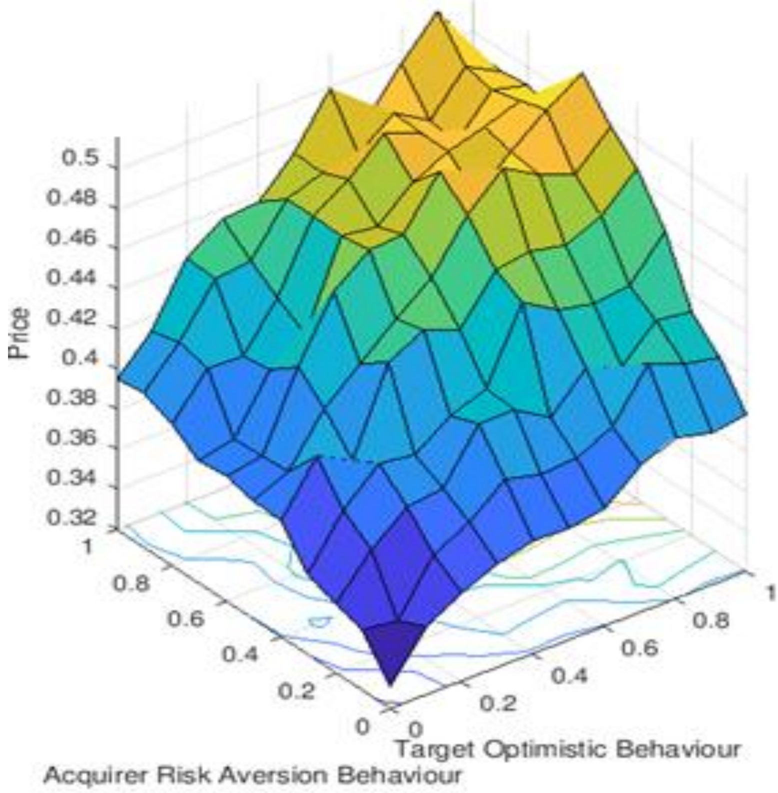


**Figure 6 C. Prospect Theory Loss Aversion = 28%**

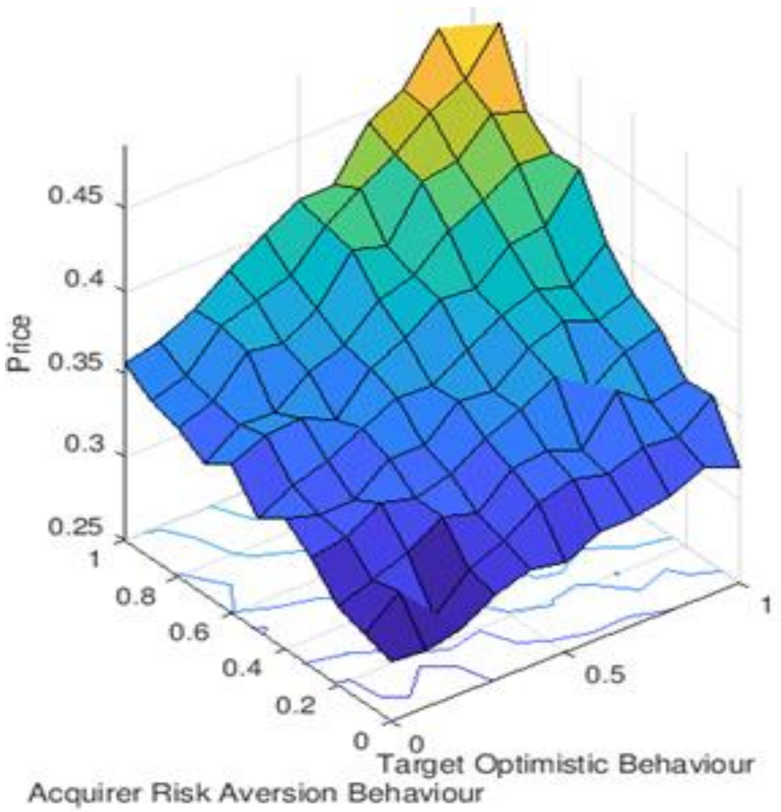


**Figure 7 C. Prospect Theory Loss Aversion = 50%**

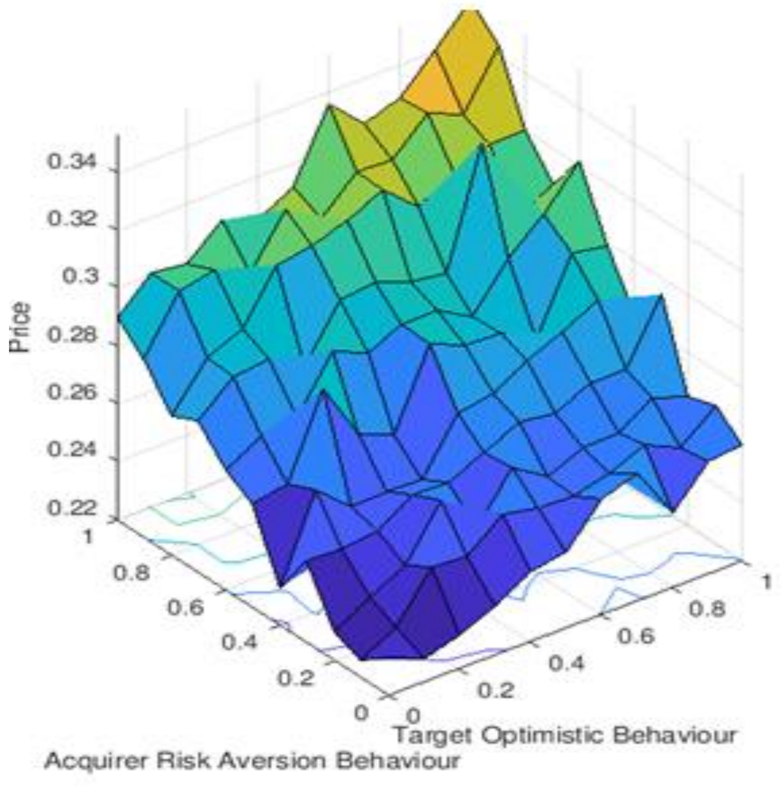


**Figure 8 C. Prospect Theory Loss Aversion = 100%**

### 4.4 Merger & Acquisition pricing with Multiple Acquirers

Further, the model is extended to include three acquirers rather than a single acquirer (as was the case for figures 1 – 8). Figures 9 – 12 clearly show the difference in the results as the additional two acquirers are added to the prisoner's dilemma game. Utility has immediately increased in figure 9, especially for the situation where the risk aversion and optimism factors are high.

The overall utility in the figures 9 – 10 is much higher than figures 1 – 8 and also figures 11 – 12. This occurs as the competition between the acquirers increases the utility between the target and each of the acquirers. Essentially, each acquirer competes to pay more to acquire the target as they feel that they can potentially obtain higher synergies by acquiring the target and, as a result, they may be willing to pay more for this M&A transaction. Figures 11 – 12 however, on the contrary, have lower utility as competition seems to reduce as the loss aversion co-efficient increases from 0% in figure 9 to 100% in figure 12. In figure 12, a gain is perceived to be only one time more valuable than a loss, due to the increased loss aversion co-efficient. Therefore, due to the lack of bias towards gains, the acquirers offer less and the target company is satisfied with lower utility.

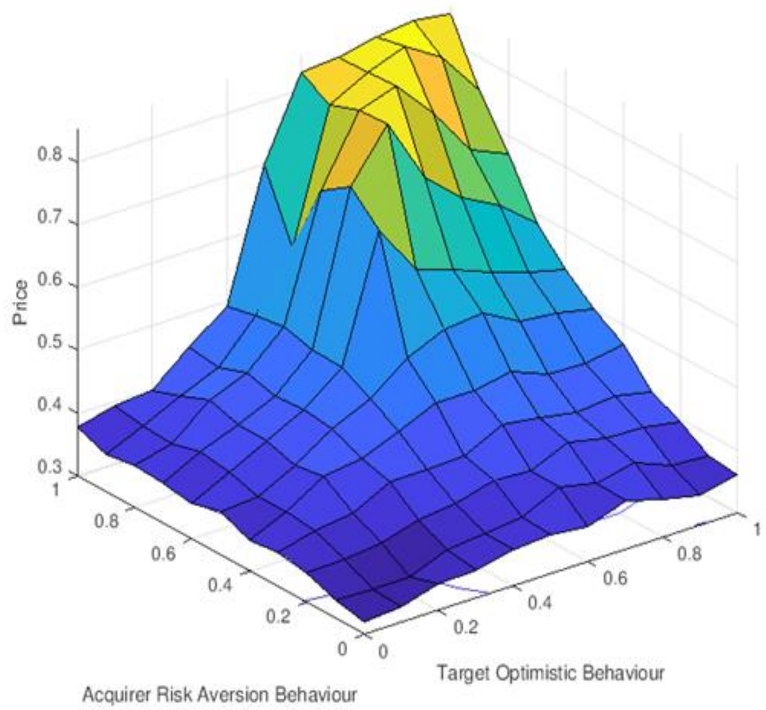


**Figure 9 Multiple Acquirers Loss Aversion = 0%**

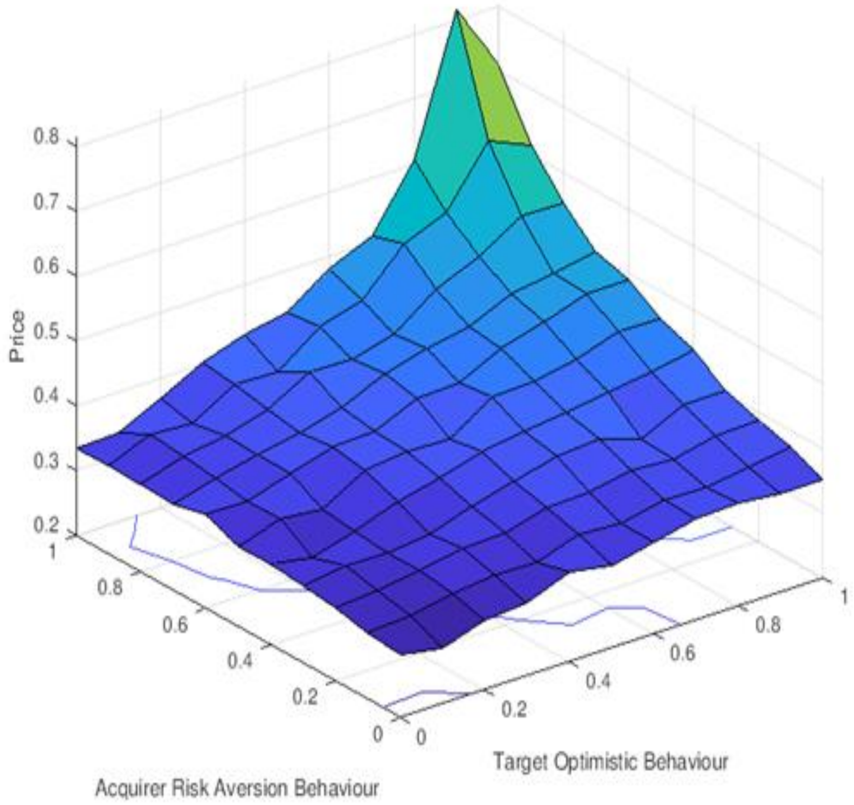


**Figure 10 Multiple Acquirers Loss Aversion = 28%**

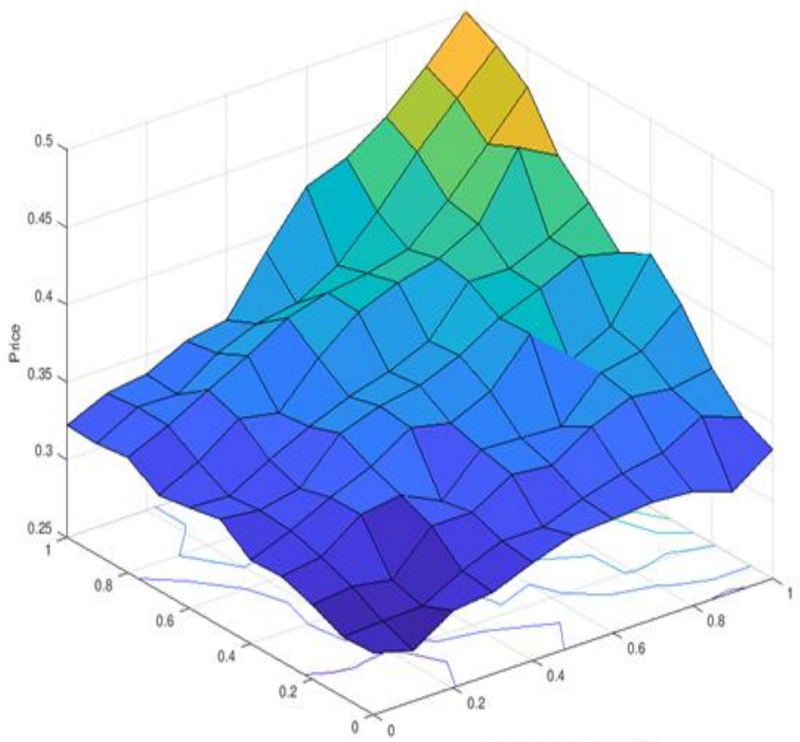


**Figure 11 Multiple Acquirers Loss Aversion = 50%**

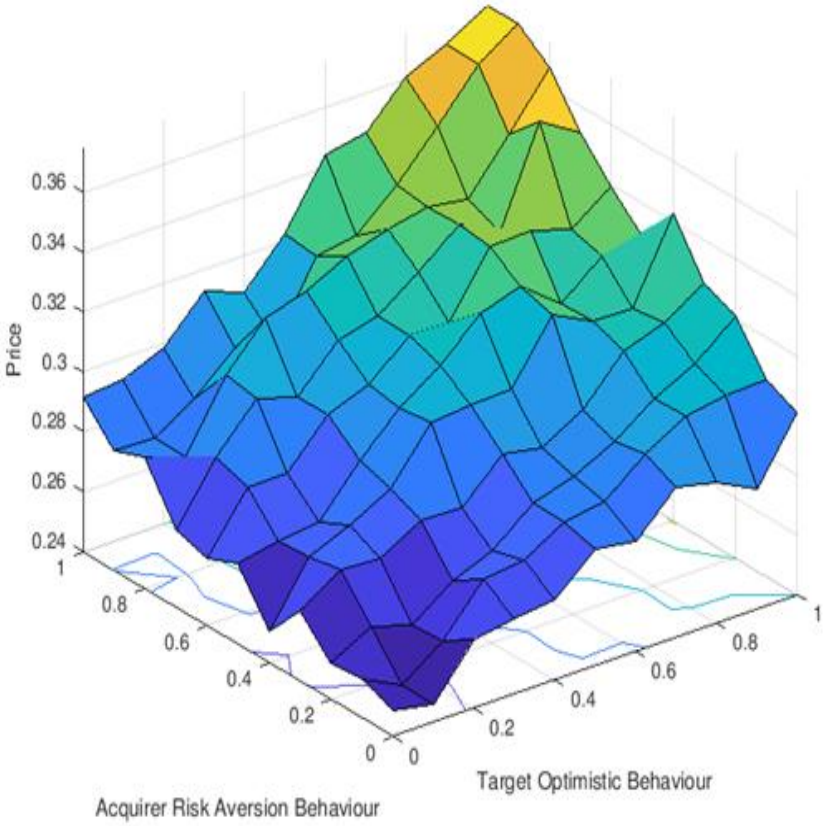


**Figure 12 Multiple Acquirers Loss Aversion = 100%**

In simplistic terms, the above figures 1 – 12, can be shown in the decision tree (CART) provided below. The results show that the optimal outcome for the acquirer and target company is when the acquirer is risk taking and target is optimistic with returns reducing as the loss aversion co-efficient increases (as gains and losses have the same weight), but increasing as certainty increases in the outcome. However, figures 3 and 5 also support the condition where the M&A transaction price is medium and the target is optimistic but the acquirer is risk averse (shown by the black arrows in the diagram below). The optimal solution that is similar to the outcome in chapter 3 is the condition where the target is optimistic and acquirer is risk taking (shown by the red arrows in the diagram below). These results are explained using real world examples of the Sanofi – Ablynx and Bunge – Archer Daniel Midlands mergers in Chapter 6. In principle, the presence of multiple acquirers puts an upward pressure on the merger price, making the merger price increase compared to when a single acquirer would be present.

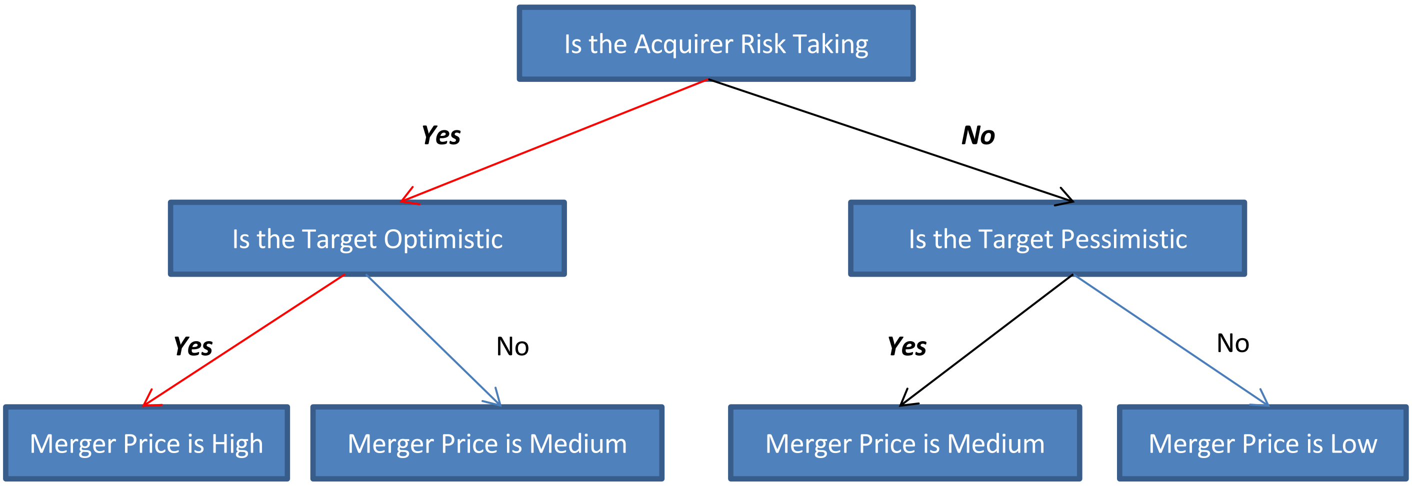


**Diagram 4.1 CART Decision Tree for Multiple Acquirer and Target Firm**

## 4.5 Conclusion

In summary, this chapter has analysed behavioural Merger & Acquisition (M&A) transaction pricing using an agent based model. The model is developed using prisoner's dilemma game theory, prospect theory and cumulative prospect theory. Initially, in this chapter we model a single acquirer and target firm, which is extended to include multiple acquirers (to be specific three acquirers) and a single target firm in the later part of this chapter. While, the single acquirer model is different to the previous chapter, as it considers the certainty effect, the multiple acquirer model adds further to the dynamics of the single acquirer model. This model is developed in MATLAB 2017 as was the model in the previous chapter. The behavioural trait continuum for the acquirer being risk averse and risk taking and the target firm being optimistic and pessimistic are still the same. Also, the loss aversion co-efficient from prospect theory is also applied to this model, as was the case in the previous chapter. Results from this model show that the M&A transaction price only falls when the loss aversion co-efficient is raised to 100 percent. Prior to that, the M&A transaction price still remains high (see figures 1 – 2) and the outcome starts to become biased towards a higher level of the target firm's optimistic trait (see figure 3). However, when the loss aversion co-efficient increases to 100 percent (in figure 4), the overall M&A transaction price falls as the target firm does not require a higher price.

The model is then modified to include cumulative prospect theory (in figures 5 – 8), where humans will be risk averse on large gains and risk taking on large losses and vice versa. This model is an extension of the prospect theory model, however the outcomes from this model are reasonably similar to those obtained in chapter 3. The only difference is that initially in figure 5, the optimistic trait of the target firm becomes more dominating, though, the overall M&A transaction price drops in line with the results in chapter 3 as the loss aversion co-efficient increases from 0 to 100 percent.

However, when this model is extended to include multiple acquirers (see figures 9 – 12), the M&A transaction price is substantially higher than compared to the previous chapter. This occurs as the target firm can afford to be optimistic and the competition between the different acquirers increases the overall M&A transaction price. Nonetheless, as the loss aversion co-efficient is increased from 0 to 100 percent, the M&A transaction price starts to fall rapidly, and it is similar to the outcome when a single acquirer was present, when the loss aversion co-efficient is 100 percent (see figure 12). This shows that the presence of multiple acquirers is important in the game and as the loss aversion co-efficient in reality (based on Kahneman and Tversky 1979) is 28 percent. It shows that having multiple acquirers will have a significant positive impact on the outcome of the game.

In conclusion, the results in this chapter are comparable with the results obtained in the previous chapter and they extend the results, as I have multiple acquirers present in this chapter. These multiple acquirers have a positive impact on the M&A transaction price compared to the single acquirer model reviewed in the previous chapter.

C H A P T E R   F I V E

# Behavioural Merger and Acquisition Pricing: Application to Verizon Mergers with AOL and Yahoo[3]

## 5.1 Introduction

This chapter intends to develop an agent based model to analyse M&A transaction pricing, however in this chapter we apply the model from chapter 3 to real world examples in order to understand how well this model predicts real world M&A transactions. The literature review related to the discussion in this chapter has been reviewed in Chapter 2. The subsequent sections will look at the methodology, results and the final section will provide a summary of the discussion that has occurred in this chapter.

## 5.2 Methodology

The model in this chapter was developed using MATLAB 2017b and was built using prisoner's dilemma game theory, prospect theory and cumulative prospect theory. The way this game is setup, it that there is a pool of a 1000 acquiring and target firms in total and, for each game, a single acquirer and target firm is selected to play this single round game. The acquirer has a behavioural trait continuum from risk averse to risk taking and the target firm has a behavioural trait continuum from optimistic to pessimistic. These are assigned to them using a random number in MATLAB 2017 at the start of the experiment. For each game, an acquirer and target firm is picked to play, and a prisoner’s dilemma game theory model is utilized to analyse their utility based on the type of game that they are playing. Code for these games is provided in Appendix A. The model initially uses game theory and prospect theory’s loss aversion co-efficient to provide figures 1 – 4 (in the results section below), subsequently being extended to include cumulative prospect theory for figures 5 – 8 and the prospect theory’s certainty effect for figures 9 – 12. In order to develop an agent based model that replicates and helps explain the M&A transactions that occurred between AOL and Verizon (Malone and Turner 2010) and Yahoo and Version (Kharpal 2017), the stock price of the target company was

[3] Parts of this chapter are published in the Strategic Change journal.

assumed to be $50 per share. Why was the $50 stock price considered in this model? The reason for this consideration is that the starting stock prices of the AOL (Malone and Turner 2010) and Yahoo! (Kharpal 2017) pre-merger were $50 coincidently. In order to be able to compare the results of this model with the AOL and Yahoo! mergers, it was critical that the model in this thesis uses the same starting stock price.

This allows a stable starting point that can be assessed as a pre-negotiation (initial starting point) and final agreed price for the M&A transaction. In effect, the M&A transaction model in this chapter analyses the M&A transaction problem in the following ways providing the results in figures 1 – 12 in section 5.3 below:

1. A base M&A transaction game is setup to analyse how the transaction pricing changes when there is a single acquirer (with risk aversion – risk taking characteristics) and target company (with optimistic – pessimistic characteristics). This base model has a loss aversion co-efficient from Prospect theory (Kahneman and Tversky 1979) included in the model, which states that humans value losses more than gains. See MATLAB code for this model in Appendix A – Model 1.

2. The base model is then extended to include Cumulative Prospect Theory (Kahneman and Tversky 1992) and the loss aversion co-efficient is increased to 50 percent (meaning that gains are only half as valuable as losses). See MATLAB code for this model in Appendix A – Model 2.

3. The base model is extended to include Cumulative Prospect Theory (Kahneman and Tversky 1992) and certainty effect (where the outcome can be nearly certain instead of being probable). The certainty effect is important as humans support different outcomes when outcomes are certain, when viewing losses and gains. See MATLAB code for this model in Appendix A – Model 4.

## 5.3 Merger & Acquisition Pricing using Prospect Theory

This model looks to analyse the change in the M&A transaction price due to the behaviours of risk aversion and optimism of the acquirer and target company respectively. The results show that when loss aversion is low as in figure 1 (i.e. in this case the gain is four times as valuable as a loss), it is seen that that the highest price is received when both the acquirer is risk taking and the target company is optimistic.

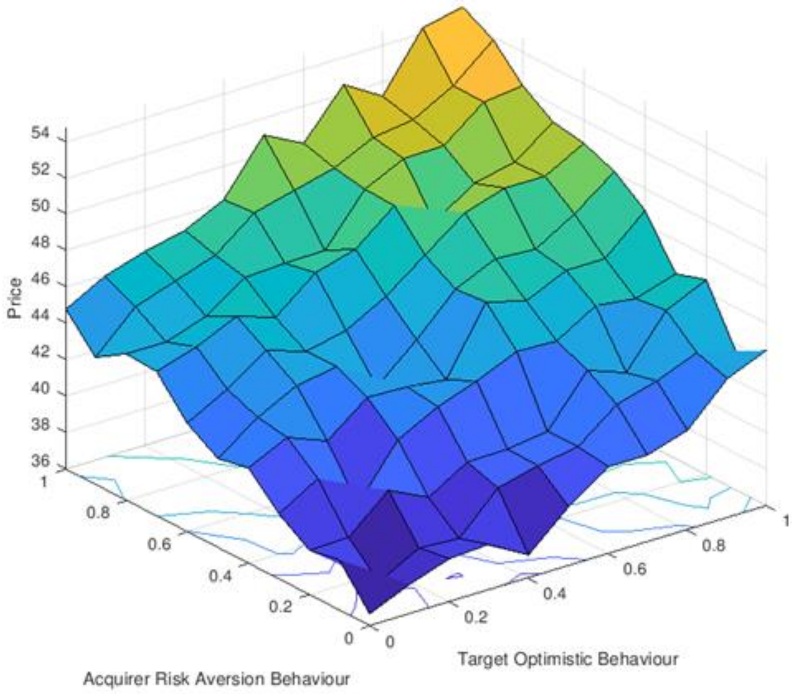


**Figure 1 Prospect Theory Loss Aversion = 0%**

However, as the level of loss aversion increase from 0% (i.e. gains four times as valuable to losses) to 28% (i.e. gains are approx. 3.5 times more valuable than losses), I notice that the overall price paid for acquiring the target company starts to drop. This price drops further as the loss aversion co-efficient increases to 50% in figure (i.e. gains are half as valuable as losses) and 100% in figure 4 (where gains and losses are as valuable). The reason this happens, is that when gains are more valuable than losses, when the price falls, the target company shareholders will reject the offer if they think it is not valuable enough. Loss aversion co-efficient is an important part of Prospect Theory (Khaneman and Tversky 1979). The combination of loss aversion, risk aversion and optimism provide us three dynamic behavioural factors that can be important to the M&A transaction decision as both the acquiring and target companies try to understand what price is suitable to them.

A recent example was the merger of AOL and Verizon, where Verizon dropped the price being paid for AOL by 10.3% (Malone and Turner 2010). If the AOL shareholders felt that Verizon's lower offer was not as valuable, then they would have rejected that offer (Malone and Turner 2010).

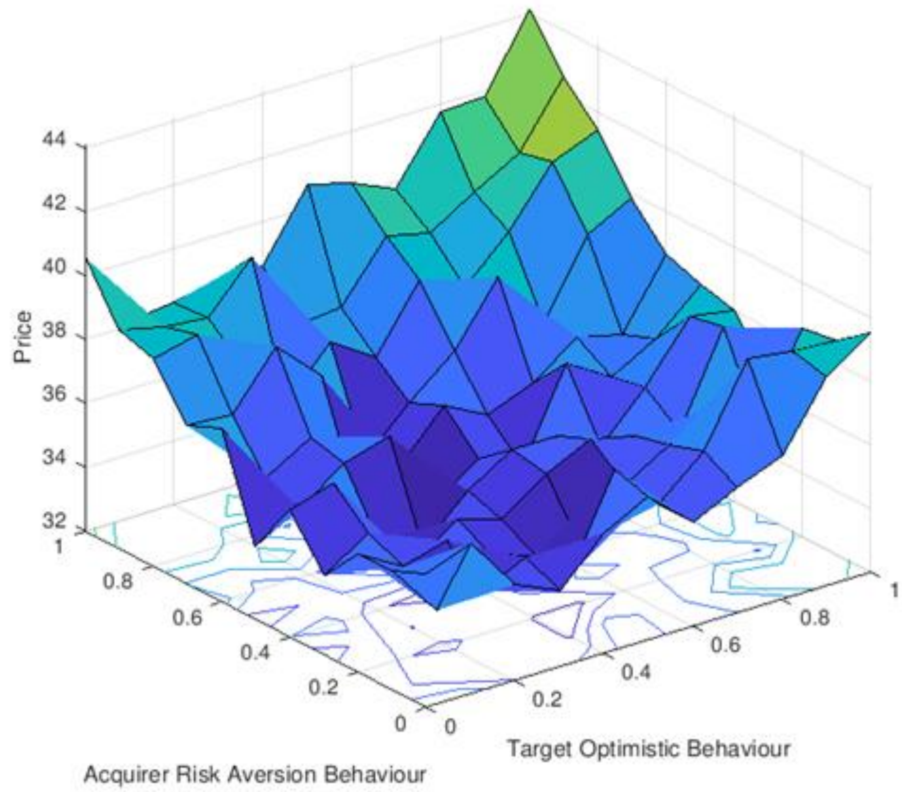


**Figure 2 Prospect Theory Loss Aversion = 28%**

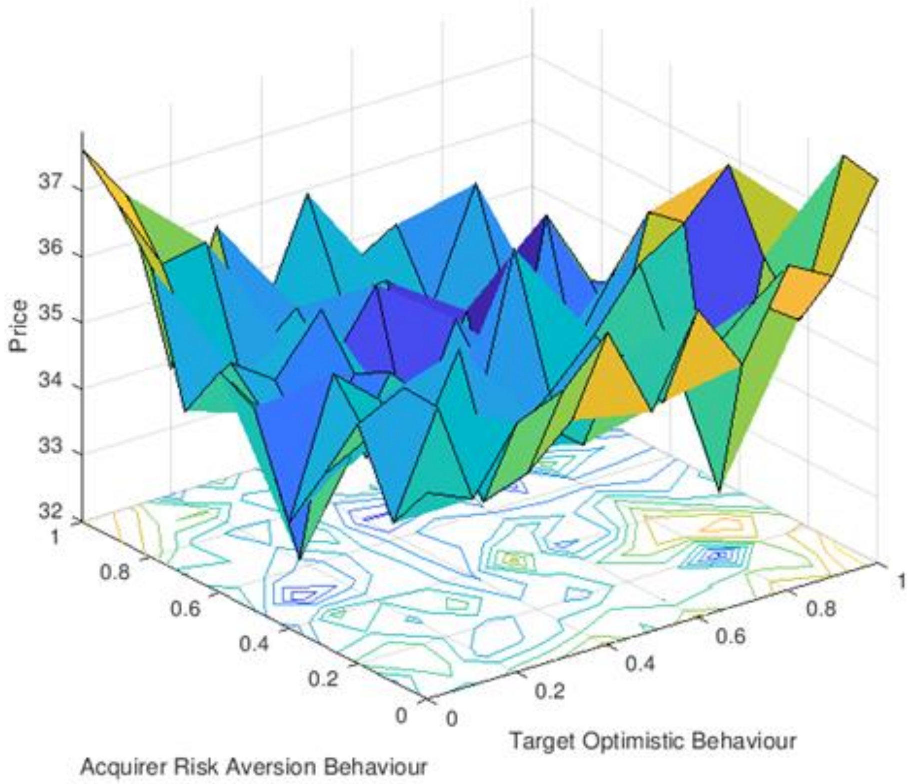


**Figure 3 Prospect Theory Loss Aversion = 50%**

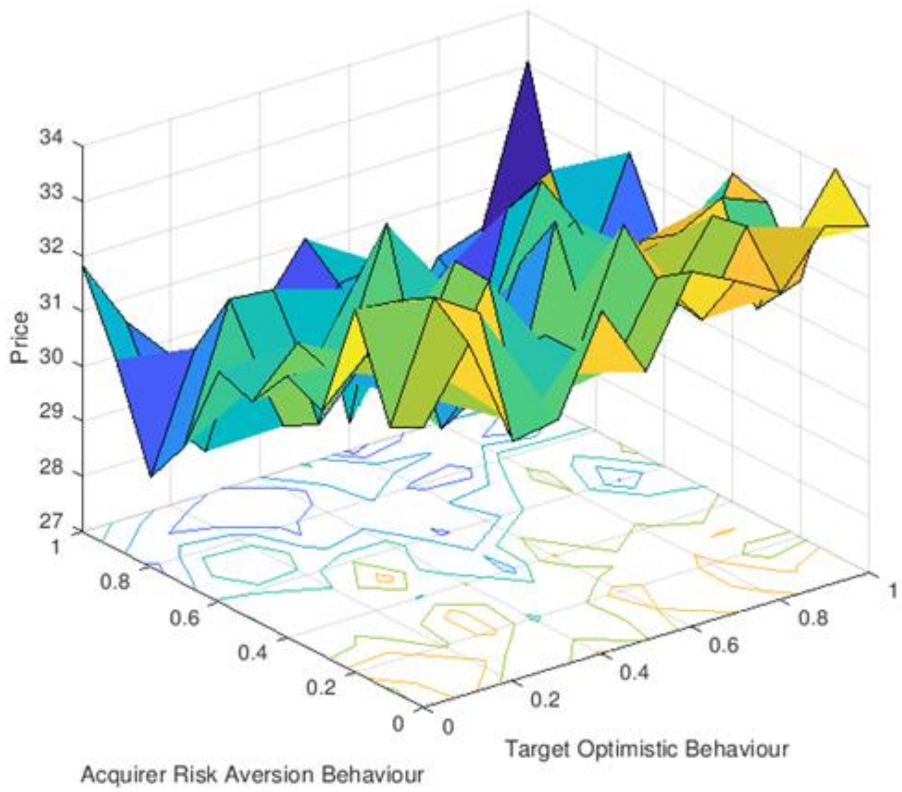


**Figure 4 Prospect Theory Loss Aversion = 100%**

However, the deal went through. It may due to the fact that they were less optimistic that another company would come and pay the same price to purchase AOL and, on the opposite side, Verizon wanted to make sure that it was being risk averse and not paying too much to purchase AOL (Malone and Turner 2010). When, Verizon purchased Yahoo (Kharpal 2017), Verizon was concerned about the data breach issue that occurred with Yahoo and this made Verizon probably take a risk averse position, thus reducing the price it was willing to pay to acquire Yahoo. Noticing the data breach issue, Yahoo shareholders also became less optimistic about obtaining a potentially better offer than provided by Verizon and as a result accepted this lower offer.

So, as a result, I see the impact loss aversion, risk aversion and optimistic behaviours can have on the dynamics of M&A transaction pricing. The dynamics of the M&A transaction game transforms between figure 1 (where both risk taking behaviour of the acquirer and optimistic behaviour of the target are important) to figure 4 (where only the optimistic behaviour of the target firm are important). This transformation takes place as the loss aversion co-efficient has a significant impact on the outcome of this M&A transaction. As the loss aversion co-efficient increases, paying more to purchase a target company becomes less valuable to an acquirer, as they increase their risk taking trait. In effect, a risk taking acquirer will push to reduce the price rather than increase the price as they now do not need to pay a premium (as gains and losses are perceived to be equal). This seems like an interesting insight and seems to be clearly supported by the M&A transactions that occurred between Verizon and AOL and Verizon and Yahoo. Verizon was risk taking in both these transactions as it felt the value of AOL and Yahoo was less than they were demanding. At the end, Verizon was able to purchase them for a lower price than initially discussed. If Verizon was risk averse and felt that it would miss out on the transaction then it would be highly probable that Verizon would have paid more for these transactions.

In figures 5 – 8, I extended the model to include cumulative prospect theory, where risk attitudes differ: humans are risk averse in relation to gains and risk taking when considering losses of high probability, whereas they are risk taking for gains and risk averse for losses of low probability. In general, in figures 5 – 8, the M&A transaction price reduces on average. This occurs as the acquirer is risk averse to an increase in price and the target company is risk averse to a decrease in price. This portrays the situation where there is a high probability of a gain and a low probability of a loss. Results in figures 5 – 7 are similar, however the increase in the loss aversion co-efficient to 100 percent in figure 8, changes the dynamics of the M&A transaction game in line with what I see in figure 4.

When I consider the Verizon and AOL merger, I notice that the results differ from the real world scenario when I apply cumulative prospect theory. Prospect theory (Kahneman and Tversky 1979) state that the loss aversion co-efficient in the real world is 28 percent. So, when I consider figure 6, it directly aligns with figure 2 and the actual transaction pricing in the Verizon and AOL transaction. This outcome is similar in the Verizon and the Yahoo merger transaction. It is interesting to notice that the outcome in the Verizon and AOL as well as the Verizon and Yahoo mergers have been similar. The actual outcome is in line with both figures 2 and 6. Where the price of the AOL and Yahoo stock fell prior to the final conclusion of the M&A transaction complete, which means that the outcome from both figures 2 and 6 are the most relevant to the Verizon and AOL and Verizon and Yahoo M&A transactions, and they directly correlate to the real world outcome. In this instance, due to the failing business prospects of AOL and Yahoo, both these target firms were not optimistic. This was clear to the acquirer (Verizon) and as a result Verizon was able to negotiate a lower price for these M&A transactions.

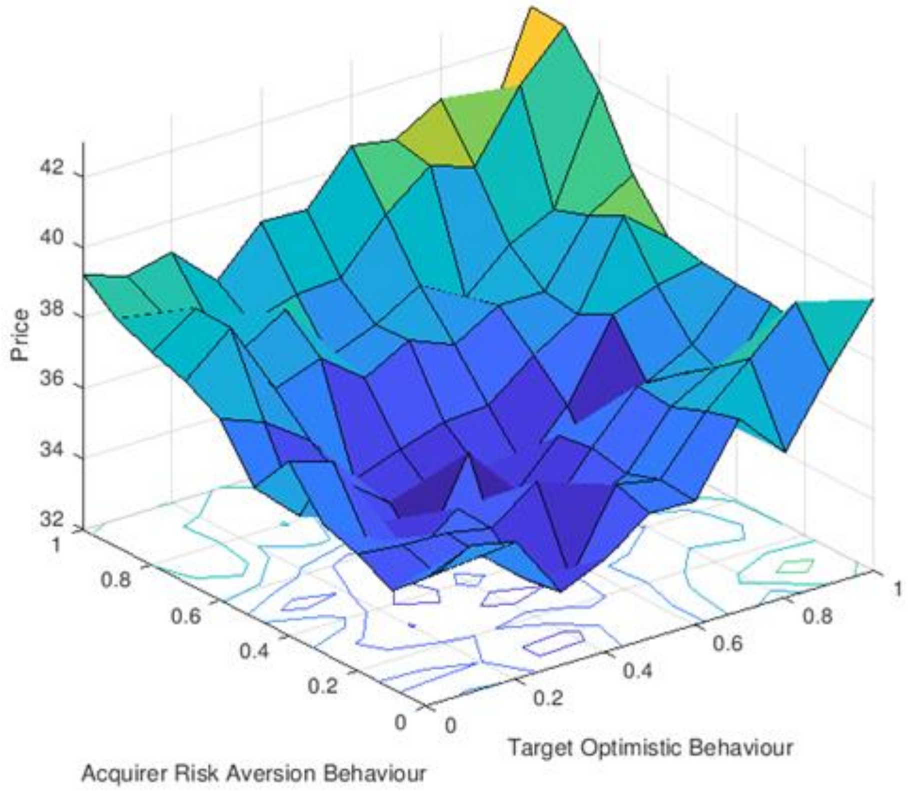


**Figure 5 Cumulative Prospect Theory Loss Aversion = 0%**

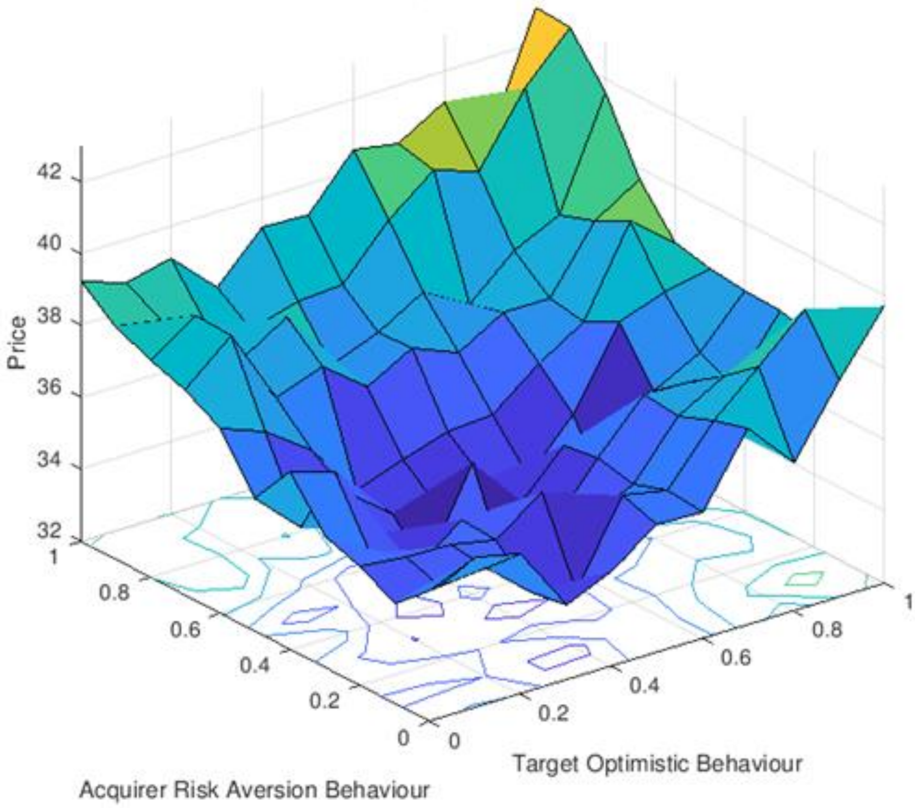


**Figure 6 Cumulative Prospect Theory Loss Aversion = 28%**

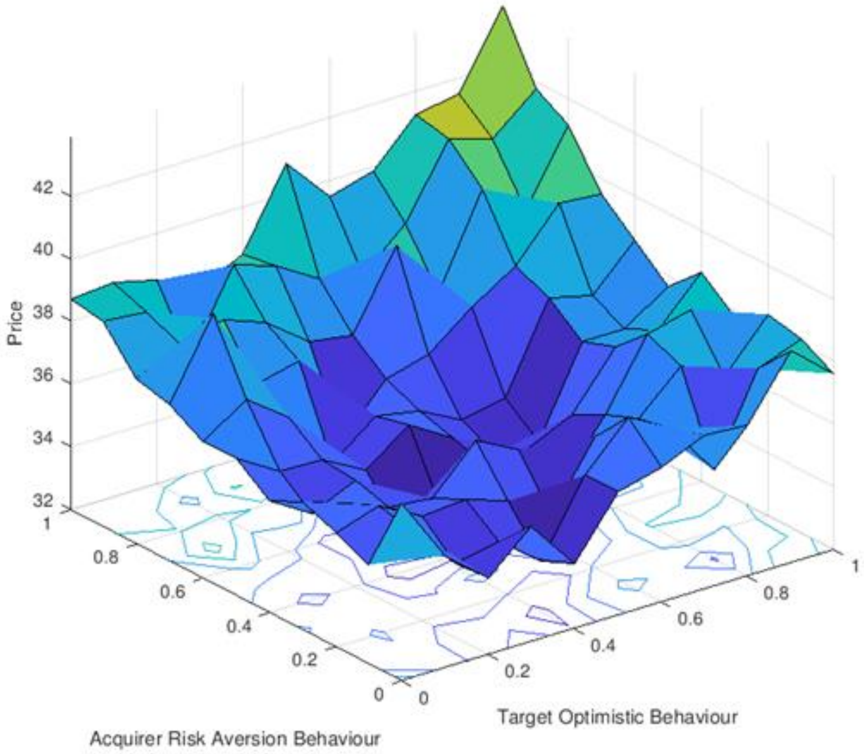


**Figure 7 Cumulative Prospect Theory Loss Aversion = 50%**

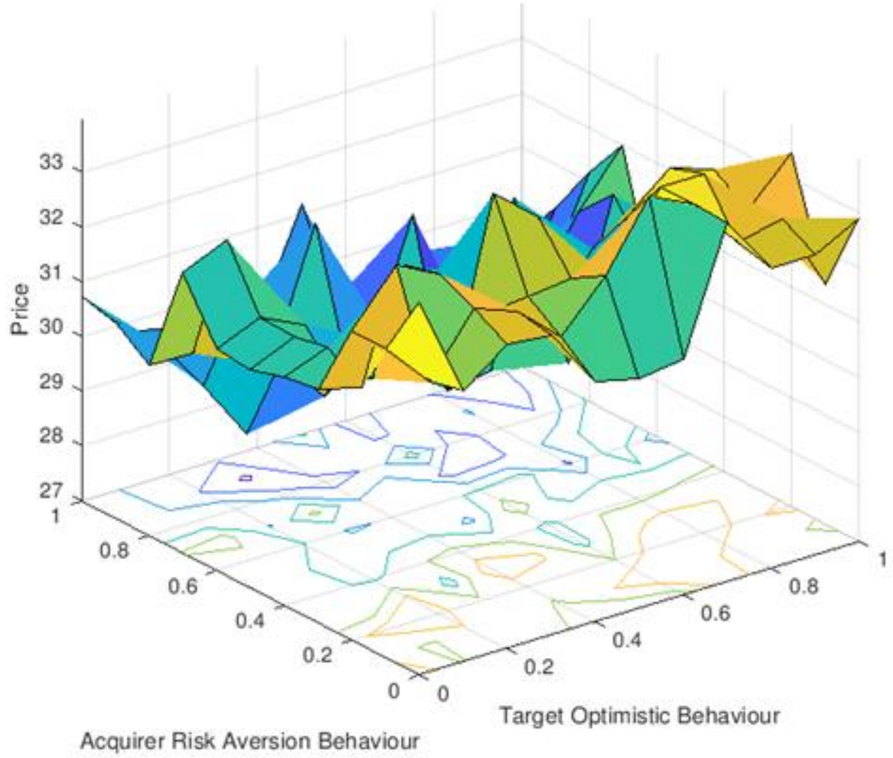


**Figure 8 Cumulative Prospect Theory Loss Aversion = 100%**

## 5.4 Applying Prospect Theory's Certainty Effect to M&A Pricing

Now, if I extend this model further to include certainty of gains rather than a high probability of gains, then I notice that the M&A transaction price falls further. This seems quite logical as risk aversion increases for gains from low to high probability and then through to certainty. When I have gains of low probability, then an acquirer is likely to be risk taking. So, when the probability of the gain increases, the acquirer will become more risk averse and substantially more risk averse when the transaction is nearly certain. Similarly, this would be the case with the target company. This occurs because humans speculate when there is low probability around gains (e.g. a lottery), but get more risk averse when the gains become highly probable or certain (Kahneman and Tversky 1979), whereas they do exactly the opposite for losses, simply as humans prefer gains to losses. In figures 9 – 12, the M&A transaction price is even lower than that in figures 4 – 8. Primarily, as the certainty of the gain has increased for both the acquirer and the target company. But, as the loss aversion co-efficient has been changed through figures 8 – 12 with the loss aversion co-efficient being 0% in figure 8 and 100% in figure 12, it is noticed that the overall dynamics of the M&A transaction price has changed with the acquirer's risk aversion and the target's optimism becoming more significant factors in the pricing equation. A sudden drop in the equilibrium price is also noticed from figure 11 to 12. This primarily seems to happen as loss aversion has increased from 50% to 100% respectively, making gains and losses equal.

When this occurs there is no requirement for an acquirer or target company to weigh gains higher than losses and, in effect, the certainty effect substantially increases the risk aversion on the gain and reduces the overall M&A transaction price. Finally, the outcome in figure 10 aligns with that provided in figures 2 and 6, these results directly correlate and support the real world transaction pricing for the M&A transactions between Verizon and AOL and Verizon and Yahoo.

If we now compare the outcomes to previous studies/models, the best study would be an empirical study by Baker, Pan and Wurgler (2009) which empirically shows that the final outcome of the M&A transaction has actually differed from the initial price offered by the acquirer to purchase the target company. Even in the real world examples shown in Chapters 5 and 6, the price of the M&A transaction has changed from the initial price. The intent of the model developed in this thesis is to forecast that end price based on the behavioural traits of the acquirer and target company at the beginning of the M&A transaction. Therefore, this model has different results compared to existing models and is expecting to improve the accuracy of forecasting the final M&A price better than previous models. Chapters 3 – 6 show that it has been able to provide a more realistic (or more reasonable) price estimate than provided by Baker, Pan and Wurgler (2009), who state that the target company's 52-week high stock price is the best indicator of the final M&A transaction price. This is not accurate, as not all target companies are publicly listed and for those that are listed. Baker, Pan and Wurgler (2009) themselves showed that the 52-week high stock price is only an indicator of the final M&A transaction price.

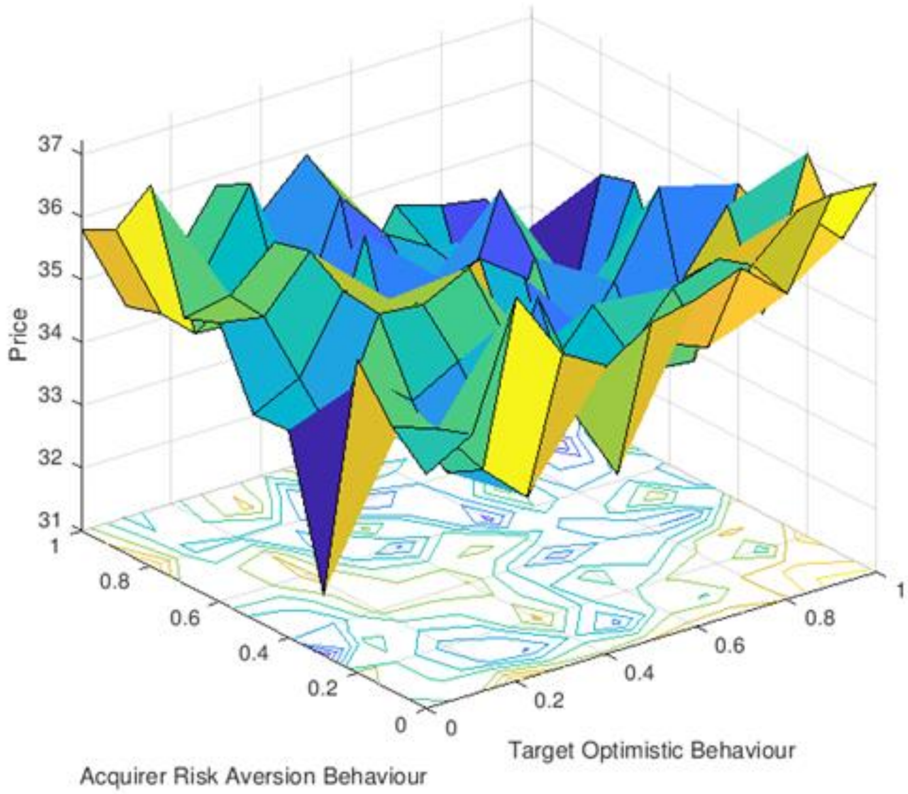


**Figure 9 Prospect Theory Certainty Effect Loss Aversion = 0%**

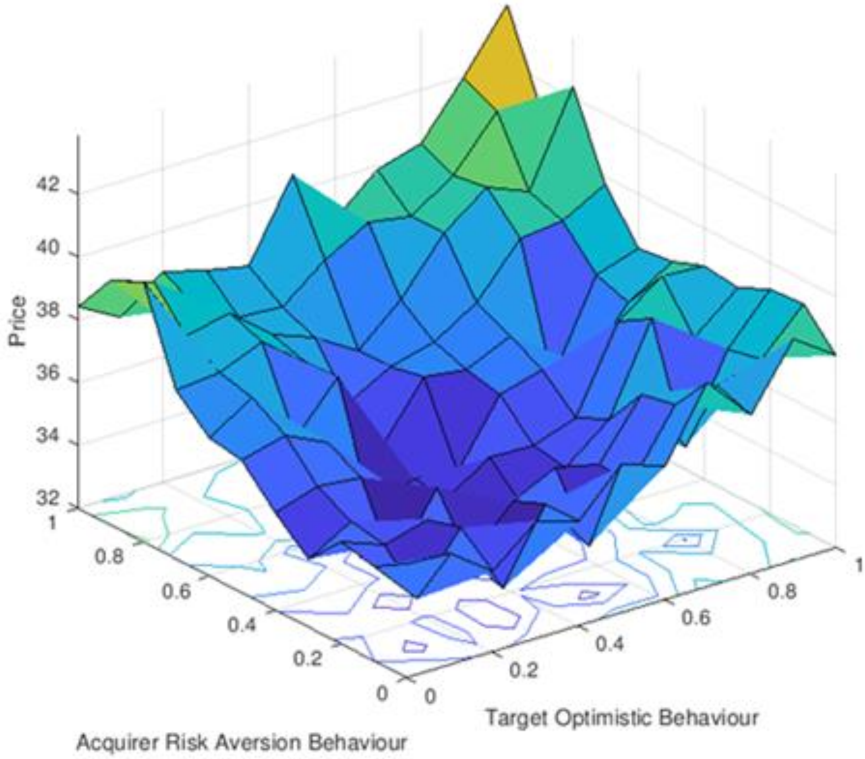


**Figure 10 Prospect Theory Certainty Effect Loss Aversion = 28%**

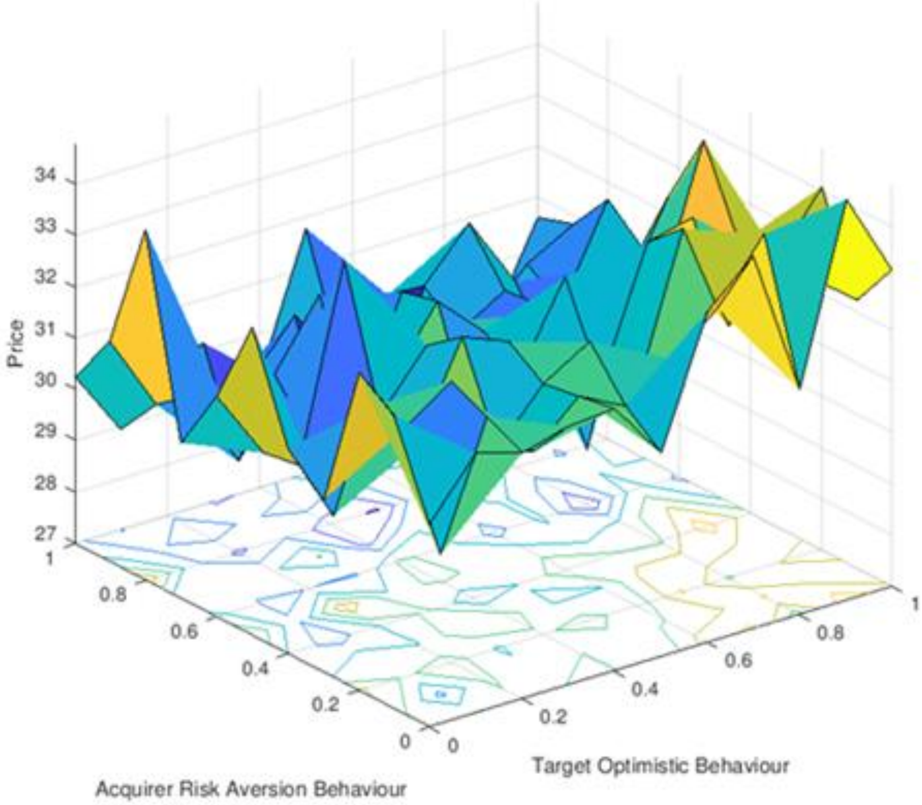


**Figure 11 Prospect Theory Certainty Effect Loss Aversion = 50%**

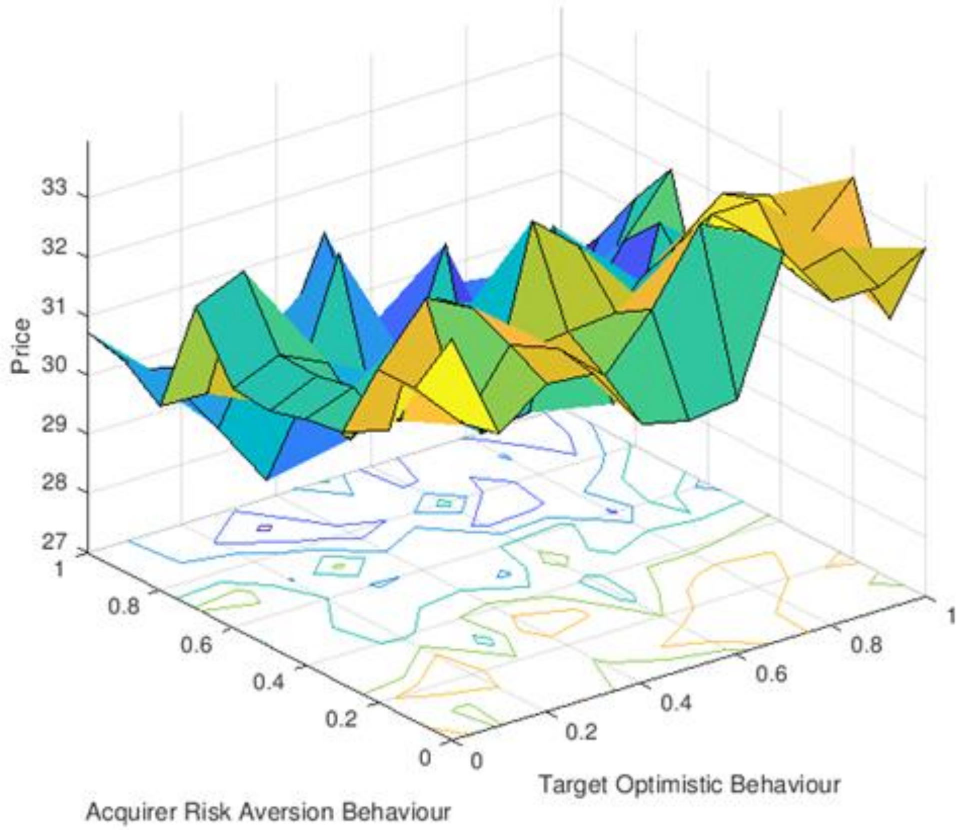


**Figure 12 Prospect Theory Certainty Effect Loss Aversion = 100%**

In simplistic terms, the above figures 1 – 12, can be shown in the decision tree (CART) provided below. The results show that the best outcome is when the acquirer is risk taking and target is optimistic with returns reducing as the loss aversion co-efficient increases (as gains and losses have the same weight), but increases as certainty increases in the outcome. However, figures 2, 6 and 10, provide the most realistic proposition in this case. Where, the M&A transaction price does not increase to the optimal level, as the increase in the loss aversion co-efficient makes the acquirer's risk aversion behaviour and target's pessimistic behaviour prominent. Due to this combination of increasing acquirer risk aversion and combined with the target's pessimistic behaviour, the overall outcome will support the acquirer and the acquirer will be able to purchase the target at a lower price. The most probable option in such a circumstance has been provided below (shown by the red arrows in the diagram below).

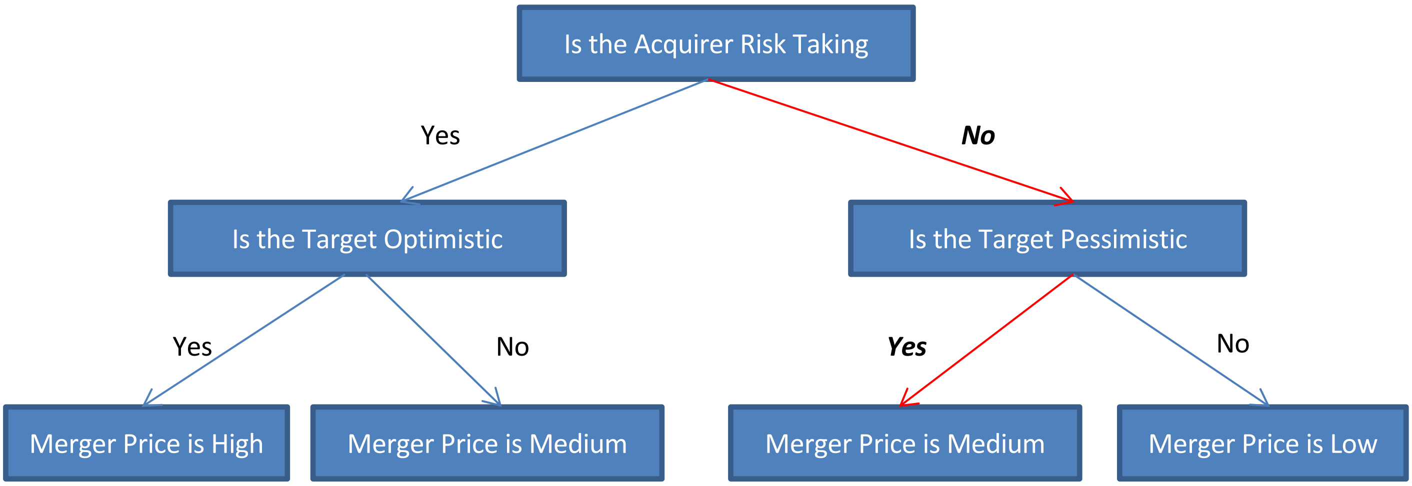


**Diagram 5.1 CART Decision Tree for Single Acquirer and Target Firm for a Commercial Outcome**

## 5.5 Conclusion

This chapter analysed the M&A transaction pricing problem to analyse the outcomes of the application of behavioural factors like risk aversion, optimism and loss aversion. Chapters 5 and 6 in this thesis analyse the commercial application of the models developed in the earlier chapters (3 and 4) and compare the outcomes with real world mergers and acquisitions that have occurred more recently. The model in this chapter considers a stock price of $50 at the commencement of the game and it analyses how the application of the behavioural traits of the acquirer and target firm and the application of prospect theory change the stock price at the end of each game. It then compares these outcomes with real world examples of mergers between Verizon and AOL, and Verizon and Yahoo in order to understand if these results are in line with those provided by real world M&A transactions. Results show that the outcomes from the model developed in this chapter are, in a sense, in line with those developed in the previous two chapters (chapters 3 and 4). The main significance is that when the target firm is pessimistic, then the M&A transaction price will fall. Also, that the increase in loss aversion co-efficient has a significant impact on the reduction of this M&A transaction price. Evidence from real world M&A transactions between Verizon and AOL, and Verizon and Yahoo shows that, due to existing market conditions and the risk aversion behavioural trait of the acquirer, the merger price for both these transactions was lower. However, if the target company had been optimistic (which was not possible due to the existing conditions), then this price may not have fallen as much as it did. But a combination of a risk averse acquirer and pessimistic target company showed that the merger price for the target company fell, which was in line with what was noticed in both the mergers between Verizon and AOL, and Verizon and Yahoo.

CHAPTER SIX

# Behavioural Merger and Acquisition Pricing using Cumulative Prospect Theory and Multiple Acquirers[4]

## 6.1 Introduction

This chapter attempts to apply behavioural finance theories and to apply it to real world examples explaining the dynamics of M&A transaction pricing in action. The examples of Sanofi and Ablynx and Archer Daniels Midland and Bunge are taken to show how this model applies to the real world. In the next section, I discuss the methodology and the final two sections of this study discuss the results of this experiment and conclusion. In effect, the M&A transaction model in this chapter analyses the M&A transaction problem in the following ways providing the results in figures 1 – 12 in section 6.3 below:

1. A base M&A transaction game is setup to analyse how the transaction pricing changes when there are multiple acquirers (with risk aversion – risk taking characteristics) and target company (with optimistic – pessimistic characteristics). This base model has a loss aversion co-efficient from Prospect theory (Kahneman and Tversky 1979) included in the model. That states that humans value losses more than gains. See MATLAB code for this model in Appendix A – Model 5.

2. The base model is then extended to include Cumulative Prospect Theory (Kahneman and Tversky 1992) and the loss aversion co-efficient is increased to 50 percent (meaning that gains are only half as valuable as losses). See MATLAB code for this model in Appendix A – Model 7.

3. The base model is extended to include Cumulative Prospect Theory (Kahneman and Tversky 1992) and certainty effect (where the outcome can be nearly certain instead of being probable). The certainty effect is important as humans support different outcomes when outcomes are certain, when

[4] Parts of this chapter are published in the Strategic Change journal.

viewing losses and gains. See MATLAB code for this model in Appendix A – Model 8.

## 6.2 Methodology

The model used in this chapter has been developed using MATLAB 2017b. To develop the model the following theories have been implemented: Prospect Theory, Cumulative Prospect Theory and Game Theory (Prisoner's Dilemma). The way this game is setup, it that there is a pool of 1000 acquiring and target firms in total and, for each game, a single acquirer and target firm is selected to play this single round game. The acquirer has a behavioural trait continuum from risk averse to risk taking and the target firm has a behavioural trait continuum from optimistic to pessimistic. These are assigned to them using a random number in MATLAB 2017. For each game, an acquirer and target firm is picked to play and specific equations are utilized to analyse their utility based on the type of game that they are playing. Code for these games is provided in Appendix A. The intent of this model is to analyse the change in the M&A transaction price due to changes in risk aversion, loss aversion and optimism. These three factors are associated to prospect theory and cumulative prospect theory. But these factors are also seen as likely factors that may impact the pricing of M&A transactions based on Kahneman and Tversky (1979) that explains how these factors impact financial decisions in humans. While there are numerous other factors that could potential impact the M&A transaction price, nonetheless they have not been considered and can be incorporated into future research. The model in this chapter also utilises a stock price of $50 to provide an example of how this stock price changes from pre to post merger negotiations. In order to develop an agent based model that replicates and helps explain the M&A transactions that occurred between Sanofi - Ablynx and Bunge – Archer Daniel Midlands, the stock price of the target company was assumed to be $50 per share. Why was the $50 stock price considered in this model? The reason for this consideration is that the starting stock prices of the Ablynx and Bunge pre-merger were $50 coincidently. In order to be able to compare the results of this model with the Ablynx and Bunge mergers, it was critical that the model in this thesis uses the same starting stock price.

In order to compare this model to the real world scenario this thesis analysed two mergers between Sanofi's purchase of Ablynx that had a secondary competing acquirer (against Sanofi) being Nova Nordisk. Also, a second merger was analysed: the potential takeover of a US grain merchant Bunge Limited by Archer Daniel Midlands with interest from Glencore in this deal. In both cases, the M&A transaction price increased due to the presence of multiple acquirers. This is in line with the outcomes provided by the model in this thesis.

### 6.3 M&A Transaction Pricing Results using Cumulative Prospect Theory

This chapter intends to analyse M&A transaction pricing between two companies (an acquirer and a target company) and where there are multiple acquirers (three acquirers trying to acquire a target). Based on the analysis, the results show that the M&A transaction price reduces when the loss aversion co-efficient is increased from 0% in figure 1 to 100% in figure 4 (in effect, a loss aversion co-efficient of 0% equates to a gain being seen as four times as valuable compared to a loss of the same size. In contrast, when I consider a loss aversion co-efficient of 100% that equates to gains and losses being seen as equally valuable), the overall M&A transaction price plummets. This occurs as the acquirer and target company do not differentiate between gains and losses in figure 4, which allows the price to drop rather than a price being biased towards gains. This means that if gains and losses were considered equal (which is not the case as Kahneman and Tversky 1979 state that the loss aversion co-efficient based on empirical evidence is 28%), then the M&A transaction price would have been lower.

These results in figures 1 – 4 are closely related to the results obtained in figures 1 – 4 in chapter 5. However, the loss aversion co-efficient has a lesser impact due to the upward pricing pressure that comes through due to the competition between multiple acquirers. The main reason that the loss aversion co-efficient has such a strong impact compared to the outcomes that I observed in chapters 3 and 4, is due to the fact that in the real world model loss aversion can be more prominent. This has also been seen clearly in the M&A transactions that occurred between Verizon and AOL and Verizon and Yahoo in chapter 5. The loss aversion co-efficient in the real world model in chapters 5 and 6 has a stronger impact in shaping the outcome of the M&A transaction and this is primarily as the difference in the perception of gain and loss is more significant. So, as the loss aversion co-efficient increases, it automatically reduces the biases towards gains. As a result, the risk taking behaviour of the acquirer becomes more prominent. If the acquirer notices that the target can be vulnerable to reduce its pricing, then the risk taking behaviour of the acquirer tends to become more predatory for the target.

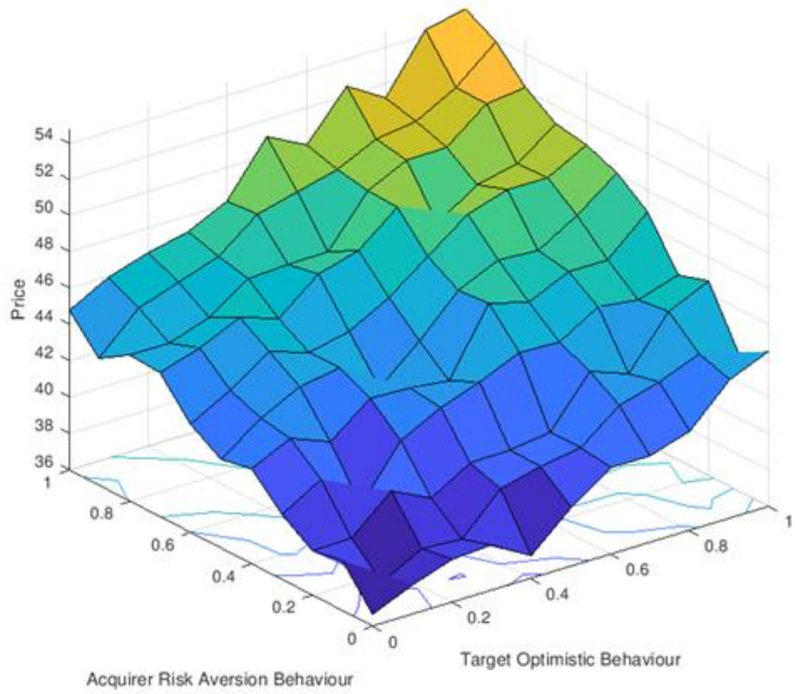


**Figure 1 Multiple Acquirer Loss Aversion = 0%**

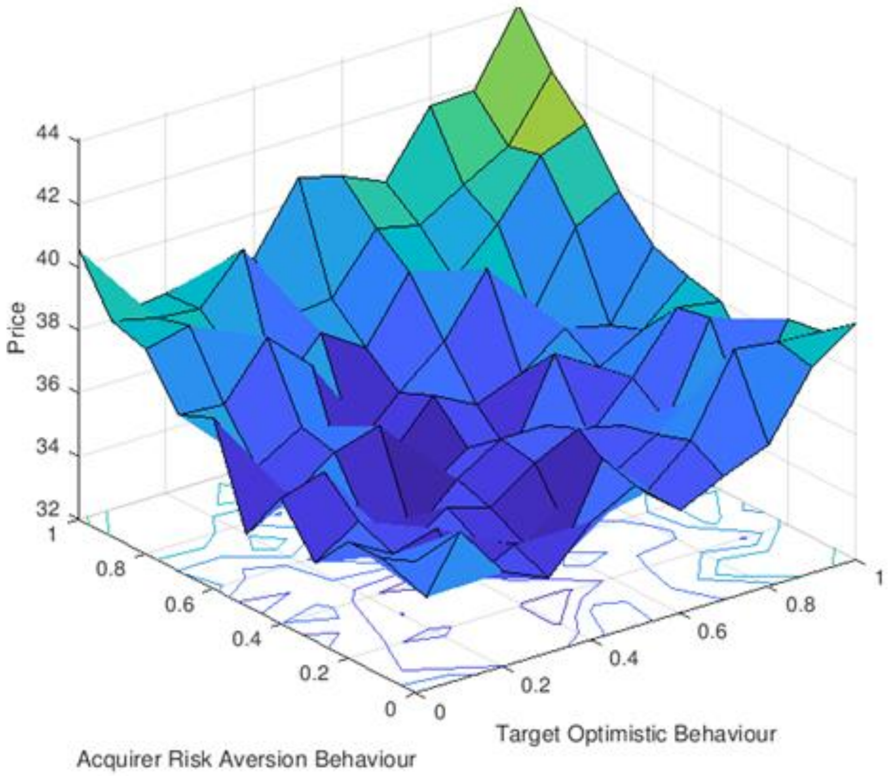


**Figure 2 Multiple Acquirer Loss Aversion = 28%**

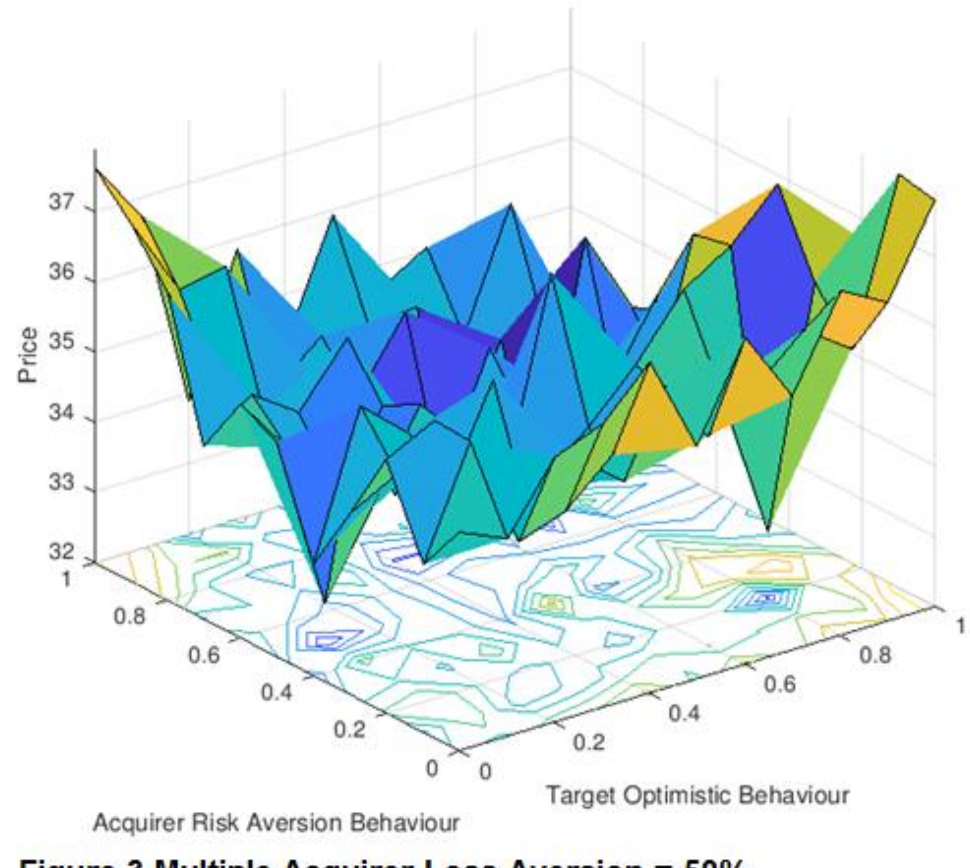


**Figure 3 Multiple Acquirer Loss Aversion = 50%**

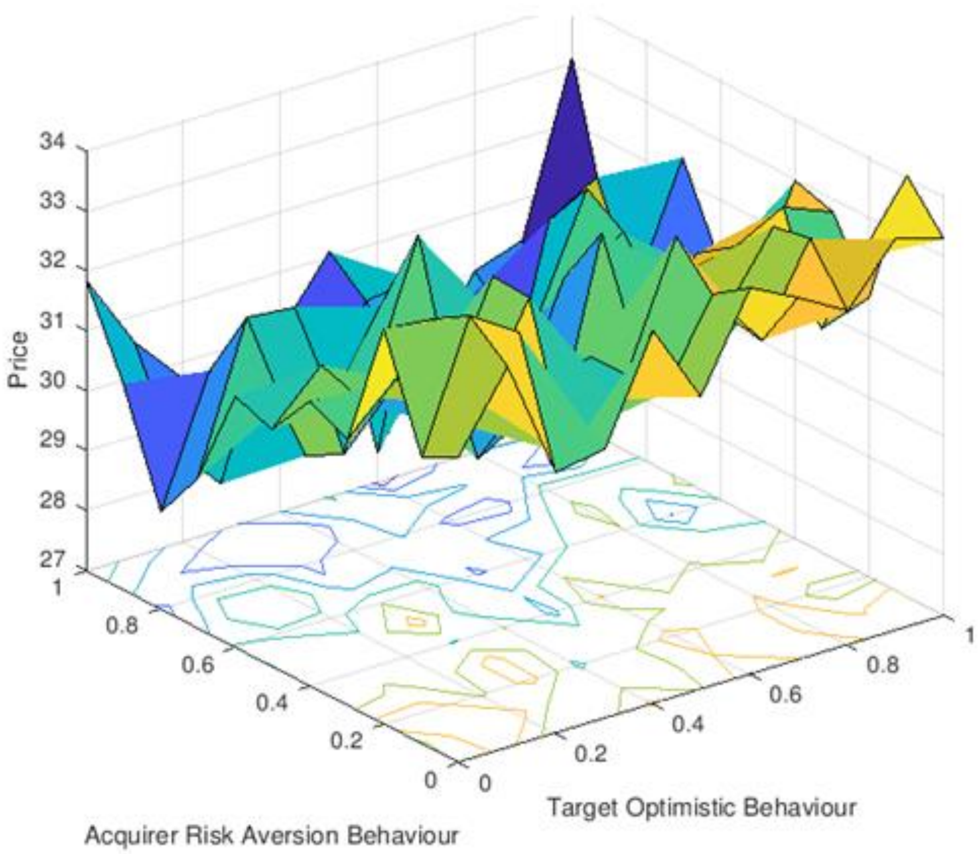


**Figure 4 Multiple Acquirer Loss Aversion = 100%**

In figures 5 – 8, when cumulative prospect theory is applied to the model (where people are risk averse for gains and risk taking for losses of high probability and vice versa) I notice that the M&A transaction price only drops slightly. This occurs due to the fact that the outcomes in figures 1 – 4, also have the same probability of gains and losses as in figure 5 – 8. As a consequence, the results marginally align with the change in the probability of the outcome (gain or loss). However, what is interesting to note is the change in the M&A transaction price due to the increase in loss aversion. When the loss aversion co-efficient increases above 28% (as in figures 3 – 4 and 7 – 8), the M&A transaction prices significantly plummet. The reason for this drop is that the perception of a gain and loss seems to be similar. For example, in figure 7, a gain is seen to be twice as valuable as a loss of the same amount and in figure 8, a gain is only one time more valuable than a loss of the same amount. So, when the difference between the perception of a gain and a loss is reduced, this automatically allows the acquirer and target company to treat gains and losses in the same proportion, which reduces the bias towards gains and allows the equilibrium price to drop.

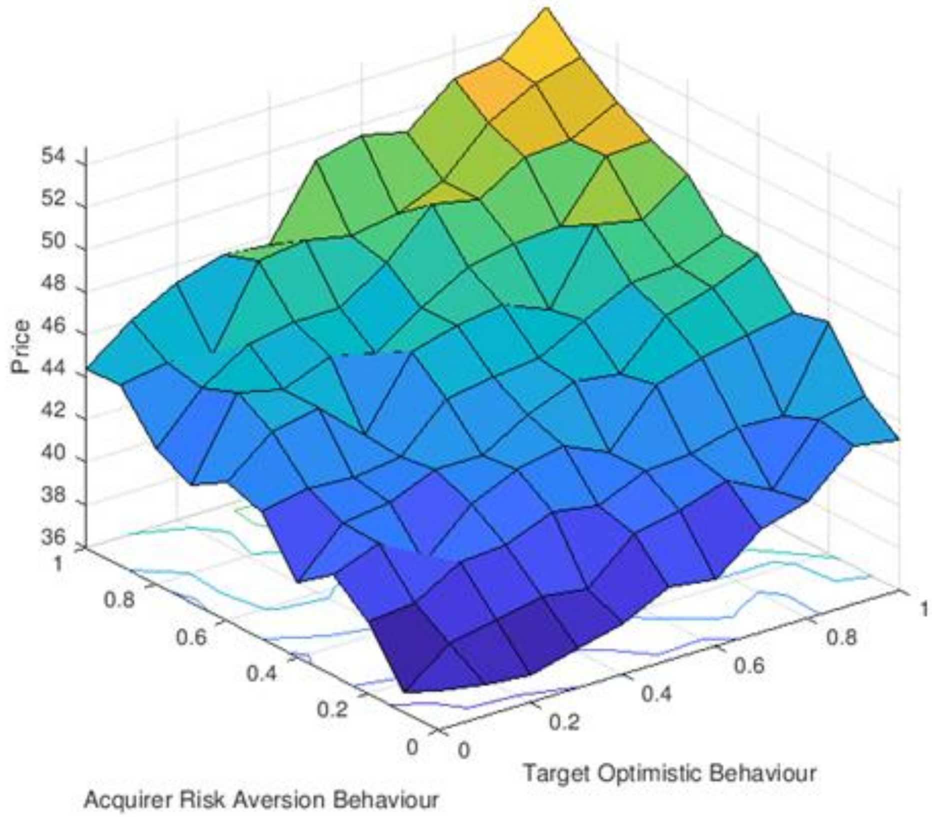


**Figure 5 C. Prospect Theory Loss Aversion = 0%**

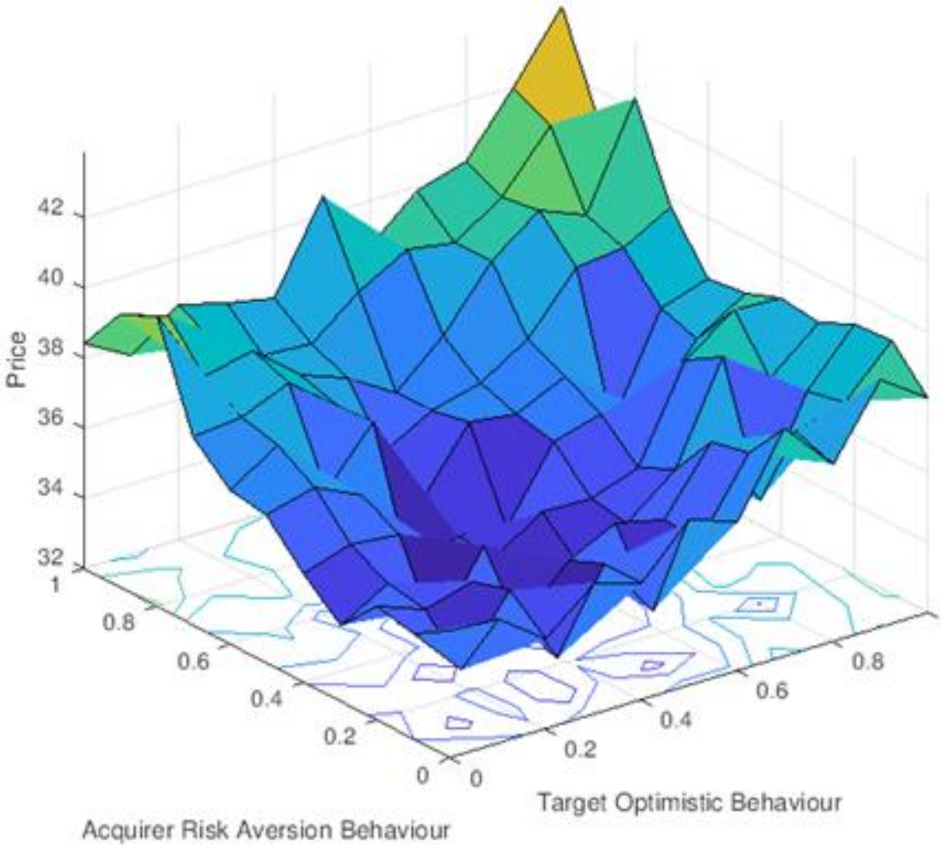


**Figure 6 C. Prospect Theory Loss Aversion = 28%**

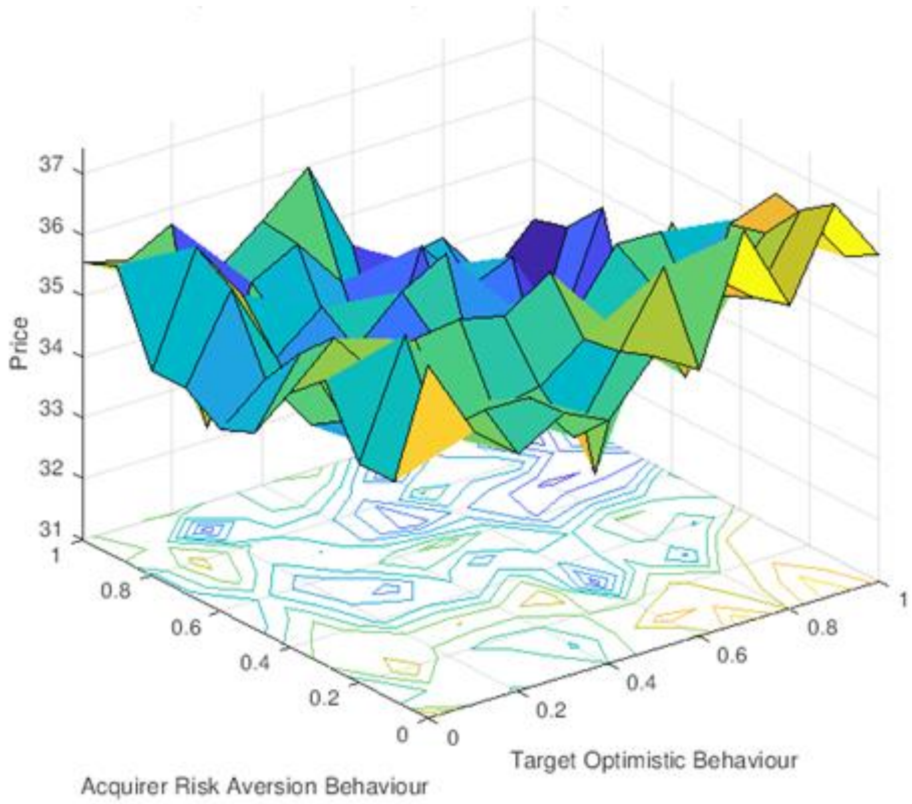


**Figure 7 C. Prospect Theory Loss Aversion = 50%**

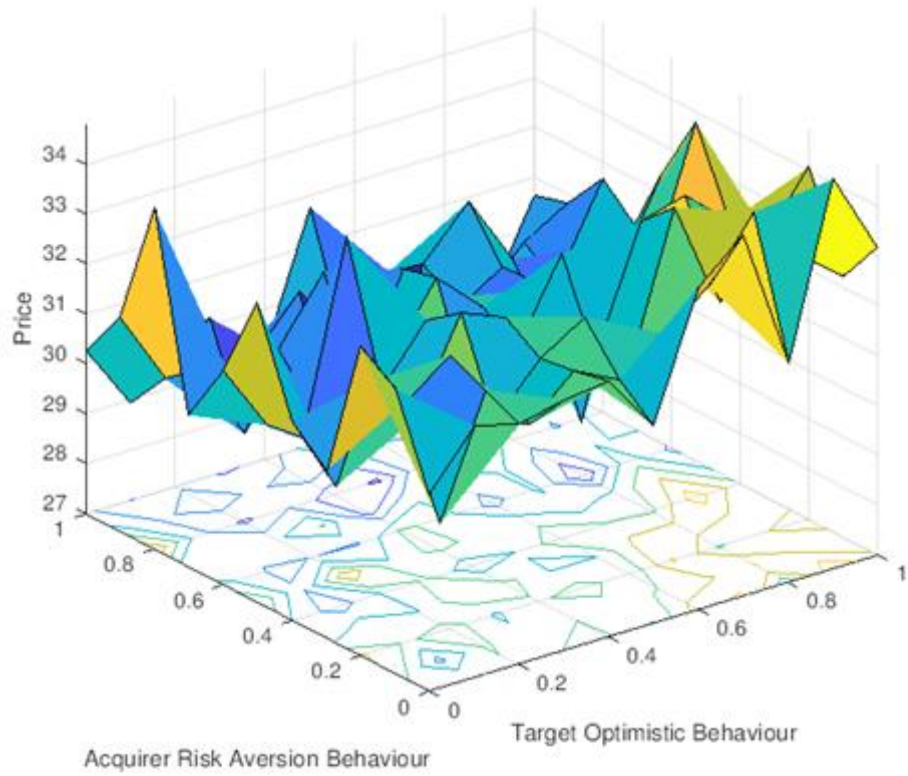


**Figure 8 C. Prospect Theory Loss Aversion = 100%**

## 6.4 M&A Transaction Pricing with Cumulative Prospect Theory and Multiple Acquirers

In figures 9 – 12, I extend the existing model to include three acquirers that compete to acquire the target company. While most mergers do not have multiple acquirers bidding for a target, nonetheless there are situations where this has occurred. The impact of having multiple acquirers would make us think that the M&A transaction price for that acquisition would increase as each of the acquirers bids up the price due to competition. Results show that this definitely is the case in figure 9, where the M&A transaction price or acquisition price keeps increasing with the optimism of the target company. Obviously, when there are three acquirers bidding to take over the target company, it will be more optimistic about obtaining a higher price for the sale. There is however a dip in figure 9, when the target is only half as optimistic and the acquirer is risk taking. This results in a situation where the target does not demand as much as it can and this results in a drop in the acquisition price.

In figure 10, I notice that the M&A transaction price is lower as the loss aversion co-efficient increases from 0% to 28% and, as a result, this reduces the importance of gains over losses. So, in effect, the M&A transaction price drops. However, the price still keeps increasing in figure 10 as the optimism of the target company increases. However, the M&A transaction price drops again in figure 11 as the loss aversion co-efficient increases to 50%.

But, in this case, the target company's optimism factor has a significant impact on increasing the M&A transaction price. Figure 12 though is very similar to figure 8, as the loss aversion co-efficient equals 100%, the impact of the additional competition between the three acquirers is negated by the fact that the weights between gains and losses has diminished. As a result, the M&A transaction price fails to increase due to the additional competition from the multiple acquirers.

According to Kahneman and Tversky (1979), based on empirical analysis, the average human loss aversion co-efficient is seen to be 28%. As a result, figures 2, 6 and 10 are the most appropriate for the outcome in this chapter when considering multiple acquirers. The results are consistent with outcomes observed in chapter 5, where I consider a single acquirer in a real world scenario. But, in this chapter the M&A transaction price tends to increase due to the upward movement in price due to the competition between the multiple acquirers. Resultantly, figure 10 in this chapter is the best representation for this model.

Results from the Sanofi – Ablynx merger and the potential merger between Bunge and Archer Daniel Midlands are in line with the results from this model. In both these cases, the merger price increased as the multiple acquirers have competed to bid up the price of the target company. In the Sanofi – Ablynx merger, the price of Ablynx stock went up by 21.2 percent after the announcement. While, in the case of the Bunge announcement of a potential takeover, the stock price increased in excess of 10 percent. This evidence shows that in reality, when there are multiple acquirers, the target company can be optimistic about the outcome of a merger and as a result, the merger price will automatically be higher than when only a single acquirer exists.

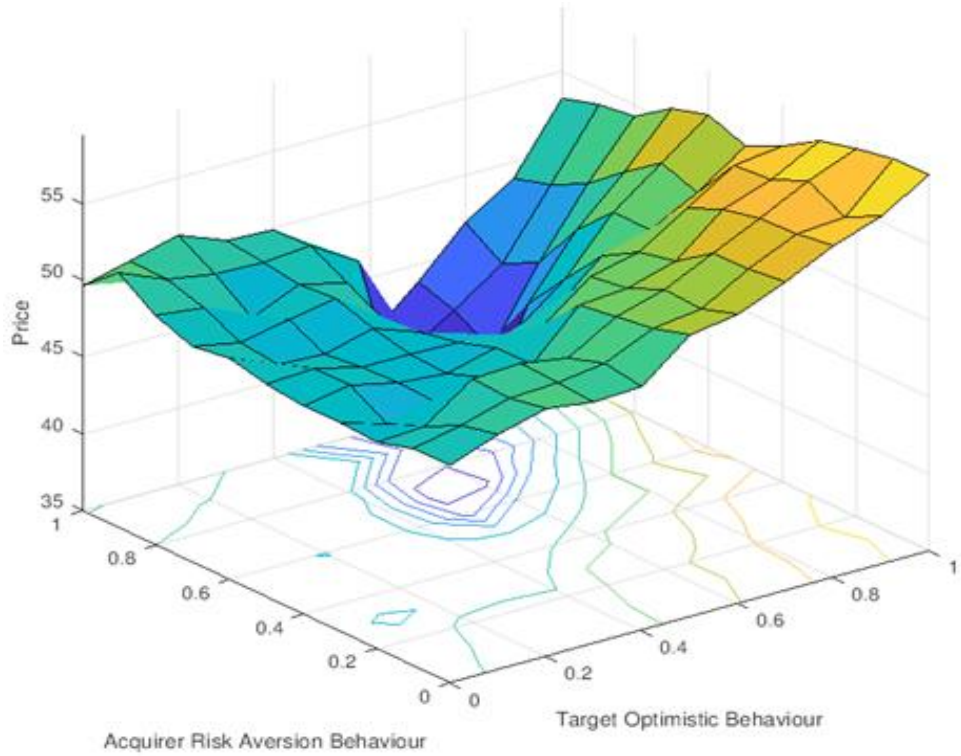


**Figure 9 Certainty Effect Loss Aversion = 0%**

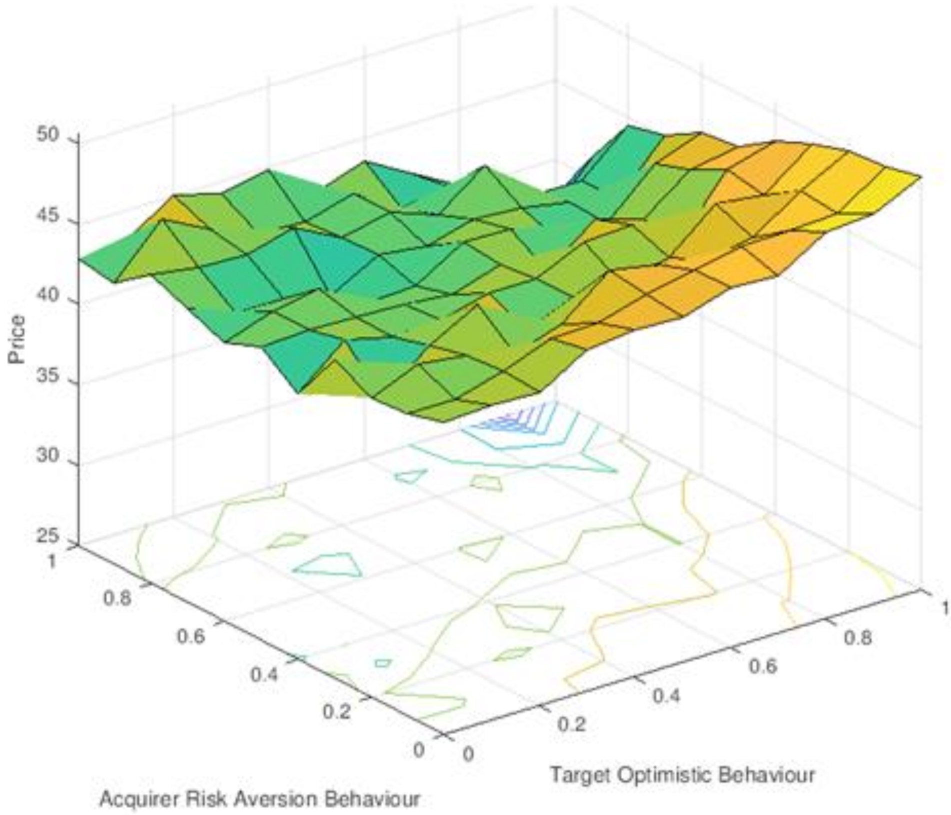


**Figure 10 Certainty Effect Loss Aversion = 28%**

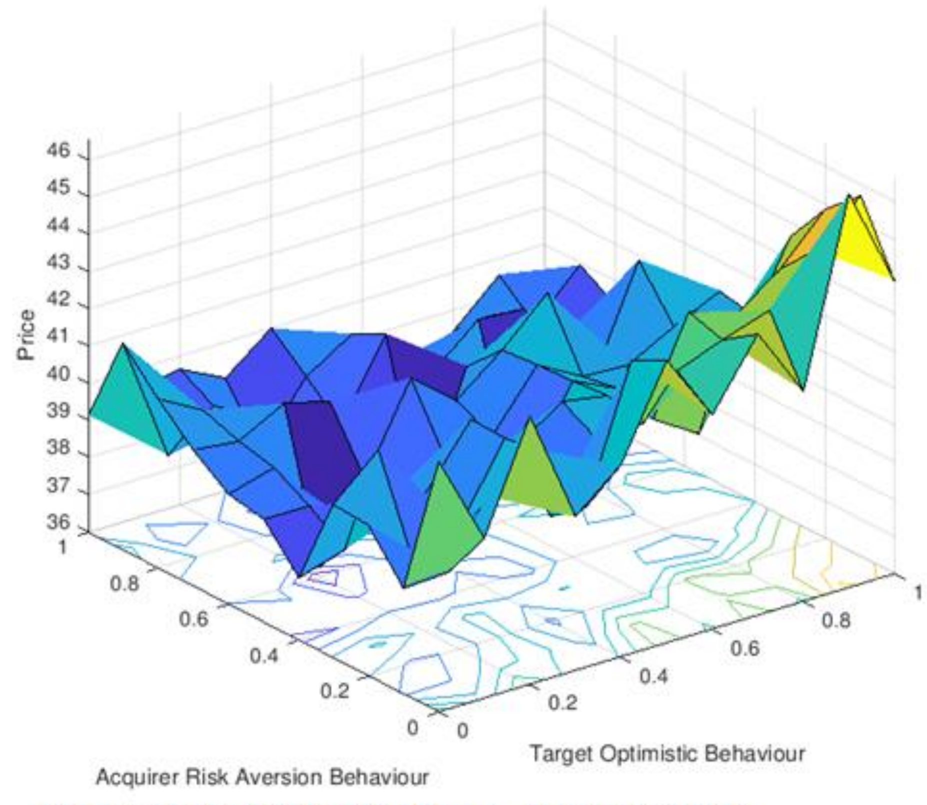


**Figure 11 Certainty Effect Loss Aversion = 50%**

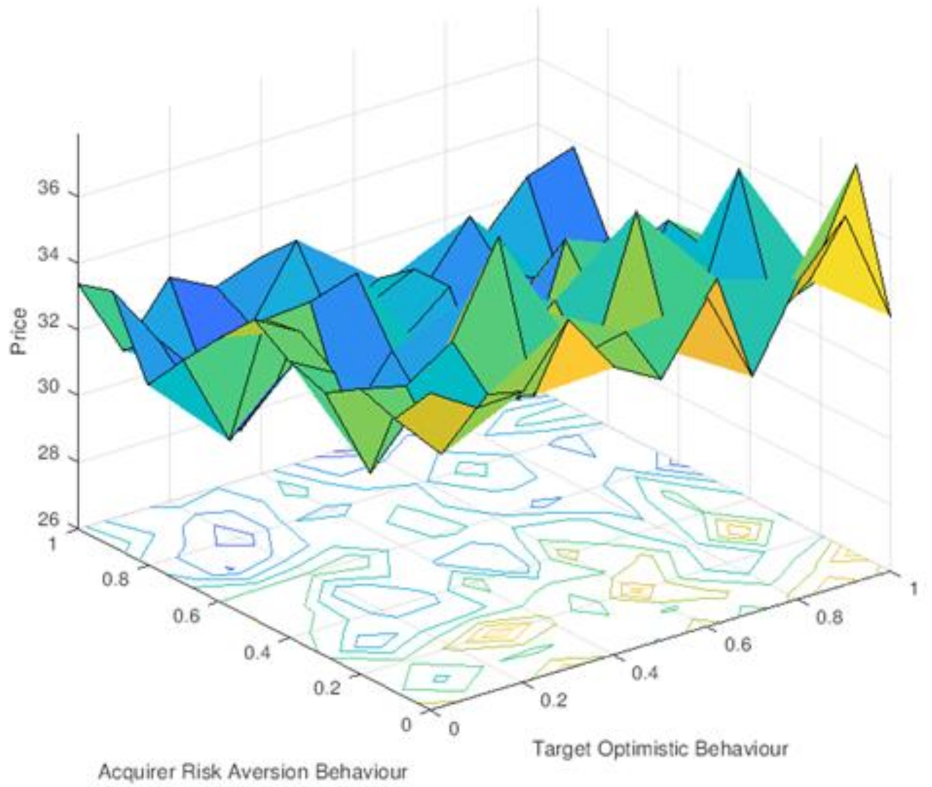


**Figure 12 Certainty Effect Loss Aversion = 100%**

In simplistic terms, the above figures 1 – 12, can be shown in the decision tree (CART) provided below. The results show that the best outcome is when the acquirer is risk taking and target is optimistic with returns reducing as the loss aversion co-efficient increases (as gains and losses have the same weight), but increases as certainty increases in the outcome. However, figure 10 provides the most realistic proposition in this case, where the M&A transaction price increases as the target firm's optimism level increases due to the competition between multiple acquirers, but reduces due to an increase in the loss aversion co-efficient. While the strategy in this case is similar to the strategy provided in chapters 3 and 4, the outcome is quite different. This occurs because the acquirer tends to reduce the price due to the higher perceptual difference between gains and losses in the real world compared to the experiments undertaken in chapters 3 and 4. Results from this chapter however support the outcomes that I have seen with the merger of Sanofi – Ablynx merger and the potential merger between Bunge and Archer Daniel Midlands.

The most probable option in such a circumstance has been provided below (shown by the red arrows in the diagram below).

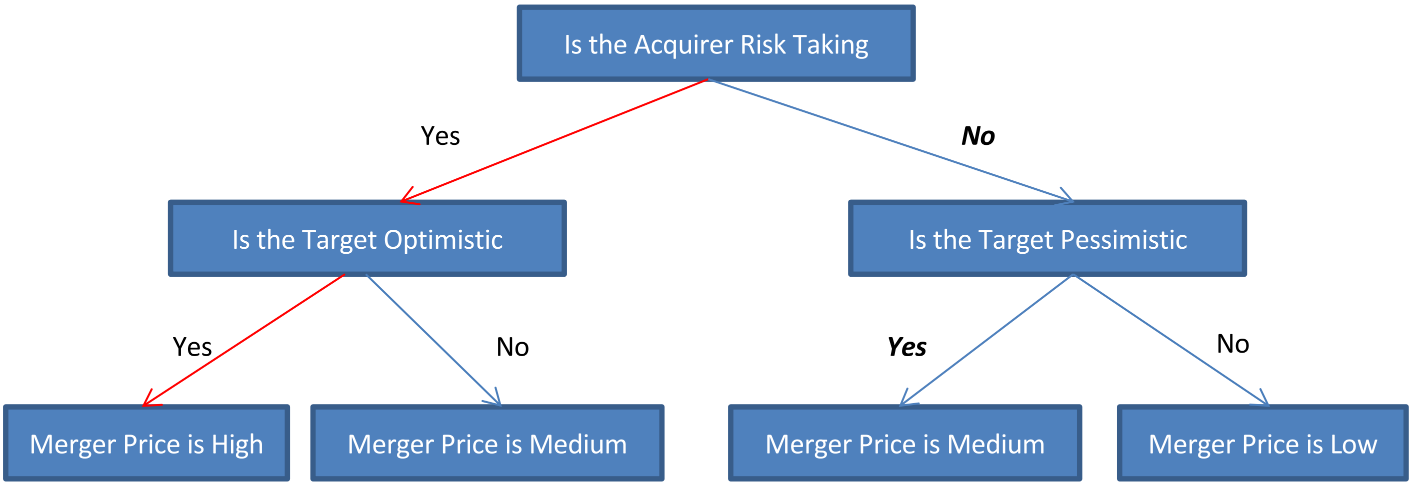


**Diagram 6.1 CART Decision Tree for Multiple Acquirer and Target Firm for a Commercial Outcome**

## 6.5 Conclusion

This chapter has further developed the models described in the previous chapters (chapters 3 – 5) and has tried to commercialise the outcomes derived in chapter 4 in order to compare the results with real world mergers and acquisitions. In order to do that, the model in this chapter was developed to start with the target firm's stock price of $50 and to understand how the behavioral traits of the acquirer and target firm, loss aversion co-efficient and impact of multiple acquirers have on the results. In line with chapter 4, loss aversion does have a significant impact on the outcome of the M&A transaction price. However, if the acquirer is risk averse and the target firm is pessimistic, the outcome aligns with that observed in chapter 5. On the other hand, the existence of multiple acquirers has a significantly positive effect on the M&A transaction price and it unwinds the impact of the loss aversion co-efficient. Evidence from real world mergers between Sanofi and Ablynx, and a potential merger between Bunge and Archer Daniel Midlands, support the results provided by this model. These results show that when multiple acquirers exist, it is relatively easy for the target company to be optimistic and this supports the competing bids from the multiple acquirers that lead to a higher bid for the target company. These results are in line with those in chapter 4 and support the positive implications of having multiple acquirers in an M&A transaction.

CHAPTER SEVEN

# Summary, Limitations & Suggested Extensions

## 7.1 Summary

Mergers & acquisitions (M&A) pricing has been a significant driver of inorganic growth. Kahnemann and Tversky (1979) have shown that human beings treat gains and losses differently. Also, Baker, Pan and Wurgler (2009) have stated that the 52-week high stock price has been seen as a significant psychological anchor for shareholders of target firms to agree to sell their stake in the company. The intent of this thesis has been to analyse M&A transaction pricing and the impact of behavioural biases on such pricing under the perception of differential synergies by the acquirer and target firm, across business cycles and in a hostile takeover condition. This thesis reviewed these issues in chapters 3 – 6 of this thesis. Results showed that psychological biases are significant in certain circumstances and should be taken into consideration when pricing M&A transactions.

## 7.2 Contribution to knowledge

This thesis contributes to knowledge by developing agent based simulation models to understand behavioral changes that will impact the pricing of M&A transactions.

This thesis has developed a novel model, as no model exists to analyse merger and acquisition transaction pricing based on behavioural traits. No other standard models exist with which this model can be compared. While, this is a limitation to this thesis, it is also clear that the model developed in this thesis provides the opportunity to open a new research area, where M&A transaction pricing can be based on behavioural trait analysis.

This thesis, as a result, adds to existing knowledge in the following ways:

1. It analyses M&A transaction pricing for behavioural biases where the acquirer and target firm have different behavioural traits and where psychological theories such as prospect theory (Kahneman and Tversky 1979) and cumulative prospect theory (Kahneman and Tversky 1992) can impact M&A transaction pricing. This is a new area of research and this thesis incorporates

some of the first papers to be published in this area of psychological M&A pricing theory. This research is important as it provides investment bankers deeper insight into how behavior will impact M&A transactions. Also, it shows how a game theoretic approach can be taken to obtain a more optimal price in such transactions. In the traditional financial models that are currently utilized by investment bankers, only one of these two factors is considered. So, depending on the assumptions that these bankers make, they can come up with different M&A transaction prices. As a result, it is critical that both the behavioural and game theoretic aspects of M&A transaction pricing be included in real world transactions to be able to obtain a more accurate outcome.

2. Additionally, it analyses M&A transaction pricing where behavioural biases and multiple acquirers exist in an M&A transaction. This thesis shows how the presence of behavioural biases and multiple acquirers has a different impact on the M&A transaction pricing compared to when only a single acquirer exists. This is important to understand as the outcomes of both these transaction structures are quite different and, if this is not well understood, it is possible that either the acquirer or target firm will miscalculate the final M&A transaction price and may end up over paying for the transaction or the transaction may fail if the price is less than what is expected by the target firm.

## 7.3 Limitations of this research

The limitations that have been identified for this thesis are as follows:

1. **Behavioural Modelling in Mergers & Acquisitions:** behavioural finance, game theory and agent based modelling is applied to different parts of the fields of finance and economics, especially to the areas of asset pricing and portfolio theory. However, there is limited (if any) models that apply behavioural finance to mergers and acquisitions, any models in this area have been clearly identified in the Literature Review of this thesis. No model exists that applies behavioural finance and agent based modelling techniques to transaction pricing of mergers and acquisitions. Therefore, there is no direct model to compare the model developed in this thesis. As a result, the

approach undertaken in this thesis is to compare the outcomes of the model in this thesis to real world case studies.

2. **Agent Based Modelling Techniques:** there is a limitation on the number of behavioural factors that can be included in a single simulation as it complicates the analysis and it becomes hard to understand the outcomes of the analysis in the graphs. In order to provide meaningful outcomes to the simulation, this thesis has considered a continuum of the risk averse to risk taking behavioural trait for the acquiring firm and optimistic to pessimistic behavioural trait for the target firm. In future experiments, it may be possible to analyse multiple factors. However, there is a risk that the researcher will have to identify the implications of each specific trait specifically to the change in M&A transaction price. In order to keep the experiments in this thesis simple, I have opted to consider only a single behavioural trait continuum for each of the acquirer and target firms.

3. **Scenario Analysis:** a few behavioral scenarios were developed in this thesis, however a significant number of additional scenarios can be developed to analyse behavioural biases in M&A transaction pricing. This thesis considered the application of prospect theory and cumulative prospect theory, and single and multiple acquirers. It is obviously possible to extend the number of existing scenarios to obtain further insight into this research problem. For example, when there are regulatory restrictions or competition law issues that may restrict the way companies can bid in a M&A transaction or if there are international transactions where the culture of the different acquirers differs across countries and that may impact the overall outcome of the M&A transaction pricing. However, though in order to keep the outcomes of this thesis reasonably simple, this thesis has opted to only consider the parameters defined earlier (prospect theory, cumulative prospect theory, single acquirer and multiple acquirer).

4. **Behavioral Finance Biases and Transaction Costs:** there can be numerous behavioural biases or transaction costs that may distort the pricing of M&A transaction that have not been included in this analysis. This thesis has purposely considered only the risk averse – risk taking continuum for the acquirer and optimistic – pessimistic continuum for the target firm. It is

possible to extend this research to consider other behavioural factors like fear, greed and hyperbolic expectations for example. Also, this thesis considered that no transaction costs existed in these transactions and, as a result, the outcome was not impacted or distorted by these transaction costs. It is possible for future research to consider including these transaction costs and it will potentially have an impact on the outcome of each game. It could also be possible that future research may find that the transaction costs differ depending on the type of scenario (may be different between single and multiple acquirers for example). However, this thesis explicitly does not consider the different behavioural biases or transaction costs.

5. **No Extrinsic factors included:** This thesis primarily aims to concentrate on the simulation of intrinsic factors and does not want to complicate the analysis with the use of extrinsic factors. Extrinsic factors can be developed as an extension to this thesis.

6. **Data Limitation:** There is a limitation of behavioural data related to mergers and acquisitions transactions. Therefore, an agent based model was developed to overcome this shortfall. Additionally, real world case studies have been utilized in chapters 5 and 6 to analyse the results, i.e. to compare the results from the agent based simulations with real world case studies.

## 7.4 Possible applications of this research

Potential applications of the research undertaken in this thesis are as follows:

1. This model can be used as a tool by acquirers and target firms to generate a potential M&A transaction price. At present, investment banks utilize financial models that do not consider behavioural traits in pricing M&A transactions. However, we have seen that no two acquirers or target firms are the same. So, it is critical to include these factors and to be able to optimize the outcome for M&A transaction pricing. As a result, it will be useful to utilize this model to analyse the price of real world M&A transactions.

2. The agent based simulation model in this thesis can be used for testing potential pricing options for M&A transactions by acquirers and target firms, before making an offer to undertake such a transaction. This model allows

investment banks to test the M&A transaction price that they have obtained using financial models to understand if this price will be appropriate keeping in mind the behavioural factors that are in play in such a transaction. In effect, it allows the investment banker to fine tune their M&A transaction price.

3. This agent based model can be extended to include other behavioral biases impacting M&A transaction pricing and the impact of such biases can be tested. While, this model only reviews specific behavioural traits at present, it is easy for a researcher to extend or change the behavioural traits in this model to analyse the factors that they believe are impacting their specific M&A transaction. Allowing them to obtain a better understanding and being able to apply the model more specifically to solve their problem.

## 7.5 Suggested Extensions

Suggested possible further extensions of this thesis can be developed which are explained below:

1. Extend the existing agent based model to analyse additional behavioral biases that impact M&A pricing. As discussed, future studies can include other behavioural biases like confirmation bias, regret aversion bias, disposition effect bias, hindsight bias, familiarity bias, self-attribution bias, trend chasing bias (for example, through merger waves), worry, fear or greed for example. The inclusion of these biases in this agent based model will allow the researcher to provide more specific M&A transaction pricing for each specific transaction.

2. Extend the model to understand how transaction costs may distort M&A transaction pricing. As transaction costs usually have a significant impact on financial transactions. It can be possible that these transaction costs may come in the way of an M&A transaction being concluded, in case the costs are too high. It could also be possible that transaction costs in some scenarios are higher than those in other scenarios. The perception of these costs in addition to the acquirer and target firms behavioural traits is also important.

As, even small transactions costs may impact the M&A transaction pricing, if the acquirer is risk averse or target firm is pessimistic.

3. The existing agent based model can be extended with machine learning application to test these findings of this model with real world data or to extend this model to improve the predictive ability of this model using real world data. While, the agent based model in this thesis develops a theoretical model to analyse M&A transaction pricing. It will be really useful to further extend this model using machine learning and to utilize real world data to more accurately test and price these transactions. Addition of machine learning will also allow the researcher to include other behavioural traits that occur in the real world or to identify specific traits from data that have not been considered in these types of transactions as yet.

4. The existing model focuses on including intrinsic factors. A potential extension of this model is to include extrinsic factors that can impact a merger and acquisition transaction. Include these extrinsic factors is likely to change the dynamics of the M&A transaction simulation and the overall result of the transaction.

Finally, in conclusion the main extensions of this model will lie in the areas of the application of behavioural traits, inclusion of transactions costs in this model and the use of machine learning and real world data to model this problem more holistically, making the outcomes of this model more applicable to specific M&A transactions. It will also be useful if researchers can extend this model to make it more useful for industry practitioners like investment bankers to be able to develop and use these models, assisting me in obtaining more specific pricing for M&A transaction considering behavioural traits and game theoretic outcomes.

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# APPENDIX A: MATLAB CODE FOR THE MODEL

**Models related to results provided in Chapters 3-6 are provided below:**

**Model 1 Relates to the discussion in Chapter 3 – Explains a single acquirer model that assesses the utility of the merger negotiation between a single acquirer and target firm.**

```
N = 1000; %number of players in the game
T = 1000; %number of rounds in each game
Games = 1000; %number of games
UtilityVector = [];
BehavioralVector = [];
UtilityMatrix = [];
BehavioralMatrix = [];
Ceiling = 1.00;
RiskFactor_Increase = 0.1;
OptimismFactor_Increase = 0.1;
Loss_coefficient = 0.00;
Risk_Factor = -0.10;
Optimism_Factor = -0.10;
for a = 0:RiskFactor_Increase:Ceiling
Risk_Factor = Risk_Factor + RiskFactor_Increase;
UtilityVector = [];
BehavioralVector = [];
Optimism_Factor = 0.0;
for b = 0:OptimismFactor_Increase:Ceiling %numbers of games to be played
Optimism_Factor = Optimism_Factor + OptimismFactor_Increase;
X = [rand(N,1) zeros(N,1)]; %create matrix X with N rows & 2 columns
for c = 0:Games
X(:,2) = zeros(N,1);
for d = 1:T
PL1 = floor(1 + (N - 1)*rand(1)); %player1
PL2 = floor(1 + (N - 1)*rand(1)); %player2
if PL1 == PL2
PL2 = floor(1 + (N - 1)*rand(1)); % re pick player 2 to ensure it is
different from player 1
end
%calculate utility at the end of round 1
utility1 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Risk_Factor*X(PL1,1)) -
((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Optimism_Factor*X(PL2,1))
- ((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 2
%update utility in X after round 2
X(PL1,2) = utility1; %overwrite Utility for player 1
X(PL2,2) = utility2; %overwrite Utility for player 2
end
X = sortrows(X,2); %sort rows based on utility
X(1:N/10,:) = []; %delete 10% of individuals
Xadd = [rand(N/10,1) zeros(N/10,1)]; %add new 10% of individuals at random
X = [X; Xadd]; %#ok<AGROW> %add new 10% individuals at random to the end of
matrix X
end
UtilityVector = [UtilityVector mean(X(:,1))]; %#ok<AGROW>
BehavioralVector = [BehavioralVector mean(X(:,1))]; %#ok<AGROW>
end
UtilityMatrix = [UtilityMatrix; UtilityVector]; %#ok<AGROW>
BehavioralMatrix = [BehavioralMatrix; BehavioralVector]; %#ok<AGROW>
end
X(N-N/10:N,:) = []; %delete newly added rows with zero utility
```

```
Buyer_Vector = 0:RiskFactor_Increase:Ceiling;
Seller_Vector = 0:OptimismFactor_Increase:Ceiling;
figure (1)
surfc (Buyer_Vector, Seller_Vector, UtilityMatrix);
xlabel('Target Optimistic Behaviour') %set x-axis label
ylabel('Acquirer Risk Aversion Behaviour') %set y-axis label
zlabel('Price') %set z-axis label
title('Change in Price with Acquirer and Target Behavioural Factors') %set
chart title
```

**Model 2 Relates to the discussion in Chapter 3 – Explains a single acquirer model that assesses the utility of the merger negotiation between a single acquirer and target firm. Where, the probability of gain or loss (loss aversion) is 50 percent.**

```
N = 1000; %number of players in the game
T = 1000; %number of rounds in each game
Games = 1000; %number of games
UtilityVector = [];
BehavioralVector = [];
UtilityMatrix = [];
BehavioralMatrix = [];
Ceiling = 1.00;
RiskFactor_Increase = 0.1;
OptimismFactor_Increase = 0.1;
Loss_coefficient = 0.28;
Risk_Factor = -0.10;
Optimism_Factor = -0.10;
Probability_GainLoss = 0.0;
for a = 0:RiskFactor_Increase:Ceiling
Risk_Factor = Risk_Factor + RiskFactor_Increase;
UtilityVector = [];
BehavioralVector = [];
Optimism_Factor = 0.0;
for b = 0:OptimismFactor_Increase:Ceiling %numbers of games to be played
Optimism_Factor = Optimism_Factor + OptimismFactor_Increase;
X = [rand(N,1) zeros(N,1)]; %create matrix X with N rows & 2 columns
for c = 0:Games
X(:,2) = zeros(N,1);
for d = 1:T
PL1 = floor(1 + (N - 1)*rand(1)); %player1
PL2 = floor(1 + (N - 1)*rand(1)); %player2
if PL1 == PL2
PL2 = floor(1 + (N - 1)*rand(1)); % re pick player 2 to ensure it is
different from player 1
end
Probaility_GainLoss = rand(1);
%calculate utility at the end of round 1
if Probability_GainLoss > 0.5
utility1 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Risk_Factor*X(PL1,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Optimism_Factor*X(PL2,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 2
else
utility1 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Risk_Factor*X(PL1,1)) -
((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Optimism_Factor*X(PL2,1))
- ((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 2
end
%update utility in X after round 2
X(PL1,2) = utility1; %overwrite Utility for player 1
```

```
X(PL2,2) = utility2; %overwrite Utility for player 2
end
X = sortrows(X,2); %sort rows based on utility
X(1:N/10,:) = []; %delete 10% of individuals
Xadd = [rand(N/10,1) zeros(N/10,1)]; %add new 10% of individuals at random
X = [X; Xadd]; %#ok<AGROW> %add new 10% individuals at random to the end of
matrix X
end
UtilityVector = [UtilityVector mean(X(:,1))]; %#ok<AGROW>
BehavioralVector = [BehavioralVector mean(X(:,1))]; %#ok<AGROW>
end
UtilityMatrix = [UtilityMatrix; UtilityVector]; %#ok<AGROW>
BehavioralMatrix = [BehavioralMatrix; BehavioralVector]; %#ok<AGROW>
end
X(N-N/10:N,:) = []; %delete newly added rows with zero utility
Buyer_Vector = 0:RiskFactor_Increase:Ceiling;
Seller_Vector = 0:OptimismFactor_Increase:Ceiling;
figure (1)
surfc (Buyer_Vector, Seller_Vector, UtilityMatrix);
xlabel('Target Optimistic Behaviour') %set x-axis label
ylabel('Acquirer Risk Aversion Behaviour') %set y-axis label
zlabel('Price') %set z-axis label
title('Change in Price with Acquirer and Target Behavioural Factors') %set
chart title
```

**Model 3 Relates to the discussion in Chapter 4 – Explains a single acquirer model that assesses the utility of the merger negotiation between a single acquirer and target firm. Where, the probability of gain or loss (certainty effect) is 99 percent – essentially supporting the certainty rule in Prospect Theory.**

```
N = 1000; %number of players in the game
T = 1000; %number of rounds in each game
Games = 1000; %number of games
UtilityVector = [];
BehavioralVector = [];
UtilityMatrix = [];
BehavioralMatrix = [];
Ceiling = 1.00;
RiskFactor_Increase = 0.1;
OptimismFactor_Increase = 0.1;
Loss_coefficient = 1.00;
Risk_Factor = -0.10;
Optimism_Factor = -0.10;
Probability_GainLoss = 0.00;
for a = 0:RiskFactor_Increase:Ceiling
Risk_Factor = Risk_Factor + RiskFactor_Increase;
UtilityVector = [];
BehavioralVector = [];
Optimism_Factor = 0.0;
for b = 0:OptimismFactor_Increase:Ceiling %numbers of games to be played
Optimism_Factor = Optimism_Factor + OptimismFactor_Increase;
X = [rand(N,1) zeros(N,1)]; %create matrix X with N rows & 2 columns
for c = 0:Games
X(:,2) = zeros(N,1);
for d = 1:T
PL1 = floor(1 + (N - 1)*rand(1)); %player1
PL2 = floor(1 + (N - 1)*rand(1)); %player2
if PL1 == PL2
PL2 = floor(1 + (N - 1)*rand(1)); % re pick player 2 to ensure it is
different from player 1
```

```
end
Probaility_GainLoss = rand(1);
%calculate utility at the end of round 1
if Probability_GainLoss > 0.99
utility1 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Risk_Factor*X(PL1,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Optimism_Factor*X(PL2,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 2
else
utility1 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Risk_Factor*X(PL1,1)) -
((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Optimism_Factor*X(PL2,1))
- ((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 2
end
%update utility in X after round 2
X(PL1,2) = utility1; %overwrite Utility for player 1
X(PL2,2) = utility2; %overwrite Utility for player 2
end
X = sortrows(X,2); %sort rows based on utility
X(1:N/10,:) = []; %delete 10% of individuals
Xadd = [rand(N/10,1) zeros(N/10,1)]; %add new 10% of individuals at random
X = [X; Xadd]; %#ok<AGROW> %add new 10% individuals at random to the end of
matrix X
end
UtilityVector = [UtilityVector mean(X(:,1))]; %#ok<AGROW>
BehavioralVector = [BehavioralVector mean(X(:,1))]; %#ok<AGROW>
end
UtilityMatrix = [UtilityMatrix; UtilityVector]; %#ok<AGROW>
BehavioralMatrix = [BehavioralMatrix; BehavioralVector]; %#ok<AGROW>
end
X(N-N/10:N,:) = []; %delete newly added rows with zero utility
Buyer_Vector = 0:RiskFactor_Increase:Ceiling;
Seller_Vector = 0:OptimismFactor_Increase:Ceiling;
figure (1)
surfc (Buyer_Vector, Seller_Vector, UtilityMatrix);
xlabel('Target Optimistic Behaviour') %set x-axis label
ylabel('Acquirer Risk Aversion Behaviour') %set y-axis label
zlabel('Price') %set z-axis label
title('Change in Price with Acquirer and Target Behavioural Factors') %set
chart title
```

**Model 4 Relates to the discussion in Chapter 4 – Explains a multiple acquirer model that assesses the utility of the merger negotiation between a multiple acquirers and target firm.**

```
N = 1000; %number of players in the game
T = 1000; %number of rounds in each game
Games = 1000; %number of games
UtilityVector = [];
BehavioralVector = [];
UtilityMatrix = [];
BehavioralMatrix = [];
Ceiling = 1.00;
RiskFactor_Increase = 0.1;
OptimismFactor_Increase = 0.1;
Loss_coefficient = 0.50;
Risk_Factor = -0.10;
Optimism_Factor = -0.10;
%Probability_GainLoss = 0.00;
for a = 0:RiskFactor_Increase:Ceiling
Risk_Factor = Risk_Factor + RiskFactor_Increase;
```

```
UtilityVector = [];
BehavioralVector = [];
Optimism_Factor = 0.0;
for b = 0:OptimismFactor_Increase:Ceiling %numbers of games to be played
Optimism_Factor = Optimism_Factor + OptimismFactor_Increase;
X = [rand(N,1) zeros(N,1)]; %create matrix X with N rows & 2 columns
for c = 0:Games
X(:,2) = zeros(N,1);
for d = 1:T
PL1 = floor(1 + (N - 1)*rand(1)); %player1
PL2 = floor(1 + (N - 1)*rand(1)); %player2
PL3 = floor(1 + (N - 1)*rand(1)); %player3
PL4 = floor(1 + (N - 1)*rand(1)); %player4
if PL1 == PL2 || PL3 || PL4
PL1 = floor(1 + (N - 1)*rand(1)); % re pick player 1 to ensure it is
different from player 2,3 or 4
end
if PL2 == PL1 || PL3 || PL4
PL2 = floor(1 + (N - 1)*rand(1)); % re pick player 2 to ensure it is
different from player 1,3 or 4
end
if PL3 == PL1 || PL2 || PL4
PL3 = floor(1 + (N - 1)*rand(1)); % re pick player 3 to ensure it is
different from player 1,2 or 4
end
if PL4 == PL1 || PL2 || PL3
PL4 = floor(1 + (N - 1)*rand(1)); % re pick player 4 to ensure it is
different from player 1,2 or 3
end
%Probaility_GainLoss = rand(1);
%calculate utility at the end of round 1
%if Probability_GainLoss > 0.50
% utility1 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Risk_Factor*X(PL1,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 1
% utility2 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Optimism_Factor*X(PL2,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 2
% utility3 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL3,1))/2) +
(Optimism_Factor*X(PL3,1)) - ((X(PL1,1)+X(PL3,1))); %Payoff for Player 2
% utility4 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL4,1))/2) +
(Optimism_Factor*X(PL4,1)) - ((X(PL1,1)+X(PL4,1))); %Payoff for Player 2
%else
utility1 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Risk_Factor*X(PL1,1)) -
((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Optimism_Factor*X(PL2,1))
- ((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 2
utility3 = ((1 - X(PL1,1)) + (1 - X(PL3,1))/2) + (Optimism_Factor*X(PL3,1))
- ((X(PL1,1)+X(PL3,1))*Loss_coefficient); %Payoff for Player 2
utility4 = ((1 - X(PL1,1)) + (1 - X(PL4,1))/2) + (Optimism_Factor*X(PL4,1))
- ((X(PL1,1)+X(PL4,1))*Loss_coefficient); %Payoff for Player 2
%end
%update utility in X after round 2
X(PL1,2) = utility1; %overwrite Utility for player 1
X(PL2,2) = utility2; %overwrite Utility for player 2
X(PL3,2) = utility3; %overwrite Utility for player 3
X(PL4,2) = utility4; %overwrite Utility for player 4
end
X = sortrows(X,2); %sort rows based on utility
X(1:N/10,:) = []; %delete 10% of individuals
Xadd = [rand(N/10,1) zeros(N/10,1)]; %add new 10% of individuals at random
X = [X; Xadd]; %#ok<AGROW> %add new 10% individuals at random to the end of
matrix X
```

```
end
UtilityVector = [UtilityVector mean(X(:,1))]; %#ok<AGROW>
BehavioralVector = [BehavioralVector mean(X(:,1))]; %#ok<AGROW>
end
UtilityMatrix = [UtilityMatrix; UtilityVector]; %#ok<AGROW>
BehavioralMatrix = [BehavioralMatrix; BehavioralVector]; %#ok<AGROW>
end
X(N-N/10:N,:) = []; %delete newly added rows with zero utility
Buyer_Vector = 0:RiskFactor_Increase:Ceiling;
Seller_Vector = 0:OptimismFactor_Increase:Ceiling;
figure (1)
surfc (Buyer_Vector, Seller_Vector, UtilityMatrix);
xlabel('Target Optimistic Behaviour') %set x-axis label
ylabel('Acquirer Risk Aversion Behaviour') %set y-axis label
zlabel('Price') %set z-axis label
title('Change in Price with Acquirer and Target Behavioural Factors') %set
chart title
```

**Model 5 Relates to the discussion in Chapter 5 – Explains a single acquirer model that assesses the utility of the merger negotiation between a single acquirer and target firm. Where, the model has model has been applied to the commercial real world example.**

```
N = 1000; %number of players in the game
T = 1000; %number of rounds in each game
Games = 1000; %number of games
UtilityVector = [];
BehavioralVector = [];
UtilityMatrix = [];
BehavioralMatrix = [];
StockPrice = 50;
Ceiling = 1.0;
RiskFactor_Increase = 0.1;
OptimismFactor_Increase = 0.1;
Loss_coefficient = 1.00;
Risk_Factor = -0.10;
Optimism_Factor = -0.10;
for a = 0:RiskFactor_Increase:Ceiling
Risk_Factor = Risk_Factor + RiskFactor_Increase;
UtilityVector = [];
BehavioralVector = [];
Optimism_Factor = 0.0;
for b = 0:OptimismFactor_Increase:Ceiling %numbers of games to be played
Optimism_Factor = Optimism_Factor + OptimismFactor_Increase;
X = [rand(N,1) zeros(N,1)]; %create matrix X with N rows & 2 columns
for c = 0:Games
X(:,2) = zeros(N,1);
for d = 1:T
PL1 = floor(1 + (N - 1)*rand(1)); %player1
PL2 = floor(1 + (N - 1)*rand(1)); %player2
if PL1 == PL2
PL2 = floor(1 + (N - 1)*rand(1)); % re pick player 2 to ensure it is
different from player 1
end
%calculate utility at the end of round 1
utility1 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Risk_Factor*X(PL1,1)) -
((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Optimism_Factor*X(PL2,1))
- ((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 2
%update utility in X after round 2
X(PL1,2) = utility1; %overwrite Utility for player 1
```

```
X(PL2,2) = utility2; %overwrite Utility for player 2
end
X = sortrows(X,2); %sort rows based on utility
X(1:N/10,:) = []; %delete 10% of individuals
Xadd = [rand(N/10,1) zeros(N/10,1)]; %add new 10% of individuals at random
X = [X; Xadd]; %#ok<AGROW> %add new 10% individuals at random to the end of
matrix X
end
UtilityVector = [UtilityVector mean(X(:,2))*StockPrice]; %#ok<AGROW>
BehavioralVector = [BehavioralVector mean(X(:,2))*StockPrice]; %#ok<AGROW>
end
UtilityMatrix = [UtilityMatrix; UtilityVector]; %#ok<AGROW>
BehavioralMatrix = [BehavioralMatrix; BehavioralVector]; %#ok<AGROW>
end
X(N-N/10:N,:) = []; %delete newly added rows with zero utility
Buyer_Vector = 0:RiskFactor_Increase:Ceiling;
Seller_Vector = 0:OptimismFactor_Increase:Ceiling;
figure (1)
surfc (Buyer_Vector, Seller_Vector, UtilityMatrix);
xlabel('Target Optimistic Behaviour') %set x-axis label
ylabel('Acquirer Risk Aversion Behaviour') %set y-axis label
zlabel('Price') %set z-axis label
title('Change in Price with Acquirer and Target Behavioural Factors') %set
chart title
```

**Model 6 Relates to the discussion in Chapter 5 – Explains a single acquirer model that assesses the utility of the merger negotiation between a single acquirer and target firm. Where, the model has model has been applied to the commercial real world example. In this case, the chance of gain or loss (loss aversion) has 50 percent probability.**

```
N = 1000; %number of players in the game
T = 1000; %number of rounds in each game
Games = 1000; %number of games
UtilityVector = [];
BehavioralVector = [];
UtilityMatrix = [];
BehavioralMatrix = [];
StockPrice = 50;
Ceiling = 1.00;
RiskFactor_Increase = 0.1;
OptimismFactor_Increase = 0.1;
Loss_coefficient = 1.00;
Risk_Factor = -0.10;
Optimism_Factor = -0.10;
Probability_GainLoss = 0.0;
for a = 0:RiskFactor_Increase:Ceiling
Risk_Factor = Risk_Factor + RiskFactor_Increase;
UtilityVector = [];
BehavioralVector = [];
Optimism_Factor = 0.0;
for b = 0:OptimismFactor_Increase:Ceiling %numbers of games to be played
Optimism_Factor = Optimism_Factor + OptimismFactor_Increase;
X = [rand(N,1) zeros(N,1)]; %create matrix X with N rows & 2 columns
for c = 0:Games
X(:,2) = zeros(N,1);
for d = 1:T
PL1 = floor(1 + (N - 1)*rand(1)); %player1
PL2 = floor(1 + (N - 1)*rand(1)); %player2
if PL1 == PL2
```

```
PL2 = floor(1 + (N - 1)*rand(1)); % re pick player 2 to ensure it is
different from player 1
end
Probaility_GainLoss = rand(1);
%calculate utility at the end of round 1
if Probability_GainLoss > 0.5
utility1 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Risk_Factor*X(PL1,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Optimism_Factor*X(PL2,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 2
else
utility1 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Risk_Factor*X(PL1,1)) -
((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Optimism_Factor*X(PL2,1))
- ((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 2
end
%update utility in X after round 2
X(PL1,2) = utility1; %overwrite Utility for player 1
X(PL2,2) = utility2; %overwrite Utility for player 2
end
X = sortrows(X,2); %sort rows based on utility
X(1:N/10,:) = []; %delete 10% of individuals
Xadd = [rand(N/10,1) zeros(N/10,1)]; %add new 10% of individuals at random
X = [X; Xadd]; %#ok<AGROW> %add new 10% individuals at random to the end of
matrix X
end
UtilityVector = [UtilityVector mean(X(:,2))*StockPrice]; %#ok<AGROW>
BehavioralVector = [BehavioralVector mean(X(:,2))*StockPrice]; %#ok<AGROW>
end
UtilityMatrix = [UtilityMatrix; UtilityVector]; %#ok<AGROW>
BehavioralMatrix = [BehavioralMatrix; BehavioralVector]; %#ok<AGROW>
end
X(N-N/10:N,:) = []; %delete newly added rows with zero utility
Buyer_Vector = 0:RiskFactor_Increase:Ceiling;
Seller_Vector = 0:OptimismFactor_Increase:Ceiling;
figure (1)
surfc (Buyer_Vector, Seller_Vector, UtilityMatrix);
xlabel('Target Optimistic Behaviour') %set x-axis label
ylabel('Acquirer Risk Aversion Behaviour') %set y-axis label
zlabel('Price') %set z-axis label
title('Change in Price with Acquirer and Target Behavioural Factors') %set
chart title
```

**Model 7 Relates to the discussion in Chapter 6 – Explains a multiple acquirer model that assesses the utility of the merger negotiation between a multiple acquirers and target firm. Where, the model is applied to a commercial real world application.**

```
N = 1000; %number of players in the game
T = 1000; %number of rounds in each game
Games = 1000; %number of games
UtilityVector = [];
BehavioralVector = [];
UtilityMatrix = [];
BehavioralMatrix = [];
StockPrice = 50;
Ceiling = 1.00;
RiskFactor_Increase = 0.1;
OptimismFactor_Increase = 0.1;
Loss_coefficient = 1.00;
Risk_Factor = -0.10;
```

```
Optimism_Factor = -0.10;
Probability_GainLoss = 0.00;
for a = 0:RiskFactor_Increase:Ceiling
Risk_Factor = Risk_Factor + RiskFactor_Increase;
UtilityVector = [];
BehavioralVector = [];
Optimism_Factor = 0.0;
for b = 0:OptimismFactor_Increase:Ceiling %numbers of games to be played
Optimism_Factor = Optimism_Factor + OptimismFactor_Increase;
X = [rand(N,1) zeros(N,1)]; %create matrix X with N rows & 2 columns
for c = 0:Games
X(:,2) = zeros(N,1);
for d = 1:T
PL1 = floor(1 + (N - 1)*rand(1)); %player1
PL2 = floor(1 + (N - 1)*rand(1)); %player2
if PL1 == PL2
PL2 = floor(1 + (N - 1)*rand(1)); % re pick player 2 to ensure it is
different from player 1
end
Probaility_GainLoss = rand(1);
%calculate utility at the end of round 1
if Probability_GainLoss > 0.95
utility1 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Risk_Factor*X(PL1,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Optimism_Factor*X(PL2,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 2
else
utility1 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Risk_Factor*X(PL1,1)) -
((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Optimism_Factor*X(PL2,1))
- ((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 2
end
%update utility in X after round 2
X(PL1,2) = utility1; %overwrite Utility for player 1
X(PL2,2) = utility2; %overwrite Utility for player 2
end
X = sortrows(X,2); %sort rows based on utility
X(1:N/10,:) = []; %delete 10% of individuals
Xadd = [rand(N/10,1) zeros(N/10,1)]; %add new 10% of individuals at random
X = [X; Xadd]; %#ok<AGROW> %add new 10% individuals at random to the end of
matrix X
end
UtilityVector = [UtilityVector mean(X(:,2))*StockPrice]; %#ok<AGROW>
BehavioralVector = [BehavioralVector mean(X(:,2))*StockPrice]; %#ok<AGROW>
end
UtilityMatrix = [UtilityMatrix; UtilityVector]; %#ok<AGROW>
BehavioralMatrix = [BehavioralMatrix; BehavioralVector]; %#ok<AGROW>
end
X(N-N/10:N,:) = []; %delete newly added rows with zero utility
Buyer_Vector = 0:RiskFactor_Increase:Ceiling;
Seller_Vector = 0:OptimismFactor_Increase:Ceiling;
figure (1)
surfc (Buyer_Vector, Seller_Vector, UtilityMatrix);
xlabel('Target Optimistic Behaviour') %set x-axis label
ylabel('Acquirer Risk Aversion Behaviour') %set y-axis label
zlabel('Price') %set z-axis label
title('Change in Price with Acquirer and Target Behavioural Factors') %set
chart title
```

**Model 8 Relates to the discussion in Chapter 6 – Explains a multiple acquirer model that assesses the utility of the merger negotiation between a multiple**

**acquirers and target firm. Where, the model is applied to a commercial real world application with a gain or loss probability (loss aversion) of 50 percent.**

```
N = 1000; %number of players in the game
T = 1000; %number of rounds in each game
Games = 1000; %number of games
UtilityVector = [];
BehavioralVector = [];
UtilityMatrix = [];
BehavioralMatrix = [];
StockPrice = 50;
Ceiling = 1.00;
RiskFactor_Increase = 0.1;
OptimismFactor_Increase = 0.1;
Loss_coefficient = 1.00;
Risk_Factor = -0.10;
Optimism_Factor = -0.10;
%Probability_GainLoss = 0.00;
for a = 0:RiskFactor_Increase:Ceiling
Risk_Factor = Risk_Factor + RiskFactor_Increase;
UtilityVector = [];
BehavioralVector = [];
Optimism_Factor = 0.0;
for b = 0:OptimismFactor_Increase:Ceiling %numbers of games to be played
Optimism_Factor = Optimism_Factor + OptimismFactor_Increase;
X = [rand(N,1) zeros(N,1)]; %create matrix X with N rows & 2 columns
for c = 0:Games
X(:,2) = zeros(N,1);
for d = 1:T
PL1 = floor(1 + (N - 1)*rand(1)); %player1
PL2 = floor(1 + (N - 1)*rand(1)); %player2
PL3 = floor(1 + (N - 1)*rand(1)); %player3
PL4 = floor(1 + (N - 1)*rand(1)); %player4
if PL1 == PL2 || PL3 || PL4
PL1 = floor(1 + (N - 1)*rand(1)); % re pick player 1 to ensure it is
different from player 2,3 or 4
end
if PL2 == PL1 || PL3 || PL4
PL2 = floor(1 + (N - 1)*rand(1)); % re pick player 2 to ensure it is
different from player 1,3 or 4
end
if PL3 == PL1 || PL2 || PL4
PL3 = floor(1 + (N - 1)*rand(1)); % re pick player 3 to ensure it is
different from player 1,2 or 4
end
if PL4 == PL1 || PL2 || PL3
PL4 = floor(1 + (N - 1)*rand(1)); % re pick player 4 to ensure it is
different from player 1,2 or 3
end
%Probaility_GainLoss = rand(1);
%calculate utility at the end of round 1
%if Probability_GainLoss > 0.50
% utility1 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Risk_Factor*X(PL1,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 1
% utility2 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL2,1))/2) +
(Optimism_Factor*X(PL2,1)) - ((X(PL1,1)+X(PL2,1))); %Payoff for Player 2
% utility3 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL3,1))/2) +
(Optimism_Factor*X(PL3,1)) - ((X(PL1,1)+X(PL3,1))); %Payoff for Player 2
% utility4 = ((1 - X(PL1,1)*Loss_coefficient) + (1 - X(PL4,1))/2) +
(Optimism_Factor*X(PL4,1)) - ((X(PL1,1)+X(PL4,1))); %Payoff for Player 2
```

```
%else
utility1 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Risk_Factor*X(PL1,1)) -
((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 1
utility2 = ((1 - X(PL1,1)) + (1 - X(PL2,1))/2) + (Optimism_Factor*X(PL2,1))
- ((X(PL1,1)+X(PL2,1))*Loss_coefficient); %Payoff for Player 2
utility3 = ((1 - X(PL1,1)) + (1 - X(PL3,1))/2) + (Optimism_Factor*X(PL3,1))
- ((X(PL1,1)+X(PL3,1))*Loss_coefficient); %Payoff for Player 2
utility4 = ((1 - X(PL1,1)) + (1 - X(PL4,1))/2) + (Optimism_Factor*X(PL4,1))
- ((X(PL1,1)+X(PL4,1))*Loss_coefficient); %Payoff for Player 2
%end
%update utility in X after round 2
X(PL1,2) = utility1; %overwrite Utility for player 1
X(PL2,2) = utility2; %overwrite Utility for player 2
X(PL3,2) = utility3; %overwrite Utility for player 3
X(PL4,2) = utility4; %overwrite Utility for player 4
end
X = sortrows(X,2); %sort rows based on utility
X(1:N/10,:) = []; %delete 10% of individuals
Xadd = [rand(N/10,1) zeros(N/10,1)]; %add new 10% of individuals at random
X = [X; Xadd]; %#ok<AGROW> %add new 10% individuals at random to the end of
matrix X
end
UtilityVector = [UtilityVector mean(X(:,2))*StockPrice]; %#ok<AGROW>
BehavioralVector = [BehavioralVector mean(X(:,2))*StockPrice]; %#ok<AGROW>
end
UtilityMatrix = [UtilityMatrix; UtilityVector]; %#ok<AGROW>
BehavioralMatrix = [BehavioralMatrix; BehavioralVector]; %#ok<AGROW>
end
X(N-N/10:N,:) = []; %delete newly added rows with zero utility
Buyer_Vector = 0:RiskFactor_Increase:Ceiling;
Seller_Vector = 0:OptimismFactor_Increase:Ceiling;
figure (1)
surfc (Buyer_Vector, Seller_Vector, UtilityMatrix);
xlabel('Target Optimistic Behaviour') %set x-axis label
ylabel('Acquirer Risk Aversion Behaviour') %set y-axis label
zlabel('Price') %set z-axis label
title('Change in Price with Acquirer and Target Behavioural Factors') %set
chart title
```