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MERGER AND ACQUISITION PRICING USING AGENT BASED MODELLING

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ABSTRACT. Merger & Acquisition pricing utilises traditional financial models like Discount Cash flow analysis and industry multiples. These methods do not consider behaviour finance biases, for example, prospect theory (Kahneman and Tversky 1979). This paper analyses merger & acquisition pricing using behavioural bias of risk aversion (acquiring company behavioural trait) and optimism (target company trait). It then extends the study to include loss aversion from prospect theory, differences in the way humans view gains and losses based on low or high probability based on cumulative prospect theory, and finally the certainty effect (where humans prefer certain outcome to probabilistic outcomes). All these factors have an impact on merger & acquisition pricing for potential deals as acquiring and target companies behave differently and such impacts are not considered by traditional finance models. Results show that as loss aversion reduces, the positive impact of risk taking and optimism behaviours improve. Also, probabilistic gains and losses can have a positive impact, but certainty has the greatest impact. Humans prefer certain outcomes and acquirers and target company behaviours are more effective in such conditions with increasing utility for both parties under such circumstances. However, in the multiple acquirer setting, competition between the acquirer significantly increases the utility, and the loss aversion co-efficient works in the opposite direction as the perceptive difference between gains and losses decreases.

JEL codes: G34; L11

Keywords: price; mergers and acquisitions (M&A); agent-based modeling

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

Literature Review

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. A study by Marchesi (2000) is one of the examples where agent based modelling has been used to analyse volatility clustering in asset prices.

Kim and Kim (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 the system that focuses on macro-level monetary policy tends to have steep fluctuations with the medium level irrational agents. On the other hand, it provides consistent micro structures and properties (which are endogenously creating) these markets. The Agent based model can also be shown to eliminate co-ordination failures and instability during normal times. As a result, a general equilibrium condition in an agent based model can be shown to result from endogenous non-rational micro interaction. This is an interesting property for crisis modelling since the endogenous close-to-equilibrium market structure could also break down from time to time. Equilibrium models on the other hand force the model economy to an equilibrium by assumption that can never break down.

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. Xu (2014) has also shown that M&A transactions can have a significant impact on economic growth.

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 macro-economic 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. Their study at the deficiencies in the Tóth et al. (2011) paper in relation to the intelligence around limit order execution, as the market order execution had underlying logic, but the limit order execution was rather random. 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. (2011) 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 is 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 validate their findings using out of sample predictions that can be tested against directional moves in 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, we 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, we 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 till 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 et al. (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.

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, 2107). 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.

Methodology

This paper utilises MATLAB 2017 to develop the game theoretic agent based model to analyse the 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.

Results: Merger & Acquisition Pricing using Prospect Theory

When setting up 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. However, if we include the concept of Loss Aversion from Prospect theory and include the loss aversion co-efficient, where gains are only seen to be 28% as psychologically valuable as losses. Then, we get the result as provided in figure 2. 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%, 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 more probably as acquirer's 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; we increase loss aversion to 100%. In this case, losses and gains have the same weight. Nonetheless, figure 4 shows that more can be gained by the acquirer being less risk averse than the target being more optimistic.

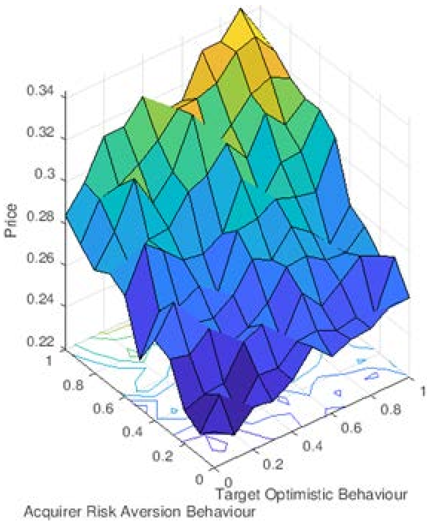

Figure 1 Prospect Theory Loss aversion 0%

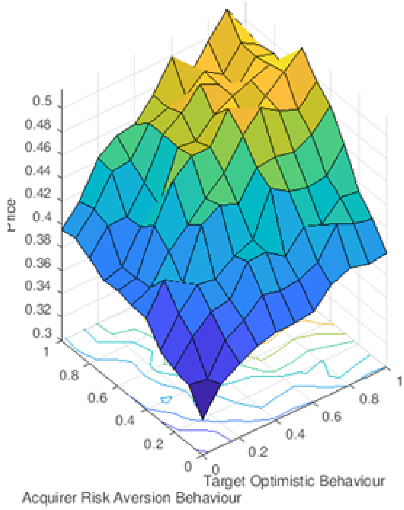

Figure 2 Prospect Theory Loss Aversion 28%

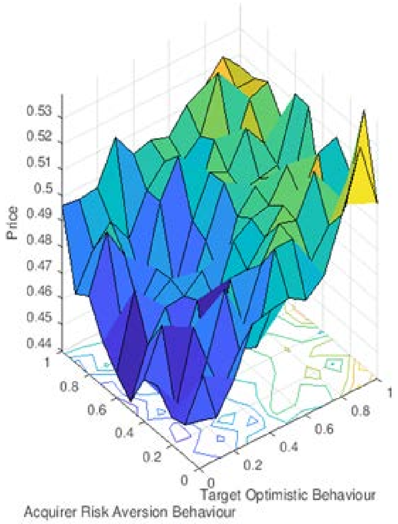

Figure 3 Prospect Theory Loss Aversion 50%

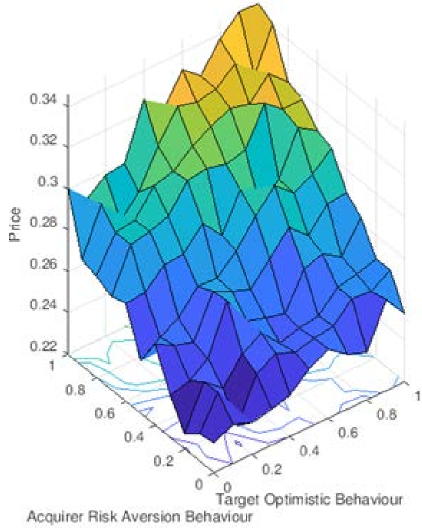

Figure 4 Prospect Theory Loss Aversion 100%

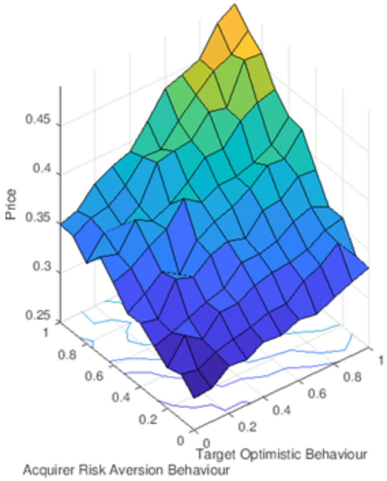

Figure 5 Cumulative Prospect Theory and Loss Aversion 0%

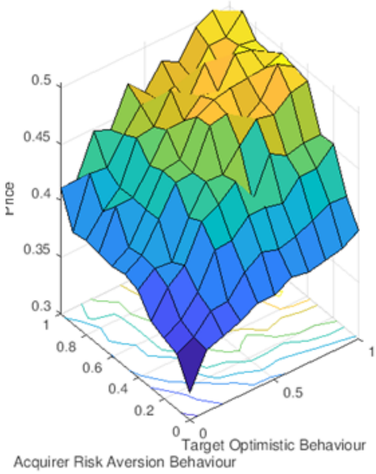

Figure 6 Cumulative Prospect Theory and Loss Aversion 28%

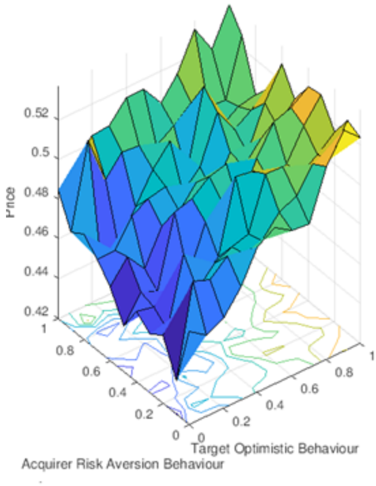

Figure 7 Cumulative Prospect Theory and Loss Aversion 50%

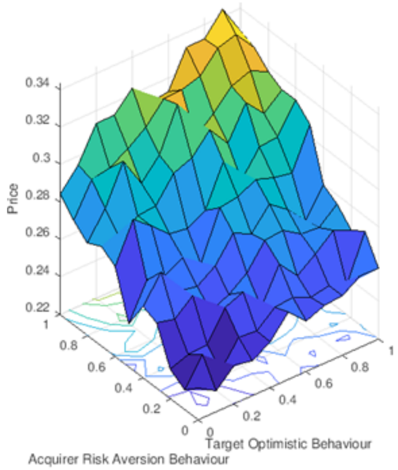

Figure 8 Cumulative Prospect Theory and Loss Aversion 100%

Applying Cumulative Prospect Theory to M&A Pricing

On the other hand, figures 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. However, in figure 5, both the risk aversion of the acquirer and the optimism of the target company show equal results. In figure 6, the cumulative prospect theory weight for loss aversion is increased to 28% for gains and losses. This shows that when the risk aversion is nearly 3 times, then the outcome is more positive than that seen in figure 5. This potentially occurs are the consequence of a positive outcome is higher. This is similar for figure 7, where we notice the results become even more positive. 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 50%, making it more valuable to be favourable to gains. On the contrary, figure 8 shows that when gains and losses have the same weight, even when preference for them may differ due to low and high probability. The effect of the acquirer's risk taking behaviour is greater than the target company's optimistic behaviour. Figure 8 looks very similar to the outcomes in figure 1, but 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 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 the loss aversion is 0% rather than 28%. This is a significant finding as the loss aversion co-efficient (difference is 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.

In comparison, figures 9–12 analyse the certainty effect explained in prospect theory. In figures 5–8, we 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 higher than a probabilistic outcome. For example, if there is a possibility of gaining $1 compared to a 20% 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 we can implement cumulative prospect theory, only when loss aversion is low (loss aversion co-efficient is 0%) in both figures 5 and 9. This is a significant finding as it says that when low loss aversion exists, outcomes with high probability are considered the same as certain outcomes. However, figures 10–12 shows 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 tends 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. But, the utility reduces when the loss aversion increases (see figures 9–12). In effect, reduced loss aversion and increased certainty provide the best outcome.

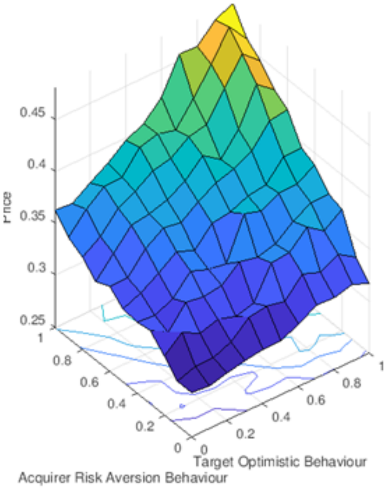

Figure 9 Certainty Effect and Loss Aversion 0%

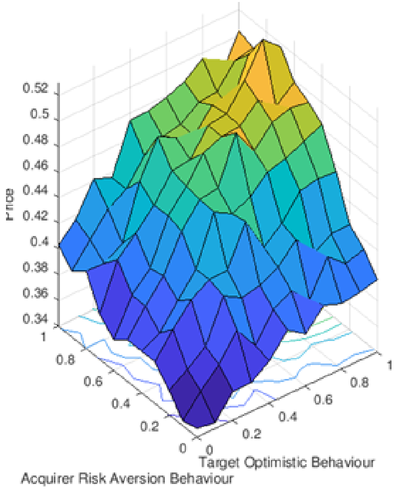

Figure 10 Certainty Effect and Loss Aversion 28%

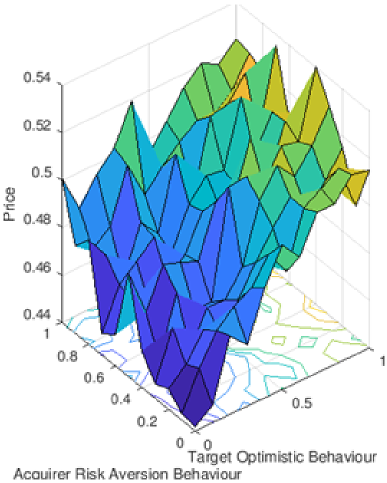

Figure 11 Certainty Effect and Loss Aversion 50%

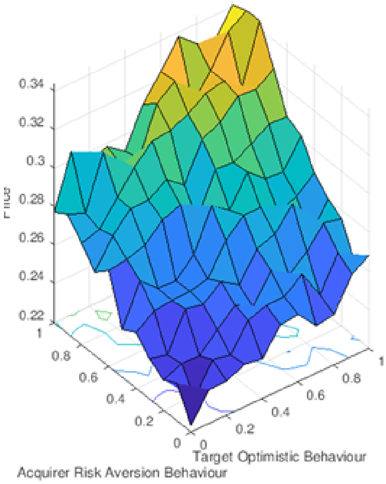

Figure 12 Certainty Effect and Loss Aversion 100%

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 1–12). Figures 13–16 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 13, especially for the situation where the risk aversion and optimism factors are high.

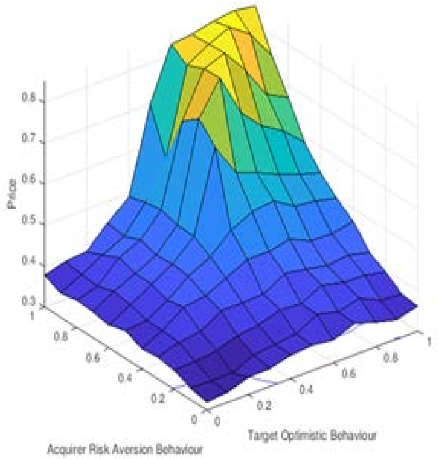

Figure 13 Multiple Acquirer Loss Aversion = 0%

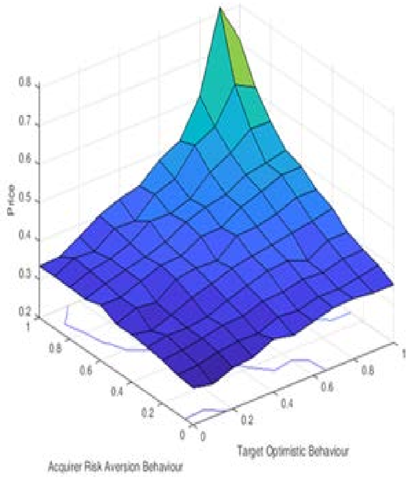

Figure 14 Multiple Acquirer Loss Aversion =28%

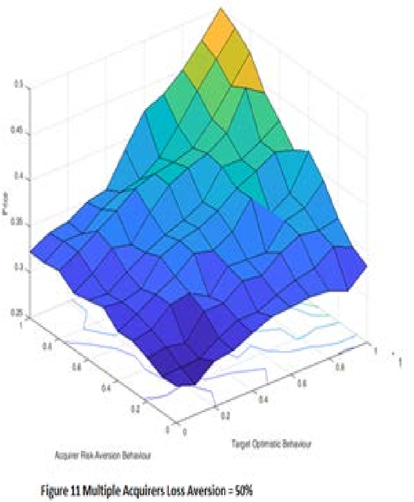

Figure 15 Multiple Acquirers Loss Aversion = 50%

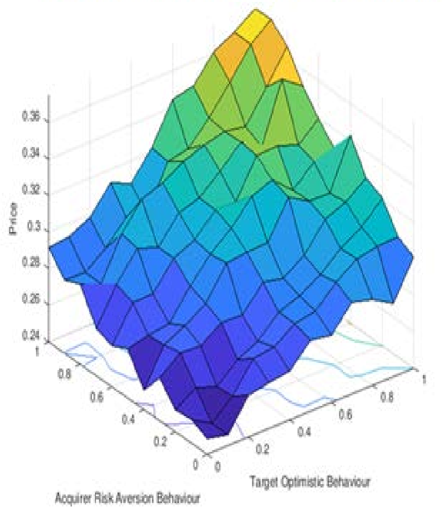

Figure 16 Multiple Acquirers Loss Aversion = 100%

The overall utility in the figures 13–14 is much higher than figures 1–12 and also figures 15–16. 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 as a result they may be willing to pay more for this M&A transaction. Figures 15–16 however on the contrary have lower utility as competition seems to reduce as the loss aversion co-efficient increases from 0% in figure 13 to 100% in figure 16. In figure 16, 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.

Conclusion

In summary, this paper analyses merger & acquisition pricing scenario that include behavioural finance biases. The idea is to understand how prices change when investment bankers assist acquiring and target firms undertake these deals. Traditional finance models do not include such behavioural biases and as a result these deals may be getting mispriced. This paper shows how the application of prospect theory, cumulative prospect theory and behavioural traits like risk taking and optimism can have a significant impact on the overall pricing of these deals. The inclusion of multiple acquirers also has a positive impact of increasing utility due to competition within the acquirers. On the contrary, the increase of the loss aversion co-efficient in the multiple acquirer model reduces utility as the model is not biased towards gains when loss aversion is 100% (where gains are perceived one time more valuable than losses). In effect, this paper explains how behavioural factors are important in M&A transaction pricing and modeling them using agent based modeling help obtain relevant insights that are not easily obtainable in the real world.

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