Risk, return and deal success

An empirical study of merger arbitrage performance and the use of prediction models to enhance profitability

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Abstract

This is an extensive empirical study where we examine the risk and return characteristics of the merger arbitrage strategy. We have analysed 4987 deals in the period 1996 to 2015 from the US market. In contrast to earlier findings, we conclude that merger arbitrage possess linear dependency with the market. Additionally our findings suggest that a merger arbitrage strategy outperforms the stock market both in terms of Sharpe ratio and alpha. Further we evaluate the possibility to enhance the performance by building a model predicting deal success. The model discovers both new and previously documented predictors of deal outcome. Using online machine learning techniques, we create an algorithm that invest in a sub-sample of the available deals, given predictions by the model. This algorithm successfully improves the annual CAPM alpha from 8.4% to 12.0% and the Sharpe ratio from 0.76 to 1.15 for a merger arbitrage portfolio from 2002 to 2015. Consequently, we conclude that factor predictability is not sufficiently priced in.

Contents

1 Introduction

This paper is an comprehensive empirical study of the hedge fund strategy, Merger Arbitrage (MA). Ambitiously, this paper aims to enlighten historical risk and return, recognize predictors of deal success and propose a return enhancing algorithm. Risk and return in merger arbitrage are a topics thoroughly researched, with the most seminal papers stemming from Mitchell and Pulvino (2001) and Baker and Savasoglu (2002). However, to our knowledge, there have been no peer-reviewed papers analyzing these specific topics on the US market in the later period after 2000. Additionally the research on the merger arbitrage market has been concentrated towards risk, return and predictors of deal outcome. The research related to performance of a prediction model is scarce. This is a topic we particularly enlighten in this study. We hope that this paper can function as an preparatory guide into the merger arbitrage universe, update and add value to existing research, and bring new insight to prediction modeling and its influence on returns.

1.1 Merger Arbitrage as an Investment Strategy

Mergers and acquisitions (M&A) are transaction in which two or more companies are either transferred or combined into a new or existing legal entity. When a bid is announced, the outcome of the bid is unknown. This is due to uncertainty concerning shareholder approval, regulatory clearances, market outcomes etc. This causes the targets share-price to typically trade below the bid price. As a merger arbitrage investor your strategy consists of exploiting this price discrepancy. You would purchase the stock of the takeover target post announcement and if the bid is accepted, sell it profitably to the acquirer.

A deal is defined as a proposed merger offer. We have two type of deal outcomes, successful and unsuccessful. A deal is considered successful if the offer is accepted and the merger is completed and considered unsuccessful if the deal is terminated or withdrawn.

Lets consider an example. There are two companies, company ACQ and company TAR. The share of company TAR trades at $50 pr share. Let us then consider that ACQ announces that they would like to buy TAR. They set the offer at a price of $100 pr share. As an merger arbitrage investor you would then buy the TAR stock with the intention of selling it to the acquirer at a later point in time at a higher price. The market price of TAR, at which you buy it for, is dependent on how markets assess the probability of the deal going trough. If the deal is successful you sell your shares to company ACQ with a profit.

Considering a portfolio of deals, your overall profit will depend on the rate of successful deals in your portfolio, as well as the average return on both successful and unsuccessful deals in your portfolio. An investment strategy could either mean buying all available deals or attempting to find the best deals available to invest in. From this point on, "merger arbitrage" will refer to the strategy investing in all deals available, if not explicitly stated otherwise.

Merger arbitrage is not arbitrage in the sense of the textbook risk free trade involving no upfront cash. Merger arbitrage, or risk arbitrage, do infact involve both risk and upfront cash. Risk in this context refers to the uncertainty in returns.

Assessment of the probability of a merger going trough requires skill and competence to accurately assess a number of factors, additionally it requires access to a great deal of market data. Hence the main practitioners of this strategy are mostly hedge funds, private equity firms and investment banks (Barclay Hedge, 2016).

Empirical research in this field provides evidence of great profitability for the merger arbitrage portfolio. Both Baker and Savasoglu (2002) and Mitchell & Pulvino (2001) find significant abnormal returns for the strategy. Branch & Yang (2003) and Wang & Branch (2009) investigate what factors can predict deal success, but we have not seen any systematic tests of whether prediction models can enhance merger arbitrage returns over a considerable time period.

1.2 Problem formulation

What factors can significantly predict merger success and can this be exploited to enhance merger arbitrage returns?

1.3 Research questions

1. What market exposure does a merger arbitrage strategy have and is this relationship linear?

   Calculating abnormal returns requires some concept of benchmark related to returns. This can be a fixed benchmark or estimated with a model. The standard approach is to use an asset pricing models like CAPM. Earlier studies have argued that observed non-linearity in the relationship between merger arbitrage returns and market returns disqualifies the use of linear models. We will test if our data suggests a similar relationship before we decide the most adequate way of calculating abnormal returns.

2. Are merger arbitrage abnormal returns significant?

   When we have selected a method for calculating abnormal returns, we will investigate if merger arbitrage returns are significant. This will, if possible, be compared to earlier results, to evaluate if the merger arbitrage strategy still is as lucrative as suggested by older research.

3. What deal specific factors predict merger success?

   We will investigate what type of deals are most likely to be successful. To evaluate this in a quantitative way we will see if deal specific factors can predict the outcome of a deal.

4. Does the deal spread and bid premium reflect all factors predicting merger success? In addition, can a portfolio based on a predictive model outperform a standard merger arbitrage portfolio?

> *Predictability is not a feature that necessarily will improve your portfolio performance in terms of abnormal returns. The true question is if market prices has internalised this potential predictability. This will be tested by evaluating if a portfolio based on a predictive model can outperform a standard merger arbitrage portfolio.*

1.4 Delimitations

Throughout this paper we will be keeping the investor's perspective in mind. This means that our emphasis will be on the elements affecting the investment strategy in question. This plays an important role in determining the scope of what deals to consider. Deals with complicated payment structures and deals where no sizable investment can be made, will be removed. We will elaborate on this in Section (3.1.1).

When evaluating the performance of a trading strategy, risk management is usually going to be an important issue. The objective of this paper is to investigate the risk and return characteristics of merger arbitrage, as well as building a factor prediction models. Consequentially, different strategies in terms of portfolio construction, re-balancing or drawdown control, will not be areas of emphasis.

1.5 Advanced organizer

The rest of the paper is organised as follows: In Section (2) we summarize earlier research and discuss the most relevant theories. In Section (3) we describe our data. Then follows a description of the delimitations given by our data. In Section (4) we present the methodology we apply to evaluate the different aspects discussed in our research questions. In addition we present a technical description of the different techniques we apply. In Section (5) we analyse and discuss the return on different merger arbitrage portfolios. Further, we assess the risk of the different merger arbitrage strategies. Additionally we evaluate the prediction models and discuss their corresponding returns. Finally, in Section (6) we will sum up our results and provide a conclusion.

2 Theory and Previous Literature

2.1 Merger Arbitrage Strategy

The merger arbitrage strategy is trading strategy that attempts to earn the deal spread. We define the deal spread as the relative difference between the value of the announced offer and the current market value of the target company's equity.[1] This can also be expressed on a per share basis:

$$\Delta = \frac{V_o - S_m}{S_m} \tag{1}$$

Δ: Deal spread
V_o: Market value of offer per target share
S_m: Post announcement market price of target share

The traditional merger arbitrage trade depends on the deal type. In mergers there are two main types of payment structures, cash and stock. In a cash deal the acquirer offers cash for the target company's equity. In a stock deal, the acquirer company offers its own stock rather than cash. In a cash and stock deal, a combination of the two are offered. For a cash deal you simply buy the target share. Your shares can then be sold to the acquirer company if the deal goes through, and you have earned the deal spread. The deal spread is defined as the percentage spread between the target's market price and the offer value. Offer value refers to the market value of whatever the acquirer company is offering per share of target equity. Your return is only dependent on the deal success and any potential dividend payments.

If the deal involves some kind of stock payment it gets a bit more complicated. Your return is now also a function of the price movement of the acquirer stock, as you are promised acquirer shares at a fixed ratio. To deal with this added risk a hedge is usually imposed. This hedge attempts to "lock in" the deal spread. Meaning that the payoff, if the deal goes through,

[1] This value refers to the current value of whatever the acquirer company is offering. In a stock deal this is the market value of the equity offered

should not depend on the price movement of the acquirer stock. This is done by short-selling the amount of stocks you will receive given deal success. The easiest way to think about this is that you are selling your expected shares before you receive them. It should be noted that this is not a perfect hedge, as it only provides a fixed payoff if the deal goes through. The risk-reducing effect is therefore ambiguous.

2.1.1 Example case: The merger between Pfizer and Allergan

On April 6. 2015, Pfizer Inc and Allergan PLC terminated what would have been the largest health care merger ever. It would also have been the largest tax-saving deal in history. This turned out to be the reason the deal failed. Pfizer and Allergan whom both are major health care companies planned a friendly merger where Pfize,r a US based company, would buy Allergan and relocate to Allergan's base in Ireland. From a merger arbitrage investors perspective, this deal starts on November 23. 2015 when Pfizer announces their bid for Allergan valued at a total of $160 billion. This amounts to a premium of 25% compared to the price one day prior to the announcement. A merger arbitrage investor would in this case by Allergan stocks with the intention of selling his shares at a later point in time to Pfizer. The sole purpose of this merger from Pfizer side was to save tax trough a so called "inversion". "Inversion" is a tax-saving manoeuvre where a US firm reorganizes in a country with a lower corporate tax-rate. The move was in line with CEO Ian Reads plan to act on Pfizer so called competitive disadvantage were foreign rivals face lower tax bills. US treasury and Obama administration imposed new rules with the goal to curb corporate inversion. This lead Pfizer and Allergan to terminate the deal due to a "Adverse Tax Law Change" clause, with Pfizer reimbursing Allergan for $150M. So this deal was called off due to a non company specific event. Merger arbitrage investors who bought Allergan shares after announcement and sold after deal failure had potential unlevered losses of about 20%. This illustrates the potential large losses to a merger arbitrage strategy. In Figure (1) below we have plotted the share-price of the Allergan stock throughout the whole deal period. The steady decrease in the share price towards "Termination" can be interpreted as a result of market participants incorporating a increasing risk of a "Adverse Tax Law Change".

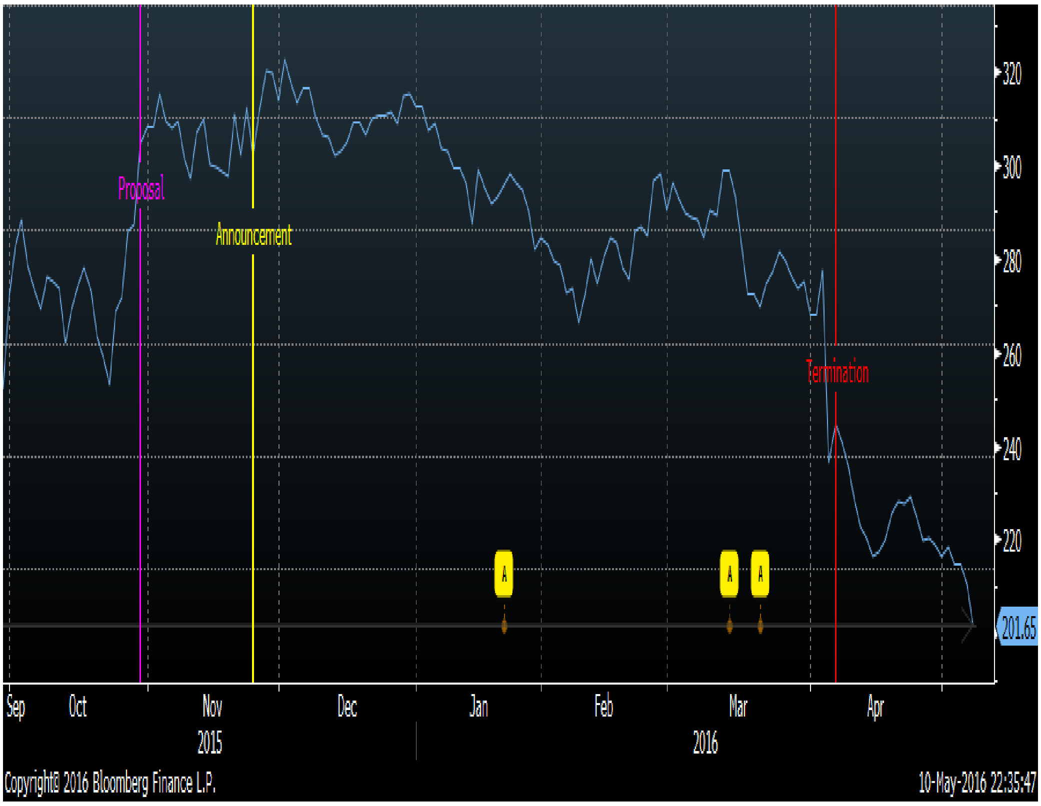

Figure 1: **Allergan shareprice in deal period**

2.2 Merger Arbitrage Returns

Almost all empirical research within this field find abnormal returns for the merger arbitrage strategy. Some of the most outstanding results can most likely be contributed to unrealistic assumptions in return calculations as pointed out by Mitchell & Pulvino (2001). These assumptions include lack of transaction cost, huge investments in illiquid stocks, but maybe most importantly, the use of event time. Event time means calculating the average annualised returns for all deals. The implied assumption is that the average return from deals can be earned continuously. This essentially over-weights short deals. Consequentially, event time is not very suitable for estimating the return of a real event based portfolio. For this purpose, the calender time technique has proved to be more realistic. It entails calculating the dollar value for all the assets in a portfolio each day. The return can then be calculated for any desired time period. This ensures that the yearly return will be what is earned in a year, not an annualized estimation of returns with widely different durations.

Table 1: **Previous Empirical Results.** In this table we have summarized some of the earlier findings. We have focused on newer studies. All numbers are annualized discreetly assuming 21 trading days per month and 252 trading days per year.

Study	Period	Market	PM	V/E	R_{exc}	α
Mitchell & Pulivno, 2001	63-98	US		V	9.3%	3.5%
Baker & Savasoglu, 2002	81-96	US		V	11.9%	9.8%
Baker & Savasoglu, 2002	81-96	US		E	12.0%	10.6%
Wang & Branch, 2009	91-01	US	X	E	14.0%	
Wang & Wdge. 2012	96-08	AUS		NC	18.2%	16.3%
Glans & Vo, 2013	00-12	US cash		V	2.1%*	-0.1%
Glans & Vo, 2013	00-12	US stock		V	12.5%*	1.0%
Glans & Vo, 2013	00-12	US cash		E	9.3%*	0.6%
Glans & Vo, 2013	00-12	US stock		E	7.8%*	0.6%

PM: Selected deals based on prediction model
V/E: Value or Equal- weighted
R_{exc}: Annual Excess Return
α: CAPM alpha
NC: Not Clarified
* Not excess the risk free rate

In Table (1) we have listed what we assess to be the must influential findings the last years relating to excess and abnormal returns. All of these are peer reviewed, except Glans & Vo (2013) which is a master thesis. This is added as we did not manage to find any peer reviewed studies for the US market effectively studying merger arbitrage returns after 2000. They have chosen to evaluate cash and stock separately and never combine these into a portfolio. This makes it harder to interpret what their results mean for the merger strategy as a whole. If we are to assume that their results are correct, it definitely looks like the profitability of merger arbitrage has decreased. It is interesting to see that alpha seems to have decreased more than annual excess return (note that this measure is not in excess of the risk free rate for Glans & Vo (2013)), suggesting that the CAPM beta must have increased. Considering the pre-millennium studies, we consider the Mitchell & Pulvino (2001) results the most realistic.

How deals are weighted in a portfolio can severely impact the overall return. The most accepted technique by today's standard is value weighting. In a merger arbitrage context that means a deal should be weighted by the market value of the target company's equity. This is a desirable feature as small companies are usually less available to big investors. The alternative is equally weighted. In this case the dollar amount invested in each deal is the same. A nice feature of this technique is that your risk is better distributed across deals. The main criticism against the equal weighted portfolio technique used for empirical analysis is that your result might not be representative of what could actually be earned by a sufficiently big portfolio.

2.3 Merger Arbitrage Risk

The source of abnormal returns in merger arbitrage is a widely discussed topic. The easy conclusion seems to be that markets do not price mergers correctly, yielding a market inefficiency. There are however proposed explanations not necessarily in violation with efficient markets. Historical data suggest that the losses when a deal fails are much larger than the potential gains when a deal goes trough (Mithcell & Pulvino (2001). Relating to this Pedersen (2015) argues that most of the initial holders of target shares are risk averse and does no want to be exposed to the risk of a deal not going trough. This creates an excess selling pressure on the target share. Baker & Savasoglu (2002) proposed that this selling pressure combined with capital constrained arbitrageurs can explain that "the price of the target firm can fall below its efficient market price". This claim is supported by their empirical study of merger arbitrage in the period 1981-1996. Their findings indicates a negative relationship between the amount of funds invested and the profitability of merger arbitrage.

2.3.1 Deal Specific Risk

Merger arbitrage is not arbitrage in the sense of a textbook risk-free trade involving no upfront cash. Merger arbitrage, or risk arbitrage as it is also referred to, do in-fact involve both risk and upfront cash. Merger arbitrage investors are exposed to risk in an asymmetrical way. If a deal goes trough the investor will earn the deal spread. This often represent a rather small return. If a deal does not go trough, the loss to a merger arbitrage investors can be severe. For instance, in 2001 the merger between General Electric and Honeywell broke down. This was a popular deal for merger arbitrage investors, and subsequently their losses were extreme. In total, merger arbitrage investors lost about \$2800 millions in this deal. The large downside risk in merger arbitrage originates from the bid premium. This is due to the fact that when a deal fails, the price of the target company will often fall back to it's price pre-announcement price. This implies that bid-premium should reflect some of the downside risk in merger arbitrage trades. As argued before, investors not willing to hold this risk can be one potential source of profits in a merger arbitrage strategy. If there were no uncertainty in the outcome of a bid, there would be no risk involved, hence no reward to an merger arbitrage investor for being exposed to this specific uncertainty. This risk will from now on be referred to as deal risk.

The underlying factors contributing to deal uncertainty are rather complex. For a deal to become successful the acquirer is dependent on the targets shareholders to approve the offer. This works in the following way: The acquirer will in most cases demand a certain number of target shares to be tendered for the bid to be successful. A shareholder in the target company will tender his share if he approves of the bid. If the pre-specified number of shares are tendered the deal is considered approved by shareholders. However there is still several other factors which can eradicate a deal. For instance, there is risk related to regulatory conditions. A deal will often need approval from certain government agencies to be approved. This include agencies such as the US Treasury which regulate taxes as well as the Federal Trade Commission and the American Justice Department which regulate and monitor competition. The recent merger proposal by Pfizer and Allergan can be considered an example of regulatory risk. Pfizer called of its €160 billion bid for Allergan after US Treasury proposed new rules that would curtail benefits of buying foreign companies for tax purposes. In addition we have the recent merger between Halliburton and Baker Hughes. The American Justice Department managed to stop this \$25 billion merger by citing the anti trust law designed to prevent anti competitive mergers or acquisitions. Clearly regulatory risk is a major factor regarding the outcome of a deal. An additional risk factor is the funding risk. If market conditions suddenly change, market liquidity might dry up and increase the funding cost. This can in some instances cause the acquirer firm to back out of the deal. In Section (2.4) we will elaborate on specific variables related to the fundamental risk factors we have discussed above.

2.3.2 Market Risk

Measuring the systematic risk of a strategy is a vital component of calculating abnormal returns as all the classic asset pricing models utilizes risk adjusted returns. Systematic risk in this context, refers to the linear dependency on a specific risk factor. The most standard approach is to run a linear regression to investigate how much of the strategy returns can be explained by different risk factors. Then see how your portfolio performed compared with the model's prediction given your portfolio's systematic risk. In the CAPM universe, the only risk an investor is compensated for bearing is market risk (Sharpe, 1964). Later Fama & French (1993) developed the Fama French Factor Model that include additional factors. Both these model assume linearity and are therefore not really equipped for handling non-linear risk.

Assuming linearity can be problematic as earlier studies seems to agree that the merger arbitrage strategy has a non-linear relationship with market returns. The general idea is that the market exposure or β is close to zero in appreciating markets, and high in depreciating markets. Mitchell & Pulvino (2001) found significantly different betas for different states of the market. This suggests a non-linear risk relationship to the market. The classic interpretation of this is that more acquirer firms backs out of deals as the lower market value of target equity increases the premium in deals with a fixed payout. Another point is that really bad market states might dry up liquidity and thereby decrease an acquirer firm's access to affordable funding. In this paper, the non-linear market risk observed by Mitchell & Pulvino (2001) will be referred to as the segmented market risk pattern, hereby denoted SMRP.

Mitchell & Pulvino (2001) describes the payoff of a merger arbitrage portfolio as similar to writing out of the money index put options. A strategy that pays a small premium in most market states, but takes a big loss in market downturns. They account for this non-linearity by using a contingent claims approach, where a replicating portfolio with uncovered index put options is used as a benchmark for calculating abnormal returns.

2.4 Merger Arbitrage - predictive modeling

Based on the information available in the market we can estimate the probability of bid being successful. This can be done by fitting an empirical model. As the dependent variable, deal success, is a binomial variable, a logistic regression have to be used. Empirical research by Branch & Yang (2003) and Wang & Branch (2009) found that logistic regressions have, historically proven to predict the probability of deal success better than the market implied probability. However, it is thoroughly debated whether one can use traditional logistic regression on dataset with rare events. Wang & Branch (2009) argues that the low frequency of failed deals in mergers & acquisitions may lead to a phenomenon which is called small sample bias. A solution to this would be to utilize a Penalized Maximum Likelihood Estimation, namely the Firth Method as proposed by Richard Williams (2015). The main intuition behind the penalty is to penalize values of the unknown parameters which one would consider less realistic. This can be used to handle separation issues if this occurs.

Past research on merger arbitrage has largely focused on the performance of such a strategy and the ability to predict deal success. In previous empirical studies (e.g Brown & Raymond 2003; Wang & Branch 2009; Denis & Marcia's 2013) a vast amount of different variables have been found significantly related to merger outcome. Below we will summarize some of the most influential findings.

2.4.1 Deal Spread

The deal spread illustrates the uncertainty in the deal. Hence, greater uncertainty implies larger deal spread. Presumably the deal spread is then negatively correlated with the probability of deal completion. Empirical studies by Samuelson & Rosenthal (1986) and (Brown & Raymond, 1986) found deal spread as a useful predictor of the probability of deal completion.

2.4.2 Termination Fee

In this context, a termination fee is a fee paid by either part not fulfilling the deal. The size of the fee and who it applies to varies among deals. One can argue that termination fees make it costly to step away from a deal. Empirical research on this topic proves this argumentation legitimate. Officer (2003), Boone and Mulherin (2007) and Butler and Sauska (2014) provide evidence of larger termination fee in completed mergers compared to terminated, and that termination fees are positively related to takeover completion.

2.4.3 MAC and MAE's

In Denis & Macias (2013) study they provide evidence that material adverse events(MAEs) are the underlying cause of 69% acquisitions termination and 80% of the re-negotiations. Acquisitions with fever MAE exclusions are characterized by wider deal spreads. Their empirical results showed that a takeover where the material adverse change (MAC) structure included a greater number of exclusions were more likely to be successful.

2.4.4 Acquirers initial holdings

It is argued by Sing (1998) and Walkling (1985) that the acquires initial holdings in the target could increase the probability of deal success. This is due to the fact that acquirer will have influence on management and board. The empirical results are ambiguous. Sing (1998) finds backing support in his own study. In their more recent study Wang & Branch (2009) there is no support of Sings argument.

2.4.5 Nature of bid

Classification of a bid depends on the relationship between the acquirer and the target. A friendly takeover takes place when the bid is approved by the management of the target company. If the management of the target company does not approve the bid and the acquiring part still pursue a deal, it's classified as a hostile takeover. In a study by Narayanan (2004) hostile bids had a 14.2% higher probability of failure, compared to friendly bids. History (Hoffmeister & Dyl 1981, Koch and Sjöström (2003) and Wang & Branch 2009) suggests that a friendly takeover is more likely to succeed.

2.4.6 Relative target Size

Problematic integration could be a potential risk factor when acquiring large firms Wang & Branch (2009) looks at the targets market size relative to the acquirers market size. They find this ratio to be a significant predictor of deal outcome. Branch & Yang (2006) argues that the relative size of the target has a negative influence on the probability of takeover success. However, a study by Schwert (2000), did not yield any significant results when looking at the relationship between takeover success and the relative target size.

2.4.7 Percent Sought

Percent sought is the percentage amount of outstanding equity the acquirer intend to acquire. It varies from the minimum amount you need to gain control and 100%. Empirical study on this field provide evidence that deal success is negatively related to percentage of equity the acquire is seeking, Wang & Branch (2009).

2.4.8 Payment Type

There are several payments structures in an M&A transaction. Cash offer, stock offer and a combination of those two are the most common ones. Branch and Yang (2003) argues that cash offer may signal a greater certainty about the value of the target firm and eventually profitability. Due to the volatility in the bid premium of a stock-offer it has been argued that target stockholders prefer this payment. Since cash offers are more certain in their final value one can argue that a cash offer presents a more certain value of the bid. Wang & Branch (2009) cannot find a relationship between payment type and deal outcome.

2.4.9 Bid Premium

Bid premium is defined as the percentage difference between the offer price and the pre-announcement price of the target. Intuitively, a larger premium should be more attractive, and hence imply a greater probability of deal completion. On the other hand, if we relate bid premium to deal spread, we can assume that a failed deal will bring the targets share price back to it's pre-announcement level. This let us view the bid premium minus the deal spread as the potential loss to a deal. A lot of research is done on this topic. The results are ambiguous. Research by Walkling (1985) provides evidence of a positive relationship between bid premium and deal success. More recent studied by Baker & Savasoglu (2002), Mitchell & Pulvino (2001) and Wang & Branch (2009) could not find any significant relationship between the bid premium and the probability of takeover success.

2.4.10 Target Stock-price Run Up

Targets stock price run up can be calculated as the cumulative abnormal return (CAR) in the targets market price ahead of the announcement. Schwert (1996) and Banerjee & Eckard (2001) both documents abnormal increase in target's stock price prior to the announcement of the M&A. It is argued that this run-up shifts the ownership to more neutral hands, hence increasing probability of successful takeover. Wang & Branch (2009) find the target's price run-up to be significant in predicting deal success.

3 Data

In this study we have fetched data over a considerable time-period from the US market. Our data can be split into two categories, merger data and market data.

3.1 Merger Data

We will first describe how our pool of deals is selected. Then in Section (3.1.2), we will describe the data. In Section (3.1.3) we will discuss the challenges and potential pitfalls.

3.1.1 Data Selection

All merger data is from Bloomberg. Our initial data-set consists of data gathered on every merger and acquisition with a public target company in USA between 1996 and 2015. They are fetched through the Bloomberg interface MA <GO>. We fetch a total of 10 037 deals. This includes deals with an announcement date between 01-01-1996 and 01-01-2016. From this sample we exclude a total of 5 050 deals for reasons explained below.

We remove all ongoing deals so all our deals can be classified as successful or unsuccessful. This reduces our sample to 9 818 deals.

We will only consider cash, stock and cash & stock deals. This excludes all deals with more complicated payment structures, as investing in these deal is far from straight forward. A lot of these more intricate payment structures call for complicated hedging techniques involving options. The consequence is that there is not a consensus way of investing in these deals, so that you are only exposed to deal risk. This does of course not mean that it cannot be done, or that these deals are not interesting to study. This paper is mainly concerned with investigating the characteristics of merger arbitrage profitability and if risk adjusted returns can be enhanced by prediction modelling. Consequentially, developing ways of including these complicated deals is outside the scope of this paper. This reduces our sample to 7919 deals.

Furthermore, all deals where the targets market capitalization is below $10M are excluded. This is a result of illiquidity in many of the small-cap companies which leads to limited trading possibilities. Additionally the data available for these deals are limited or inaccurate which could lead to spurious results and unrealistic returns. This restriction reduces our sample to 5457 deals. We also exclude deals where the daily volume is below $50 000 USD. Due to missing data for a lot of days, we have used the average daily volume for the 20 days before announcement. This reduces our sample to 5190 deals. This is merely done to avoid illiquid stocks which would be untradeable or extremely expensive to trade due to market impact.

Finally we remove all deals that Bloomberg cannot find any returns for and some deals that lack the most basic information in a way that prevents us from realistically including it in our portfolio. Our assumption is here that if we cannot find basic information on the deal, like how much is offered per share, the deal would not have been included in the portfolio of a merger arbitrageur. This reduces our sample to 4987 deals. This sub sample will from this point on be referred to as the full sample or the merger arbitrage market. Table (2) summarises the data selection process just described.

Table 2: **Data Selection**

Restriction	Excluded	Deals left
All deals		10037
Deal status	219	9818
Payment type	1899	7919
Market value <$10M	2462	5457
Daily volume <$50k	267	5190
Missing data	203	4987

The set of deal specific factors we will consider are based on significant factors from earlier research. We have also included factors we find particularly interesting. All factors are described in Section (4.3.2). Deal specific factors for prediction modelling are extracted directly from the Bloomberg terminal. Due to huge amounts of missing data in the earlier years, we will only work with data for deals after 01-08-2001 when doing predictions. The rest of the analysis will be with the full sample. We will also extract the outcome of the deal. As we only have completed deals in our data, this variable can have two states, successful and unsuccessful.

3.1.2 Data Properties

Now that we have a our pool of deals, we will fetch daily returns with the Bloomberg Excel formula "BDH" for both the target and the acquirer company for all deals from the announcement date until one business day after completion date. Completion date refers to the date when the outcome of the deal is announced, regardless of whether the deal is successful or not. This extra day is added, so we are able to lag trading days as explained in Section (4.1). We also extract the ratio of acquirer stock offered per target share for deals with a stock element. Below, in Table (3) we have presented the distribution of deals in some of our discrete variables conditional on deal outcome. It is thus an indication of whether deals with a certain characteristic is over or under-represented in successful or unsuccessful deals.

Table 3: **Ratio of factors in our data-set: 1996-2015**
The columns represent successful and failed sub samples of our data-set and the full sample. The rows represents the ratio of the binary factors in each of the data-sets, represented by column. Industry and sub groups are classified according to Global Industry Classification Standard by MSCI and Standard & Poor's

	Successful	Failed	Total
Cash	62%	70%	64%
Stock	28%	19%	26%
Cash or Stock	10%	10%	10%
Hostile	1%	15%	3%
Friendly	99%	85%	97%
Target Institutional Owners	8%	34%	12%
Different Subgroup	68%	72%	68%
Same Sub Group	32%	28%	32%
Different Industry	32%	48%	35%
Same Industry	68%	52%	65%
Number of deals	4153	834	4987

Table 4: **Data Summary: 1996-2015**
In this table we have summarized our merger data. Length of deal is measured as the number of days between the announcement and the completion. Cash are calculated as number of cash deals of total deals. Successful and Friendly deals are calculated as the percentage of total deals. Average deal value is the average deal value in million USD.

Year	Deals	Cash deals	Successful deals	Friendly deals	Average Deal Value	Average length of deal
1996	7	0%	100%	100%	1337	179
1997	9	44%	100%	100%	5297	119
1998	436	39%	88%	100%	2427	138
1999	417	48%	83%	99%	1488	123
2000	471	54%	85%	97%	2091	123
2001	351	53%	88%	95%	1251	126
2002	211	63%	85%	94%	870	116
2003	247	60%	86%	91%	950	130
2004	234	62%	85%	92%	2051	138
2005	274	71%	83%	88%	2061	117
2006	360	79%	84%	95%	2379	127
2007	363	80%	82%	99%	2020	123
2008	216	77%	75%	98%	2452	101
2009	168	58%	80%	97%	1713	120
2010	255	79%	86%	99%	1502	121
2011	212	74%	83%	99%	2194	120
2012	206	83%	88%	99%	1323	123
2013	185	77%	85%	100%	1920	124
2014	202	58%	85%	100%	4628	137
2015	163	66%	87%	100%	3948	100
Avg	249	61%	85%	97%	2195	125

Table (4) shows some selected features of our data each year. Deals are assigned to the year they are completed. The three years with most deals is 1998, 1999 and 2000. The percentage of successful deals appears to be close to the sample mean for all these years. The year with the lowest success percentage is 2008. This is consistent with the notion that less deals go through in depreciating markets. It is interesting to notice that there is no similar reduction in success percentage in the other big market downturn during the dot-com bubble in 2000.

3.1.3 Data Challenges

Some of the acquirer stocks have returns on days the US market is not open. This is because trading days wary between markets, and we have not excluded deals with a non-US acquirer company. This can be problematic when regressing portfolio returns on market returns. These extra days with no return will be paired with the portfolio returns for that day, showing a pattern not based on the covariance in returns, but on the closed days of different markets. Another problem is that reported prices in less liquid stocks might not represent the stock's market value very well. If a stock is not traded for several days, the market's perception of it's value can have changed without this being reflected in a changed price. This information would not be available until a trade is made. Both these problems are solved by working with monthly returns.

Fetching market prices in Bloomberg proved to be quite challenging. The historical adjusted closing price is the dollar amount you would have paid for a stock at time t after adjusting for all corporate action between time t and now. This price is often used for calculating returns so you don't have to account for every corporate action yourself. Consequentially this is the standards measure for historical prices in Bloomberg. We are also interested in the real price at time t since any calculation related to spreads or premiums requires the actual price. This is due to the fact that the the value of the offer is not adjusted. The two values are therefore not comparable.

We strongly suspect that non-adjusted prices fetched from Bloomberg are wrong. When calculating deal spread as in Formula (1), we get some strange results. Some examples are deal spread like 14 000 %, suggesting that the acquirer offers to pay 140 times the current market value of the target company, or -99,99 %, suggesting that the acquirer offers to pay 0.0001 times the market value of the company. Both these are equally unlikely. We are confident that the offer terms, meaning cash offer and stock ratio, are correct. These can easily be controlled against other sources, like the announcement text. This leaves the non-adjusted market prices as the only possible incorrect data. We could potentially get prices from other sources and compare, but will no prioritize this as we already have all the data needed to calculate historical returns and implement and test prediction models.

The lack of this data impacts the paper in one major way. We will not be able to calculate deal spread or bid premium. This is usually used as proxies for the payoff in successful and unsuccessful deals, respectively. This will be elaborated on in Section (4.3). Luckily, Bloomberg has bid premium in their systems, so this can be fetched directly. Deal spread, on the other hand, is, at this point, impossible to fetch automatically from Bloomberg. Since we do not have the expected payoff given deal success, we cannot create a model that accounts for payoffs. This is important because a model that can pick out more successful deals is not necessarily useful if the selected deals just have lower expected payoffs, effectively giving you safer deals with lower expected returns. We will solve this by testing the performance of the model with a simulated portfolio.

Preferably, we want to have the market value of the target company for every trading day for the entire deal period. Value weighted rebalancing, as mentioned in Section (2.2), can then be performed at any desired frequency. The market capitalization of the target companies had limited availability. For some deals we could only fetch it for a few days within the whole deal period. To be able to rebalance at any desired frequency, we would have to rely on some sort of average. Using averages for value weighted rebalancing could be problematic. Target stocks paying dividend or with huge movements in the price, could be wrongly weighted. Accounting for this in an individual manner could be a good solution. As we have almost 5000 deals we will not prioritize this.

For the market values used in the linear regression we will use an average of the past 125 trading days. As this is used to calculate the relative size between the acquirer and the target company, we do not see this simplification as a problem.

3.2 Market data

The relevant returns for Fama French Factors are fetched from French's homepage (French, 2016). The market data is provided by the Center for Research in Security Prices (CRSP). CRSP is considered to be the most accurate and bias-free resource. Market returns in our data-set includes all US firms listed on the NYSE, AMEX, and NASDAQ-index. This return will be seen as a proxy for market returns, and from this point on referred to as market returns or CRSP. We have used the Treasury bill as proxy for the risk-free rate. The treasury bill are provided by Ibbotson Associates.

4 Methodology

4.1 Merger arbitrage returns

The merger arbitrage strategy in it's most basic form is investing in all mergers after announcement and holding them until the outcome of the deal is determined. A deal is included in the portfolio when the market closes the first business day after the announcement. If the merger is announced when the market is open, the stock can obviously be bought the same day. This unnecessary extra day for some deals is a compromise out of convenience. The consequences of adding a deal too early is far more problematic than adding one too late, as you typically see a pretty extreme one day return when the offer is announced. This one day return is in general inaccessible to a merger arbitrage investor. Imagine that a deal is announced after the market has closed. If you buy this at close the same day, you have effectively bought it before the market has reacted to the information. Adding it to early will therefore yield upward biased returns. The same logic applies for closing the position, as you typically see a big decline if a deal is announced unsuccessful. All positions are therefore closed when the market closes one business day after completion.

A: Deal is announced
C: Deal is completed (deal outcome is known)
Open: Deal is included in portfolio
Close: Deal is excluded from portfolio

Based on the lack of quality data on the target company's market value, we have decided to use equally weighted returns. Doing value weighted returns with inaccurate market values can impact our results in ambiguous ways, depending on things like price changes and dividends structure for the target companies in the deal periods. Understanding how this might impact our results will be very complex, making our results harder to interpret.

Equally weighted returns obviously has some drawbacks, as mentioned in Section (2.2), but at least we have an idea of how this choice affects the overall result.

In the portfolio calculations below, we have chosen to express changes in value by means of stock prices in stead of stock returns. This is despite the fact that our calculations have been based on stock returns. This choice is made to make the formulas more intuitive and easier to read. Our real calculations are equivalent to the formulas presented.

Rebalancing will be done only when a new deal is included in the portfolio or when a deal is completed, and therefore removed from the portfolio. At the time of rebalancing, all cash available will be distributed evenly into all available deals. The number of shares in each deal will only change on rebalancing and is calculated as follows:

$$\omega_{it} = \frac{\Pi_{t-1}}{n_t * P_{it}^T} \tag{2}$$

ω_{it}: Number of target shares in our portfolio for deal i at time t
Π_{t-1}: Value of equity at close at time $t-1$
n_t: Number of deals in the portfolio at time t
P_{it}^T: Adjusted closing price at time t for the target company in deal i.

Hedging will be relevant for all deals with a payoff including a stock element. This includes pure stock deals and deal with both cash and stock payouts. Based on the ambiguity of the risk reducing properties of this hedge, described in Section (2.1), we will also calculate the portfolio without the hedge to investigate these properties. The hedge (δ_{it}) is the number of acquirer shares shorted for deal i at time t and is calculated like this:

$$\delta_{it} = \lambda_i * \omega_{it} \tag{3}$$

δ_{it}: Number of acquirer shares shorted for deal i at time t
λ_i: Ratio of acquirer stock offered per target share for deal i

We assume that the cash proceeds will be unavailable to the investor and will yield a return of 0%. Interest on short proceeds will be taken into account when transaction cost is added. We assume no margin on our short position. The equity of our portfolio at the end of each trading day is calculated in the following way:

$$\Pi_t = \sum_{i=1}^{n_t} \omega_{it} P_{it}^{T} - \sum_{i=1}^{n_t} \delta_{it} P_{it}^{A} + \sum_{i=1}^{n_t} \chi_{it} \tag{4}$$

Π_t: Equity at time t
P_{it}^{A}: Adjusted closing price at time t for the acquirer company in deal i
χ_{it}: Cash position from the short proceeds for deal i at time t

The return for any time period can be calculated as the relative difference between π_t at different points in time. This is denoted r_t and is calculated in the following way:

$$r_t = ln\frac{\Pi_t}{\Pi_{t-1}} \tag{5}$$

The reason we use the natural logarithm of returns rather than raw returns are mostly due to statistical convenience. Consider the assumption that prices are normally distributed, then $ln(1 + r_t)$ is normally distributed. This is particularly convenient since most of the classic statistics presumes normality. Additionally we have that the sum of normally distributed variables are normal. This entails that compounded returns are equal to the difference in the natural log between initial and final period:

$$\sum_{i=1}^{n} ln(1 + r_t) = ln(r_t) - ln(r_0) \tag{6}$$

By comparison, if we take the product of normally distributed variables they will not be normal. This is the fact of arithmetic compounded return. In addition logarithmic returns are symmetrical which is a favorable feature when comparing different returns.

As mentioned earlier, abnormal return calculations will depend on the properties of the returns. A linear relationship with the different states of the market will enable us to use a linear model like CAPM. A non-linear relationship will complicate things and non-linear elements like options might be used to account for this. We therefore have to investigate the claims from earlier studies of a non-linear relationship before determining the method of calculating abnormal returns.

We will later introduce a factor prediction model to attempt to improve the returns of the merger arbitrage portfolio. It is therefore interesting to calculate both abnormal returns in terms of classic asset pricing models and in comparison to the simple merger arbitrage portfolio consisting of all deals.

4.1.1 Transaction cost

Two transaction costs will be considered, trading cost and shorting cost. Trading cost is the cost of completing an order and includes bid-ask spread, market impact and broker fee. Shorting cost is the net interest paid on the borrowed stocks for a short position (interest paid - interest received on short proceeds).

The trading cost is assumed to be constant in trade size, in other words a fixed percentage of the invested amount. Our assumed rate is set to 10 basis points, hereby denoted bps[2]. This is based on approximate averages from earlier studies (Engle, Ferstenberg and Russel, 2012 & Frazzini, Israel and Moskowitz, 2012). For each day with rebalancing, the total amount of funds being moved from one asset to another is calculated like this:

$$\Omega_t = \sum_{i=1}^{n_t} |\omega_{it} P_{it}^T - \omega_{it-1} P_{it-1}^T| + \sum_{i=1}^{n_t} |\delta_{it} P_{it}^A - \delta_{it-1} P_{it-1}^A| \tag{7}$$

Note that the short positions also trigger trading cost in addition to the shorting cost. The trading cost is calculated as follows:

$$\varphi_t = 2\rho\Omega_t \tag{8}$$

φ: Total trading cost for day t
ρ: Fixed trading cost per invested dollar

The factor of two accounts for the fact that trading cost occurs both when exiting and entering a position. Both of which have to be done to move funds from one stock to another.

[2]Basis point = 1/100th of 1%

Frazzini, Israel and Mosokowitz (2012) observed higher costs for short positions compared to long positions, but not on a significant level. We will however assume an extra cost as we expect extra shorting activity in the acquirer stocks, by other merger arbitrage investors. It is reasonable to think that this will drive up the cost of shorting shares. We assume an average annual cost of 100 bps. for shorting shares. The shorting cost for a given day is calculated like this:

$$\phi_t = ((1+\varrho)^{\frac{1}{252}} - 1)\sum_{i=1}^{n_t} |\delta_{it} P_{it}^A| \tag{9}$$

ϕ_t: Total shorting cost for day t
ϱ: Net annual shorting rate

Value of equity after transaction cost will then be:

$$\Pi_t^* = \Pi_t - \phi_t - \varphi_t \tag{10}$$

Π_t^*: Value of equity after transaction cost for day t

When calculating returns after transaction cost, Π_t^* will be replace Π_t in (2) and (5). This is so the cost is pulled out of the portfolio at the time it has to be paid so it does not generate any cumulative return.

Estimating transaction cost for a constructed strategy will always yield inaccuracies as different investors face different terms and because cost like market impact are extremely hard to measure. It is further complicated by the fact that the supply-demand dynamics of stocks can potentially change as a result of merger offers. Ideally one would study the transaction cost for a similar strategy for a similar time period. Since this is out of the scope of this paper we will use estimates from earlier studies and stress-test our assumptions to see how much changes in transaction cost will change the results.

4.1.2 Portfolios

For the sake of structure, we have summarized the most basic features of the different portfolios in Table (5).

Table 5: **Portfolios**

Portfolio	$EWMA$	$EWMA_{NH}$	$CAMA$	$PAMA$
Period	1996-2015	1996-2015	1996-2015	2002-2015
Equally Weighted	X	X	X	X
With hedge	X		X	X
Cost Adjusted			X	X
Selected deals				X

EWMA: Equally Weighted Merger Arbitrage
$EWMA_{NH}$: Equally Weighted Merger Arbitrage No Hedge
CAMA: Cost Adjusted Merger Arbitrage
PAMA: Prediction Algorithm Merger Arbitrage

The deal selection process for PAMA will be elaborated on in Section (4.3.3).

4.2 Explaining risk

For all of the risk analysis in this section the CAMA portfolio will be considered the merger arbitrage portfolio. This portfolio has been adjusted for transaction cost. Portfolio constraint have been implemented as described in Section (3.1.1). The results of these analysis will then be used to decide the most adequate way of calculating abnormal returns.

As outlined in Section (2.3), earlier studies provide great evidence in favor of merger arbitrage returns having a non-linear risk relationship with market returns. It is shown that merger arbitrage have had high correlation with markets in depreciating markets and little to no correlation in appreciating and normal markets. This is described as a non-linear pattern containing two linear relationships segmented by a break point (SMRP).

To figure out if this relationship holds for our data-set we need to evaluate if merger arbitrage returns are related to the market in a nonlinear way. There are several different methods available. First off we do a linear regression (OLS).

$$Y = \beta X + \epsilon \qquad E(\epsilon) = 0 \qquad var(\epsilon) = \sigma^2 \tag{11}$$

A linear regression models the relationship between a dependent variable (Y) and one or more explanatory variables (X). The model's goal is to describes a linear relationship between Y and X. In this paper we use the linear regression to estimate the relationship between the merger arbitrage portfolio and some common risk factors. To estimate these relationship we apply our data to (11), as prosed in CAPM, FF3 and FF5. Equation (12) below shows the CAPM relationship.

$$r_{\mathrm{MA}} - r_f = \beta(r_m - r_f) + \epsilon \tag{12}$$

r_{MA}: Return on merger arbitrage portfolio
r_f: Risk free return
r_m: Market return
β: Portfolio's sensitivity to the the excess market return.
ϵ: Error term

To test for additional risk factors, we will test the merger arbitrage returns against Fama–French three & five factor model (Fama & French, 1993 and Fama & French, 2014). The Fama–French three & five factor model can be modeled in the following way:

$$r_{MA} - r_f = \beta_m(r_m - r_f) + \beta_{SMB}\mathrm{SMB} + \beta_{HML}\mathrm{HML} + \epsilon \tag{13}$$

(13) Fama French three factor model

β_m: Portfolio's sensitivity to the the excess market return.
SMB: Return on "Small Minus Big" - portfolio
HML: Return on "High Minus Low" - portfolio

$$r_{\text{MA}} - r_f = \beta_m(r_m - r_f) + \beta_{SMB}\text{SMB} + \\ \beta_{HML}\text{HML} + \beta_{RMW}\text{RMW} + \beta_{CMA}\text{CMA} + \epsilon \quad (14)$$

(14) Fama French five factor model

RMW: Return on "Robust Minus Weak" - portfolio
CMA: Return on "Conservative Minus Aggressive" - portfolio

In a Fama French universe as described above, SMB is the difference in returns between a portfolio of small stocks and a portfolio of big stocks, and HML is the difference in returns between a portfolio of high book-to-market stocks and a portfolio of low book-to-market stocks. In (14) RMW is the difference in return on portfolio with robust operating profitability portfolios minus the return on a portfolio of week operating profitability. At last, CMA is the return on a portfolio of conservative investment minus the return on a portfolio of aggressive investment.

To evaluate if there's a non-linear relationship between merger arbitrage and market returns, we estimate the following piecewise regression:

$$r_{MA} - r_f = (1-\theta)[\alpha_{MktLow} + \beta_{MktLow}(r_{MktLow} - r_f)] \\ \theta[\alpha_{MktHigh} + \beta_{MktHigh}(r_{MktHigh} - r_f)] + \epsilon \quad (15)$$

(15) Segmented/Piece-wise regression

In the equation above θ is a dummy which decides the break-point of the regression. The goal is to choose a θ that maximizes R^2. This is done trough an iterative process, more specifically maximum likelihood. The estimated model then provides a model which is overall non-linear, although it consists of two of linear segments. A non-linear relationship can helps us explain complex relationships, like the non linearity previously observed in merger arbitrage returns. If the model provides evidence for such a relationship we should observe a negative θ, a β greater than 0 in depreciating markets and a beta of about 0 in appreciating markets. Such a relationship would illustrate the SMRP discussed in Section (2.3.2)

If we see evidence for SMRP we will use the contingency claims approach suggested by Mitchel & Pulvino (2001) to assess the abnormality of returns. If we do not find evidence for SMRP we will utilize the alpha measure to assess the abnormality of returns. Alpha, in this context, is the difference between the observed and predicted returns for the merger arbitrage portfolio. It is calculated as follows.

$$\alpha = r - \sum_{j=1}^{n} \beta_j \mathrm{X}_j \tag{16}$$

α: Measure of abnormal return
r: Observed portfolio return
β_j: Sensitivity to risk factor j
X_j: Risk premium for factor j
n: Number of risk factors in model

CAPM, FF3 and FF5 assumes that in efficient markets, the return to a portfolio or assets can be explained by the models specific factors (X_j). This means that in efficient markets the expected value of alpha should be zero. An alpha greater than zero implies a return in excess of whats expected, given it's factor exposure, and an alpha less than zero implies a return short of whats expected, given it's factor exposure.

4.2.1 Probability of deal success given market returns

To further understand how market returns affect the returns of a merger arbitrage portfolio, we will regress the ratio of successful deals on the market return. This can be done in several ways. We sort our merger data by date of completion, then calculate the ratio of successful deals in that month. This will be regressed on the market return. It is not clear what period of market returns should be chosen as the independent variable. We will do the regression for same month, the month before, tree months before and six months before. We apply the following regressions:

$$\eta_t = \beta_t r_t + \epsilon_t \tag{17}$$

$$\eta_t = \beta_t r_{t-1} + \epsilon_t \tag{18}$$

$$\eta_t = \beta_t \sum_{t=-3}^{t-1} r_t + \epsilon_t \tag{19}$$

$$\eta_t = \beta_t \sum_{t=-6}^{t-1} r_t + \epsilon_t \tag{20}$$

η_t: Deal success ratio in month t
r_t: market excess log return in month t

Since we are working with log returns, the sum of returns equals the cumulative return for the period.

4.3 Prediction modeling

4.3.1 Risk and prediction models

The historical probability of deal success, unconditional on the deal, can be calculated in the following way:

$$p_{historical} = \frac{N_{success}}{N_{total}} \tag{21}$$

The outcome of a deal is binary, which means that the outcome of a deal shares the characteristics of a Bernoulli distribution. Assuming only binary risk we can calculate the expected return as follows:

$$E(r) = p\Delta + (1-p)\gamma$$

$$\Delta = \frac{S_{offer} - S_{market-price}}{S_{market-price}} \tag{22}$$

$$\gamma = \frac{S_0 - S_{market-price}}{S_{market-price}}$$

In Equation (22) Δ is the the expected return if a deal is successful and γ is the expected return if a deal fails.

Further, if we assume efficient markets and risk neutral investors, then on average the $E(r)$ should be 0. This is intuitive since our assumptions implies all risk being accounted for in the up and down-state. Hence the deal-specific probability can calculated as:

$$\pi = \frac{-\gamma}{(1+\Delta)-(1+\gamma)} \tag{23}$$

Intuitively the probability of a successful takeover can also be viewed as the following relationship:

$$\pi = \frac{S_{market-price} - S_0}{S_{offer} - S_0} \tag{24}$$

The intuition here is that the probability of success is based on how much of the offer that is already reflected in the market-prices.

As described above, the outcome of a merger or acquisition bid can be assigned to one of two values. The outcome of a bid is either successful or unsuccessful. Given the assumptions mentioned above the risk can be assessed in a binary setting. Considering this, we will estimate logistic regressions to determine the probability of deal success. We assume that the probability of success is a function of the observable factors. Considering this we define the logistic regression model in the following way:

$$\pi_{SUCCESS} = \frac{1}{1+\epsilon^{-\Sigma_k \beta_k X_k}} \tag{25}$$

Where $\pi_{SUCCESS}$ is the probability of the dependent variable equaling success. X_k is observable factor k, and β_k is the sensitivity of the corresponding factors. If β_k is greater than zero, then an increase in X_k, ceteris paribus, will lead to higher probability of success. Correspondingly, if the value of X_k decrease it would lead to a lower probability of success. Ultimately, if the value of β_k is negative, then the relationship between X_k and β_k will be the opposite.

Given all deals variables, we can calculate the probability of deal success based on the coefficients given by the model. The model will give each deal a probability of success between [0,1]. The level of certainty you require to invest in a deal can be referred to as the probability cut off. In a risk neutral and strictly Bernoulli world, the cut off point would be evident. In this model, the risk return is not given and the cut off point is not that straightforward determinable. In a paper by Branch & Yang (2003) a cut off of 0.5 is used. We will also implement this as our standard cut off. However, by performing a stress test we will evaluate how different levels of cut off point influence the overall performance, in relation to both returns and forecasting power.

The logistic regression model is fitted trough maximum likelihood estimation. Assessment of goodness of fit and the predictive power concerning logistic regressions are widely discussed topics. Following the arguments of Menard (2000), Tjur (2009) and Allison (2014) we will evaluate the prediction power with the assistance of the following Pseudo-R^2's.

McFadden R^2_{McF}:

$$R^2_{McF} = 1 - \frac{ln_(L_M)}{ln_(L_0)} \tag{26}$$

L_M = Likelihood of model with predictors
L_0 = Likelihood of model without predictors

The intuition is that if L_M does not predict the outcome better than L_O , L_M will not be much larger than L_O, and so $\frac{L_M}{L_O}$ is approximately 1, which would yield a low R^2 in this case.

Tjur R^2:

$$D = \bar{\hat{\pi}}_1 - \bar{\hat{\pi}}_0 \tag{27}$$

$\bar{\hat{\pi}}_1$ = Average fitted value success
$\bar{\hat{\pi}}_0$ = Average fitted value failure

The intuition here is that if a model makes good predictions, the cases with deal success should have high predicted values and the cases without deal success should have low predicted values, which would yield a high R^2.

Cox and Snell $R^2_{C\&S}$:

$$R^2_{C\&S} = 1 - (\frac{L_0}{L_M})^{2/n} \tag{28}$$

N = sample size
L_M = Likelihood of model with predictors
L_0 = Likelihood of model without predictors

The intuition behind Cox and Snell is the same as in McFadden. The likelihood ratio reflects the improvement of the full model over the null model, hence, a smaller ratio, is evidence of greater improvement.

At last, we will evaluate if there is any problems regarding multicolinearity. To do this we will calculate variance inflation factor (VIF) and a pearson correlation matrix. VIF will be calculated as follows:

$$VIF_i = \frac{1}{1 - R_i^2} \tag{29}$$

R_i^2 = Coefficient of multiple determination of the regression of the variable i on all other predictor variables.

If there is linear dependence between predictors, then R^{2_i} would be high. This leads to a small denominator and consequently a high VIF. In literature, there is great discrepancy regarding what is considered a maximum acceptable level of VIF. Most commonly recommended is a maximum value of 10. (e.g., Hair, Anderson, Tatham, & Black, 1995; Kennedy, 1992; Neter, Wasserman, & Kutner, 1989). However a maximum value of 4 has also been recommended by Pan & Jackson (2008)

4.3.2 Risk Factors

As with any regression, the accuracy of the results are dependent on how many of the relevant independent variables one can identify. It is therefore desirable to discover as many of these as possible. It is unlikely to identify all relevant variables, as not all aspects of the world can be represented easily into workable data. This does not mean that one should dismiss these results, but rather view them as suggestive evidence towards the greater truth. In the selection process we have included all major factors from earlier studies, as well as include new ones we find interesting. This should reduce the probability that we miss something major and give us a better chance of a good fit.

Variables used in this study and their respective calculations are presented below[3].

- Announced deal value in millions:

$$X = \text{ Total value deal}$$

- Nature of Bid:

$$X = \begin{cases} 1 = \text{Friendly} \\ 0 = \text{Neutral} \\ -1 = \text{Hostile} \end{cases}$$

- Relative Size of Acquire to Target

$$X = ln\left(\frac{\frac{1}{125}\sum_{n=m}^{125}\text{MVA}_n}{\frac{1}{125}\sum_{n=m}^{125}\text{MVT}_n}\right)$$

[3]For additional description of factors see Section (2.4)

MVA_n: Market value acquirer company for business day n
MVT_n: Market value target company for business day n
m: 125 business days before announcement

- Payment Type:

$$X = \begin{cases} 1 = \text{Cash} \\ 0 = \text{Cash and Stock} \\ -1 = \text{Stock} \end{cases}$$

- Has Contingency Payment:

$$X = \begin{cases} 1 = \text{Yes} \\ 0 = \text{No} \end{cases}$$

- Net Debt in Target

$$X = \text{ Net debt target}$$

- Percent owned:

$$X = \text{ \$ Owned in deal}$$

- Percent sought:

$$X = \text{ \% Sought in deal}$$

- Target Institutional Owners of shares outstanding in %

$$X = \text{ \% Institutional Ownership in deal}$$

- Target ROC WACC ratio

$$X = \ ln\left(\frac{\text{ROC}}{\text{WACC}}\right)$$

ROC = Return on Capital
WACC = Weigthed Average Capital Cost

- Target Debt to Equity

$$X = \ ln\left(\frac{\text{Debt}}{\text{Equity}}\right)$$

- Price Run Up

$$X = \sum_{t=-6}^{-1} r_t$$

r_t: Log return for day t in target equity
t= 0: Announcement date

- Sector:

$$X = \begin{cases} 1 = \text{Same Sector} \\ 0 = \text{Different Sector} \end{cases}$$

- Sub Industry:

$$X = \begin{cases} 1 = \text{Same Sub Industry} \\ 0 = \text{Different Sub Industry} \end{cases}$$

- Bid Premium

$$X = \frac{V - S}{S}$$

V: Market value of offer per target share
S: Pre announcement market price of target share

4.3.3 Return modeling: Batch and Machine learning

Logistic regressions solely predicts probability of deal success. Whether one would have outperformed a buy and hold market portfolio by applying it, is ambiguous. Thus modeling predicted outcome is not sufficient to evaluate the performance of the model in a market environment. We solve this by creating two different portfolios based on a logistic regression model. First we will estimate a logistic regression based on a large-set training set, approximately 75% of the total data set, and apply this model on the last 25% of the deals. Then we will invest in those deals predicted by the model. This is so called batch-learning process.

We will also evaluate how an "Online Machine Learning" algorithm would perform from the very start of our data-set. This test will be based on a continuously updated trading algorithm, which we will later refer to as CUPA[4]. We will construct a portfolio with a trading signal which is based on a specific prediction model. The prediction model will be updated each time there is completed deal. This makes it possible to unbiasedly evaluate if a portfolio based on the logistic regression, outperforms a standard portfolio of all available deals.

In Figure (2) below we have visualized the processes of the algorithm. At each point in time when a deal is either completed or announced the algorithm will be fed with this information. The announced data will consist of data on every deal announced at day_t. The completed data will consist of every deal closed up till day_{t-1}. Then each deal closed up till day_{t-1} and it's corresponding factors will be added to a historical data matrix and implemented in the prediction model. Correspondingly, each deal announced at day_t will be evaluated based on the prediction model. The prediction model will give every deal predicted a probability of success in the interval $0-1$. It will then decide for each specific deal if it will trade or not. The certainty level at which the model will give a buy signal is optional. In our portfolio we will invest in every deal with an estimated success probability greater than 0.5. Which means that an estimated probability greater than 0.5 will give a trade signal and an estimated probability less than 0.5 will give a no trade signal. Returns are then calculated as explained in section (4.1).

[4] Continuously Updated Prediction Algorithm

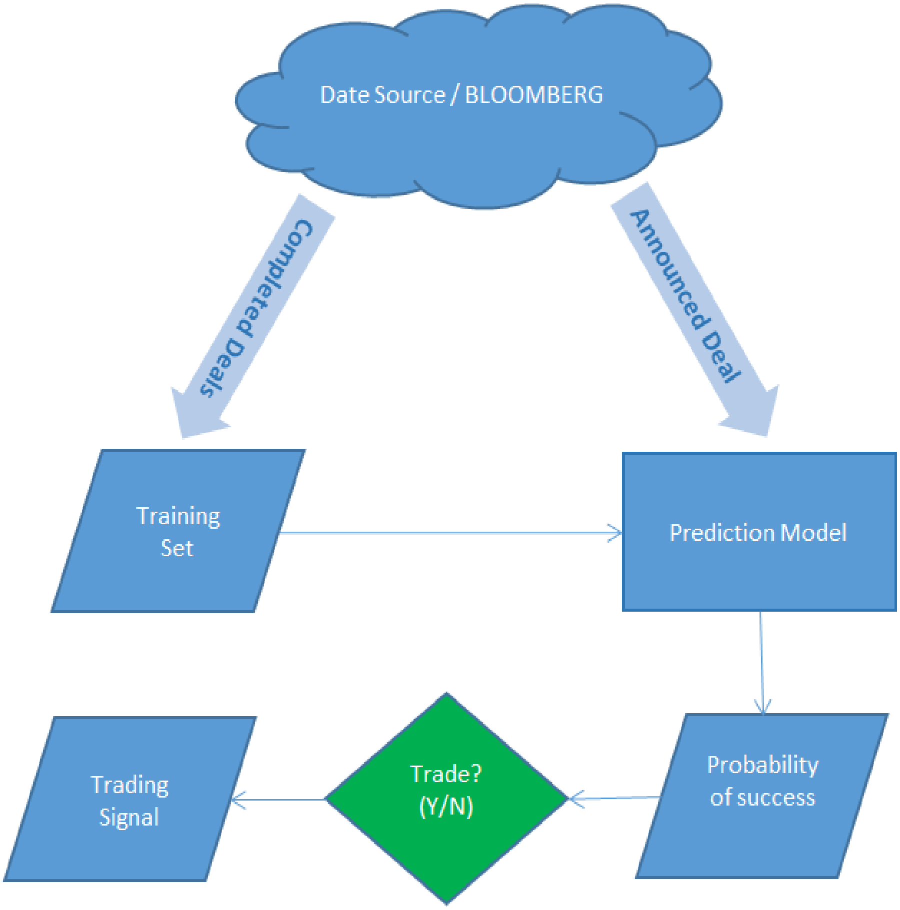

Figure 2: **CUPA Flow Chart:**
Paralellogram represent input/output, rectangles represent process and rhombus represent decision

Everyday the algorithm is fed with information. At each day it takes the information regarding deals closed and include them into its training set. Subsequently this information gets available for the prediction model. Further, it gets information regarding each deal announced since last update. Based on this information it predicts the probability of deal success. Given the predicted deal success and the demanded certainty level it gives a trading signal which is either 0 or 1.

5 Empirical Results and Analysis

5.1 Merger Arbitrage Returns

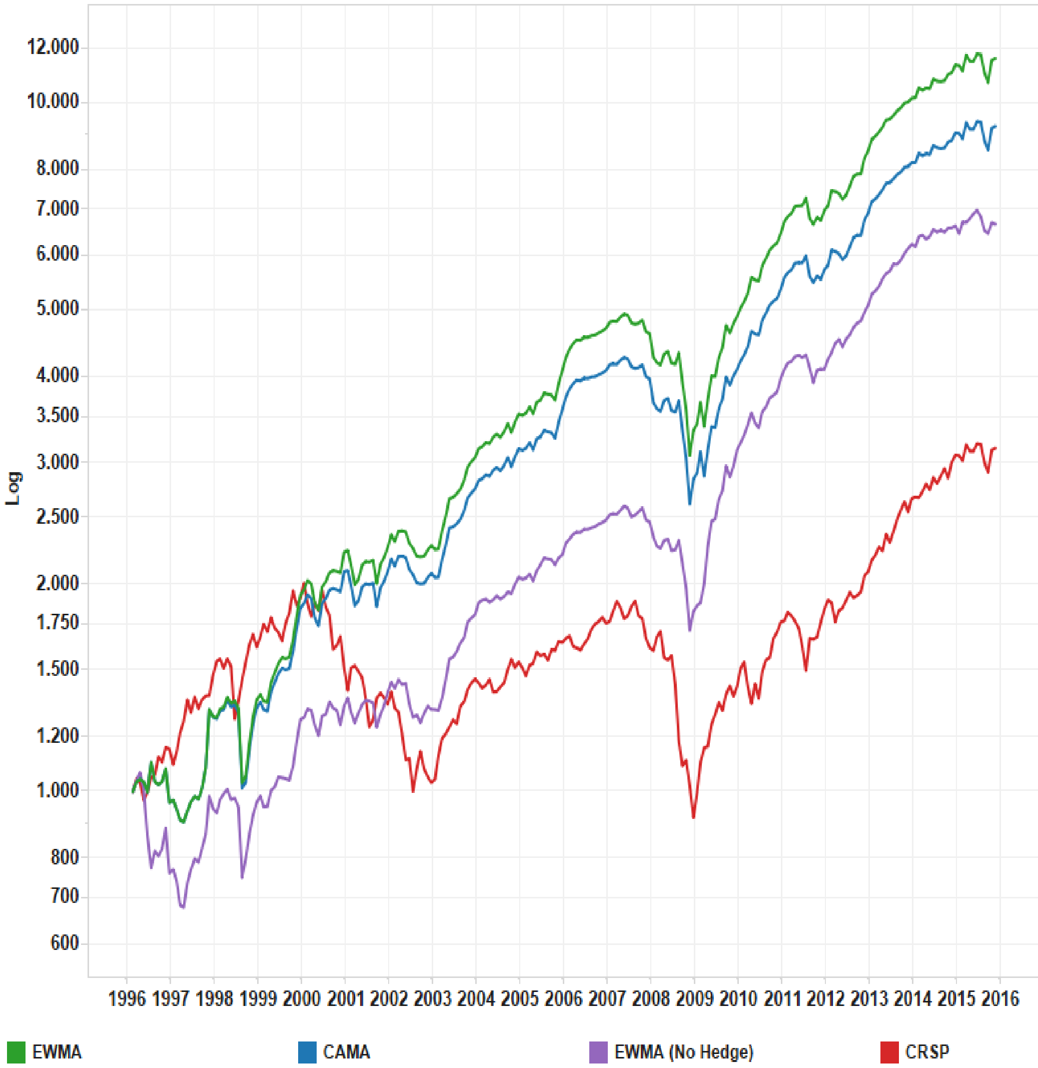

Figure 3: **Total return index:** This graph shows the value of $1000 invested at the beginning of 1996 in each of the following strategies:(1) Equally-weighted merger arbitrage (EWMA), (2) Equally-weighted merger arbitrage with transaction cost (CAMA) , (3) Equally-weighted merger arbitrage w/o hedge (EWMA nh) and (4) CRSP excess market return. Horizontal axis corresponds to years and y-axis to portfolio value.

In Figure (3) we have visualised the development of the four different estimated portfolios over our full sample. Each portfolio invested $1000 at the start of 1996. All portfolios are excess of the risk free rate. Over a 20 year period from 1996 to 2015 all of the merger arbitrage portfolios outperform the market (CRSP). Not surprisingly, each portfolio suffers large losses during the financial crisis in 2008. However, while the CRSP portfolio suffers from large losses during the dot-com bubble and its aftermath, the merger arbitrage portfolios seems to be more or less unaffected.

In Table (6) we have annualized the excess return characteristics of the four portfolios. The CAMA portfolio has a both greater return and a lower standard deviation than CRSP. The sharp ratio is more than twice as large, suggesting that investing in a merger portfolio over the last 20 years yielded two times the excess return per unit of total risk, compared to the market. Another interesting thing to notice is that the hedge seem to increase the total risk of the EWMA portfolio. One would expect that the volatility would decrease, as the payoff in successful deals are now fixed, in stead of a function of the price movement in the acquirer company's stock. We will investigate this further in Section (5.2.4).

Table 6: **Annual Performance: 1996-2015**
Returns are annualised daily log returns. Standard deviation are annualized daily standard deviation.

	Annualised return	σ	Sharpe Ratio
EWMA	14.8%	15.7%	0.93
EWMA (No Hedge)	10.5%	14.0%	0.74
CAMA	12.0%	14.0%	0.85
CRSP	5.5%	16.0%	0.34

The difference between EWMA and CAMA in this table represents the annual transaction cost. This amounts to about 2.8%. This is quite high, but seems appropriate for a strategy that is frequently rebalanced and involves shorting. It is important to keep in mind that this annual cost will depend on our assumed transaction cost. In Section (5.4) we will present a stress test of the assumed rates and fees. Here we will establish how sensitive our results are to these assumptions.

Table (7) shows the annualized returns for the CAMA portfolio. It had it's best year in terms of returns in 2009 with a total return of 38.78%. It suffered losses in a total of four out of 19 years. Not surprisingly the maximum loss occurred in 2008 where the total losses amounted to 32%. 2008 is also the year with the lowest fraction of successful deals.

Table 7: **Yearly Portfolio Performance CAMA: 1996-2015**

Year	Successful Deals	CAMA Return	CAMA σ
1996	100%	-6%	21%
1997	100%	31%	19%
1998	88%	8%	16%
1999	83%	35%	9%
2000	85%	13%	16%
2001	88%	0%	12%
2002	85%	0%	10%
2003	86%	29%	7%
2004	85%	15%	6%
2005	83%	15%	8%
2006	84%	14%	6%
2007	82%	-4%	7%
2008	75%	-32%	23%
2009	80%	39%	23%
2010	86%	27%	8%
2011	83%	7%	11%
2012	87%	19%	11%
2013	85%	17%	5%
2014	85%	10%	7%
2015	87%	1%	13%
Annual	85%	12%	14%

5.2 Risk

5.2.1 Characteristics

Before looking at the regression output, we will consider the distribution of monthly returns for the CAMA portfolio and the CRSP index. In Table (8) we compare some summary statistics for the CAMA returns, with the market returns, here represented by the CRSP index. In Figure (4) and (5) we have plotted the historical distributions for the CAMA portfolio and the CRSP index respectively.

Table 8: **Descriptive Statistics: 1996-2015**
This table provides descriptive statistics for the distribution of monthly return for the CRSP Index and the CAMA portfolio

	CAMA	CRSP
Min.	-0.22	-0.19
1st Qu.	-0.01	-0.02
Median	0.010	0.012
Mean	0.010	0.005
3rd Qu.	0.030	0.034
Max.	0.217	0.108
Std.	0.040	0.046
Skewness	-1.5	-0.8
Excess kurtosis	11.6	1.4

The historical CAMA distribution has a similar mean and median. This is a symmetric feature as the data is close to equally split at it's average return. We do not observe the same for the CRSP distribution. Here the median value is greater than the mean, indicating that extreme values on the left side are not matched by equally extreme values on the right side. We see that the two distributions have roughly the same standard deviation. Still, there are some major differences in the distribution of the data. This can be read from the massive difference in excess kortosis. Kurtosis describes the tendency for a distribution to be heavy tailed. A positive excess kurtosis means that a distribution has more extreme returns than a normal distribution. We see in Figure (4) that this results in a steeper distribution.

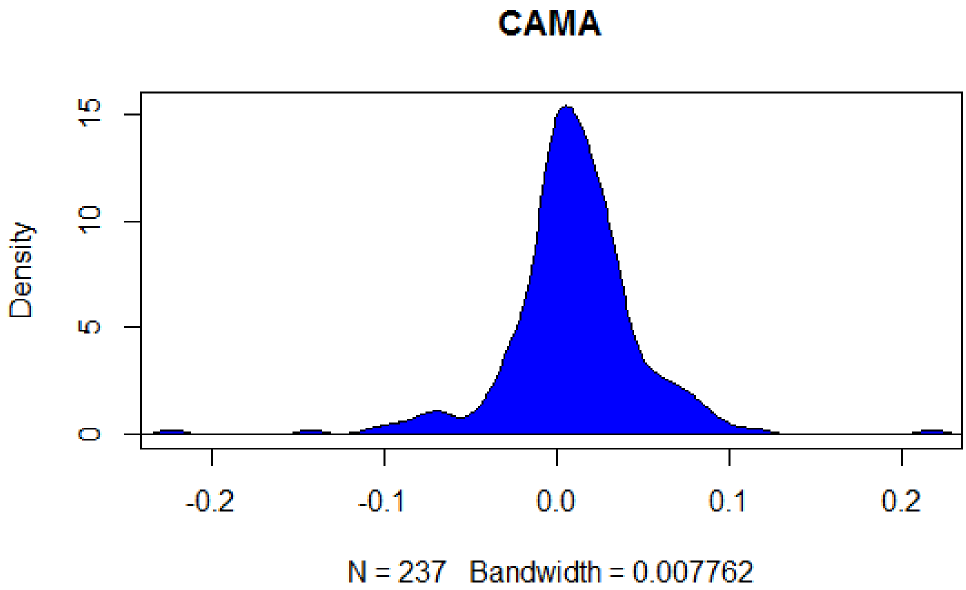

Figure 4: **Density CAMA:** This plot illustrates the distribution of monthly CAMA returns

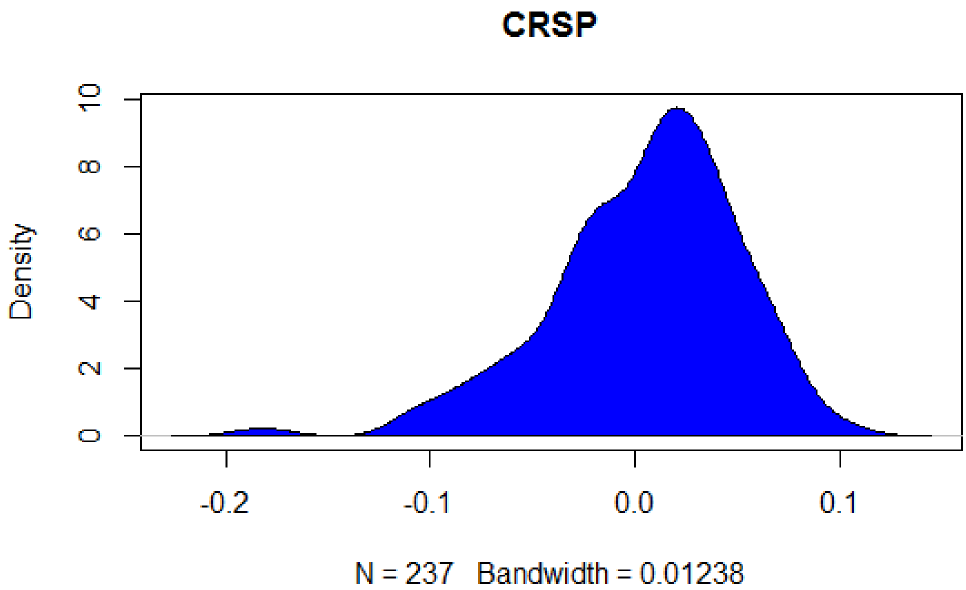

Figure 5: **Density CRSP:** This plot illustrates the distribution of monthly CRSP returns

On a broader level, any major discrepancy from the normal distribution is a potential problem for models and statistical calculations that assume normally distributed returns. If we consider the CAPM, FF3 and FF5 models, the variance of return are assumed to be a sufficient measure of risk. This assumption is dependent on normally distributed returns. In addition, a t-test assumes that samples are drawn from a normally distributed population. Considering the density plots in Figure (4) and (5) both distributions looks fairly bell-shaped. A more systematic way to evaluate the degree of non-normality is with the q-q plot. A q-q plot compares the quantiels for two different distributions. This let us evaluate if the two data sets come from the same distribution, have similar tail behaviour and similar distribution shapes. In this case it illustrates how the data fits the theoretical normal quantiles given the distribution's sample mean and standard deviation.

We have plotted the q-q plot for CAMA and CRSP in Figure (6) and (7), respectively. The straight line reflects where the theoretical quantile equals the sample quantile. Both the distributions fits extremely well within the one standard deviation bounds of the theoretical quantiles. The mismatch appears to be mainly in the tails of the distributions. The CAMA distribution has an s-shaped form where returns are too low in the left tail and too big in the right tail. This implies more extreme outliers than a normal distribution would produce. The CRSP distribution looks similar, but has a concave shape. This means that observations in both tails are too small to be perfectly normal.

Even if our distributions are not perfectly normal, they are acceptable for our statistical analysis to give reasonable results.

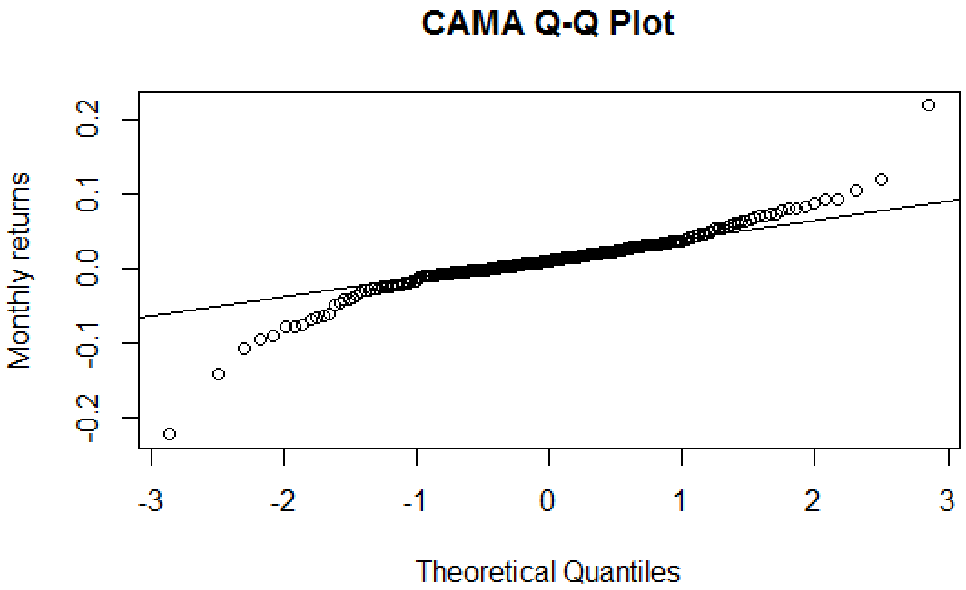

Figure 6: **CAMA Q-Q Plot:** This plot illustrates the discrepancy between sample quantiles and theoretical normal quantiles for the CAMA returns

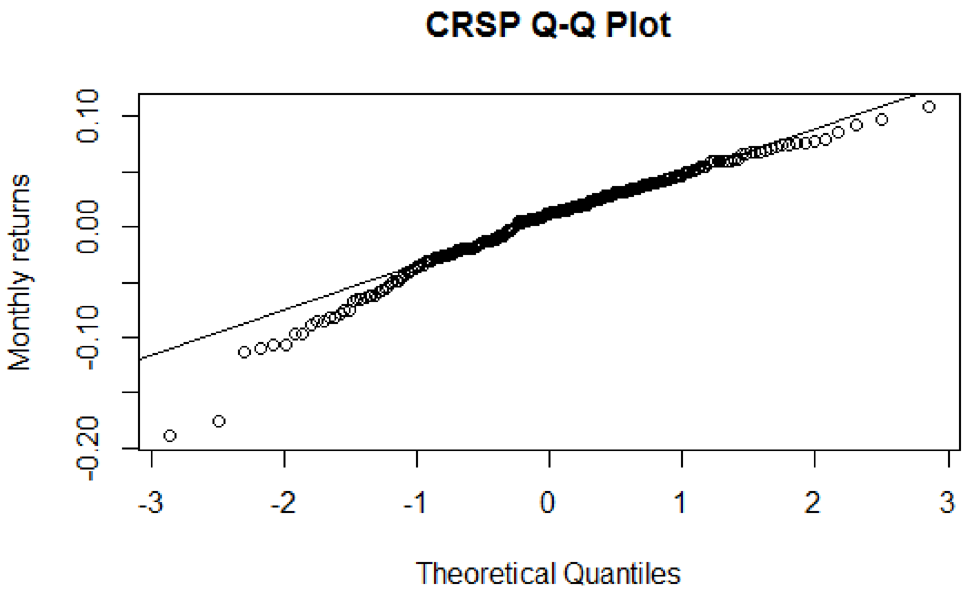

Figure 7: **CRSP Q-Q Plot:** This plot illustrates the discrepancy between sample quantiles and theoretical normal quantiless for the CRSP returns

5.2.2 Market Risk

A summary of the three linear regressions described in Section (4.2) are found in Table (9). The monthly returns of the CAMA portfolio has been regressed on the monthly CRSP return and the relevant factor returns for the Fama French three & five factor model. All returns are in excess of the risk free rate. It is generated from 237 observations of monthly returns. β_{Mkt} is positive and significantly different than zero in all tree models. This suggests that the CAMA portfolio tend to move in the same direction as the market.

Table 9: **Regression Results: 1996-2015**
This table provides output of the (CAPM), (FF3) and (FF5) OLS regressions on the CAMA portfolio as described in Section (4.1). The regressions are based on monthly returns.

	Complete Sample:		
		MA	
	(CAPM)	(FF3)	(FF5)
α	0.0078^{***}	0.0076^{***}	0.0067^{**}
	(0.003)	(0.003)	(0.003)
β_{Mkt}	0.485^{***}	0.451^{***}	0.494^{***}
	(0.056)	(0.057)	(0.066)
β_{SMB}		0.217^{***}	0.216^{**}
		(0.080)	(0.092)
β_{HML}		-0.039	-0.14
		(0.080)	(0.119)
β_{RMW}			0.159
			(0.133)
β_{CMA}			0.130
			(0.167)
N	237	237	237
R^2	0.238	0.261	0.265
Adjusted R^2	0.234	0.252	0.250
Note:		*p<0.1; **p<0.05; ***p<0.01	

α in these models can be interpreted as abnormal returns, as it is return not explained by the model. An α of 0.0078 reflects a monthly abnormal return of 0.78% or an annual abnormal return of about 9.36%. Just like the β_{Mkt}, the α is significantly different from 0 in all three models. Notice that both α and β_{Mkt} changes very marginally between the different models. In other words, adding risk factors to the CAPM model regression does not affect our results in terms of abnormal returns and market exposure.

The only other risk factor the CAMA portfolio appears to load[5] significantly on, is SMB. This suggests that the portfolio has over-weighted small companies compared to the market. This is not surprising as we are buying target companies which tend to be small and are shorting acquirer companies which tend to be big. The fact that the portfolio is equally weighed should also account for some of this, as our portfolio will have a higher weight of small companies compared to the CRSP index, which is value weighted.

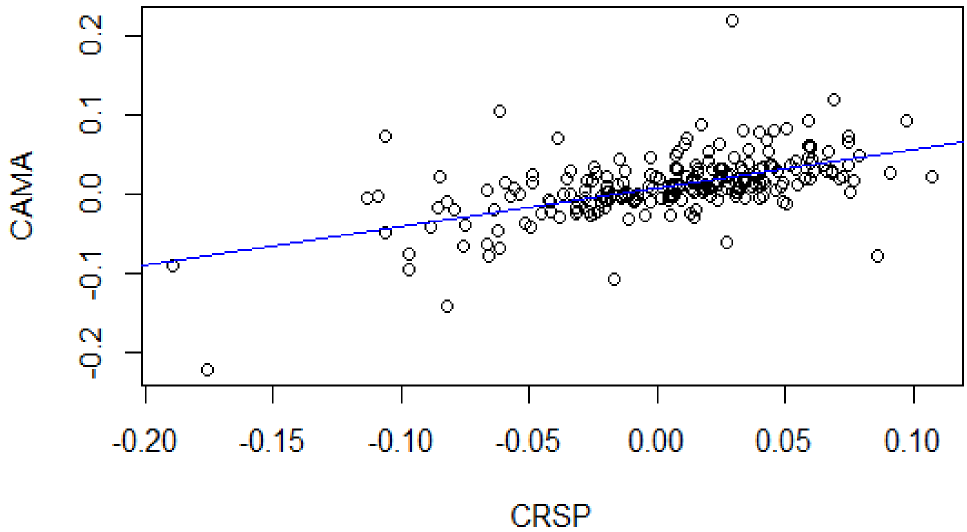

Figure 8: **CAMA-CRSP Regression: 1996-2015**
This plot illustrates the relationship between the EWMA portfolio and the excess return on the market

In Figure (8) we have plotted the CAPM regression described in Formula

[5]loading refers to the degree of linear dependency, measured in β

(12). It appears to fit quite good. This is surprising as we did not expected the data to appear so linear. But looks can be deceiving, so we will investigate this linearity further.

In Table (10) we run the same regressions as in Table (9), only here we have divided our data set by monthly market excess return. This is done to investigate if the regressions give different results for different market states. The β_{Mkt} is of particular interest as earlier research suggests a non-linear relationship. The break point has been set to -4%. This is the break point that minimizes the sum of squared residuals in Mitchell & Pulvino's (2001) data. As our data (1996-2015) barely overlaps with their data (1975-1998), it will be interesting to see if our results are similar. The two different states will be referred to as "high" and "low", referring to their relative position to the break point.

The first thing to notice is the $\beta_{MktHigh}$. It is significantly different from zero in all tree models. Our data suggests that the EWMA portfolio return is correlated with excess market returns in good market states. This is not consistent with earlier findings and definitely raises some questions about the established consensus risk characteristics of this strategy.

The β_{MktLow} appears to be greater than $\beta_{MktHigh}$. This is consistent with earlier findings. The thing that stands out, is the relatively high standard errors. The standard errors essentially measures the uncertainly of the slope estimate. These numbers are driven up by size of the residuals and the small numbers of observations in the low state.

The next interesting thing to notice is that even though the estimated β_{Mkt} -values for the different states are quite different, we cannot reject the null-hypothesis that they are similar. This means that we can not conclude that the market risk associated with the merger arbitrage strategy is similar to the SMRP[6] documented by Mitchell & Pulvino (2001). Assuming that their results accurately describes merger market risk, this discrepancy can mean one of two things. Our data is either not diverse enough to describe the market risk of the strategy, or the fundamental market risk of the strategy has changed. The fact that $\beta_{MktHigh}$ is significantly different from zero in all three models, makes the latter more likely.

[6]SMRP: Segmented Market Risk Pattern, see Section (2.3.2)

Table 10: **State Regression: 1996-2015**
Regression output: CAMA regressed on CRSP for monthly excess market return greater and smaller than -4%

	Dependent variable: CAMA					
	Mkt $<$ **-4%**			**Mkt** $>$ **-4%**		
	CAPM	FF3	FF5	CAPM	FF3	FF5
α	0.034	0.040*	0.040*	0.009***	0.011***	0.010***
	(0.022)	(0.022)	(0.022)	(0.003)	(0.003)	(0.003)
β_{Mkt}	0.832***	0.772***	0.828***	0.407***	0.391***	0.427***
	(0.261)	(0.262)	(0.299)	(0.084)	(0.085)	(0.089)
β_{SMB}		0.336	0.415		0.226***	0.241**
		(0.258)	(0.272)		(0.084)	(0.099)
β_{HML}		−0.205	−0.272		0.120	−0.034
		(0.182)	(0.310)		(0.094)	(0.133)
β_{RMW}			0.363			0.117
			(0.384)			(0.142)
β_{CMA}			−0.158			0.291
			(0.425)			(0.185)
N	35	35	35	202	202	202
R^2	0.236	0.294	0.322	0.106	0.139	0.150
Adj. R^2	0.213	0.226	0.205	0.101	0.126	0.129
Note:						*p<0.1; **p<0.05; ***p<0.01

Z-Test: H0: $\beta_{MktLow} = \beta_{MktHigh}$

	Low	High
β_{Mkt}	0.83	0.41
σ	0.26	0.08
Z-score 1.72		
P-value0.086		

Table 11: **Piecewise Regression: 1996-2015**
Summary of the OLS output from the piecewise regression. $\beta_{MktHigh}$ are market return above break-point and β_{MktLow} are market return below break-point. $Breakpoint = -0.125$

	Dependent variable:		
	CAMA	t value	N
α	0.1353	1.210	
	(0.1118)		
β_{MktLow}	1.5601	2.268	2
	(0.6877)		
$\beta_{MktHigh}$	0.4153***	6.899	233
	(0.0602)		
N	235		
Break point	-0.125		
σ break point	0.169		
R^2	0.2575		
Adjusted R^2	0.2479		
Residual Std. Error	0.03932 (df = 233)		
Note:	*p<0.1; **p<0.05; ***p<0.01		

Z-Test: H0: $\beta_{MktLow} = \beta_{MktHigh}$

	Low	High
β	1.56	0.42
σ	0.69	0.06
Z-score	1.66	
P-value	0.10	

Before we jump to any conclusions, we will investigate if the break point at -4% is the best fit for our data. For this we will utilize the piecewise regression (15) described in Section (4.2). The break-point is set to maximize the fit, or in other words minimize the sum of squared residuals. This yields a break point of -12.5%. A lower break point obviously gives us fewer observations in the low state. This is problematic as the standard error will rise. The regression output is presented in Table (11) above.

It should be obvious that not much insight can be red from β_{MktLow} in this model. $\beta_{MktHigh}$ is considerably smaller than the CAPM β_{Mkt} for the full sample (Table 4.1), considering that only 2 observations have been removed. This suggests that the removed data, does not fit very well with the rest of the data. Just like earlier, we cannot say that the betas are significantly different.

In Figure (9) we have visualized the piecewise regression. We see that there is actually only one monthly return that fits the SMRP. We also see that the month with the lowest market excess return has a really small residual from the linear relationship describing most of the data.

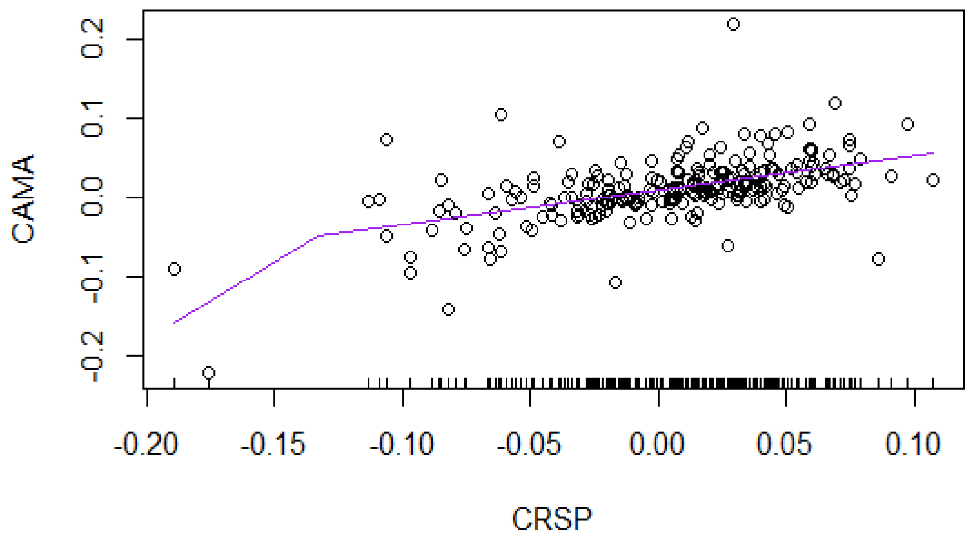

Figure 9: **Piecewise Regression 1996-2015**
Illustration of a piecewise regression estimated with maximum likelihood

Since the new fitted break point does not yield significantly different betas, we cannot confidently say that a non-linear relationship exists in our data. Considering that the market-beta is significantly greater than zero in both the full sample regression and in the high states of the segmented regressions, we conclude that the SMRP observed by earlier studies is no longer valid.

To provide some possible explanation to what can cause this shift, we can divide the change into two parts. Firstly, the strategy does not appear have higher exposure in depreciating markets. Second, the strategy seems to have significant market risk in appreciating markets. Earlier litterateur explained the high exposure in depreciating markets as mainly a function of an increased probability of unsuccessful deals. The perceived driver behind this was the acquirer firm wanted to back out of the deal, as they could buy a similar firm cheaper. One explanation for the changed market exposure in depreciating markets could be that it has gotten harder for acquirer companies to back out of deals.

Table 12: **Regression output: 1996-2015**
This table present monthly deal success ratio regressed on cumulative market returns

	Dependent Variable: Deal Success Ratio			
	r_t	r_{t-1}	$\sum_{t=-3}^{t-1} r_t$	$\sum_{t=-6}^{t-1} r_t$
Constant	0.828***	0.827***	0.826***	0.825***
	(0.006)	(0.006)	(0.006)	(0.006)
β_t	0.286**			
	(0.133)			
β_t		0.461***		
		(0.131)		
β_t			0.253***	
			(0.071)	
β_t				0.184***
				(0.048)
Observations	216	216	216	216
R^2	0.021	0.055	0.055	0.065
Adjusted R^2	0.017	0.051	0.051	0.061
Note:				*p<0.1; **p<0.05; ***p<0.01

The fact that merger arbitrage had no market exposure in good markets, were in earlier literature explained by the notion that the probability of deal success was not dependant on the market movements in appreciating markets. Measuring the potential change in this relationship is not easy, as we have no point of reference in earlier data. What we can measure is the linear dependency of market returns on the historical deal success ratio. The output from regressions expressed in Formula (17) to (20) in Section (4.2.1) is printed in Table (12).

The constant in these regressions can be interpreted as the expected deal success ratio given a cumulative excess market return of zero. We see that all the betas are significantly greater than zero, suggesting that market returns impact the relative number of deals going through. The greatest linear dependency we observe is for the second regression. In this model a 1% increase in the market return in a given month is associated with a 0.46% increase in the deal success ratio for the following month. If your success ratio depends on market returns, logically, your portfolio returns should also depend on market returns. This could be part of the reason for the market risk observed in the merger arbitrage strategy.

R^2 is a measure that express how much of the variance in the dependent variable can be explained from variance in the independent variables. In the standard OLS regressions R^2 values varies from 0.23 to 0.27. This is not in favour of great "goodness of fit", but we do not consider this a big problem. Considering that portfolios with more idiosyncratic risk should give a lower R^2, it is not a big surprise that the merger arbitrage portfolio does not fit very well. Many deal specific factors will impact your return in ways not explained by the market. In a CAPM world the risk exposure from these factors could be perfectly hedged away. This is most likely not entirely true in the real world. The main concern with a low R^2 is that there may be other non-diversifiable systematic risk factors not accounted for in these models.

5.2.3 Abnormal returns

Based on the findings in the previous section we assume that the chosen models are sufficient when it comes to pricing risk in merger arbitrage. Hence, we will base our abnormal return calculation on linear asset pricing models. Our abnormal returns will therefore not be directly comparable to earlier estimates based on contingent claim analysis. Our yearly abnormal returns are presented in Table (13). The numbers are from the CAMA portfolio and hence after transaction cost. They are all greater than zero on a 99% confidence interval.

Accepting these number at face value indicates 20 very good years for merger arbitrage. There are however some things to keep in mind when evaluating these numbers. First of all, they are based on an equal weighted

Table 13: **CAMA Annual log abnormal returns: 1996-2015** These number are the annualized alphas from table (9).

	CAPM	FF3	FF5
α	9.4%	9.1%	8.0%

portfolio of deals, hence small companies are over-weighted. This can lead to upward biased returns because the SMB risk factor has a positive premium (Fama & French, 1993). This is only a problem for the CAPM alpha, as FF3 and FF5 accounts for exposure to the SMB factor. This effect appears to be marginal, as the FF3 alpha is only 30 bps smaller than the CAPM alpha on an annual basis. A higher proportion of smaller companies is also associated with higher trading cost. This is especially true for large portfolios where an order can push the stock price up, increasing market impact. In our calculations trading cost is assumed to be a fixed percentage of the total amount of funds moved. This can produce artificially high return as trading cost is not a function of the size of the companies traded. This is a potential source of bias and could partially explain why these alphas are so big.

Another problem with equal weighting is that the portfolio potentially earns part of the bid-ask spread on re-balancing. Consider a daily rebalanced, equally weighted portfolio with two stocks, stock A and stock B. Both currently have the same price and a fixed bid-ask spread. The closing price will thus be the either the bid price or the ask price. The next day stock A closes at the bid price and stock B closes at the ask price. Because the dollar amount should be equal in the two stocks, the position in A will be increased. This is financed by a decrease in the position in B. A small premium will be made on close as we buy on the bid and sell on the ask. The problem is that this profit cannot be achieved in a real portfolio as one cannot buy at the bid or sell at the ask. Our portfolio is not daily rebalanced, but rather rebalanced whenever a deal is introduced or excluded in the portfolio. Given that we on average have 249 deals per year, our portfolio is pretty close to being rebalanced every day. This is also a potential source of bias.

Finally, our returns are log returns. Log returns are always smaller than raw returns, and the difference is increasing in return. However, for daily returns this difference is going to be trivial. Log return is not a potential bias like the two first effects, but something to keep in mind when comparing the number to empirical results based on raw returns.

When comparing our results with results from earlier periods, it is not easy to determine if the strategy has become more or less profitable. The pre-millennium results vary a lot. We consider Mitchell & Pulvino (2001) to be the most seminal work in this field to this date. They do not have equally weighted returns, we can compare our results to. Their value weighted CAPM alpha is 3.5%. We do not find it very likely that equal weighting accounts for all the difference between this and our 9.4% alpha. Based on this it looks like merger arbitrage profitability has increased. Baker & Savasoglu (2002) documents an equally weighted CAPM alpha of 10.6%. This does not seem to be artificially high because of equal weighting, as their value weighted CAPM alpha is 9.8%. These results are very similar to what we have found. Looking at all this we cannot confidently say if merger arbitrage returns have changed.

Our results are quite inconsistent with the findings of Glans & Vo (2013), which are from part of the same period. Their equal weighted cash and stock portfolio both yield an annual CAPM alpha of 0.6 %. Note that this is two different portfolios. They have not accounted for transaction cost and because our estimated annual transaction cost of 2.8% far exceeds their alphas, their results suggest that merger arbitrage is not so lucrative from 2000 to 2012. Our results are based on a longer time period (1996 to 2015), but these extra years does not appear to be exceptionally profitable. It also appears that they have not hedged their stock deals, and have not included "cash and stock" deals. Since there are so many differences between their portfolio assumptions and ours, we do not consider the two results comparable.

We evaluate the magnitude of our alpha estimates to be sufficiently large to account for the potential biases described above. Hence we conclude that the merger arbitrage strategy has yielded significant abnormal returns, and appears to be a superior trading strategy. A significant positive alpha is either a violation of the efficient market hypothesis or the models does not sufficiently explain how the market evaluates the risk of the strategy. A third alternative is that the strategy cannot be implemented due to practical limitations.

5.2.4 Effect Of Hedging

We briefly pointed out that the hedging does not appear to reduce the total volatility of the EWMA portfolio. On the contrary, it increases the volatility. This might seem disappointing. We do however see a substantial increase in annualized returns when implementing the hedge (Table 6 in Section 5.1). This amounts to an impressive 4.3%. This is equivalent to a relative change of nearly 40%. Because the long positions in target companies are exactly the same for both portfolios, the difference must solely come from changes in the value of the short positions in acquirer companies. Hence it seems like the acquirer stocks in deals with a stock elements on average decrease in value over the deal period.

The true test of the hedge is to see how it affects the relationship between our merger arbitrage portfolio and the market. Table (14) shows the output from the regressions described in Section (4.2) now with the monthly returns of the EWMA portfolio, with and without hedge, as the dependant variables. The EWMA alphas are greater than those presented in Table (9) because the EWMA does not account for transaction cost. The monthly alpha increased with about 40 bps as a results of the hedge. This is equivalent of an annual increase in alpha of 4.8%.

As expected, we see a significantly greater β_{Mkt} in all tree regressions without the hedge. This suggests that the hedge does decrease market exposure. Surprisingly, we do not see a decrease in the loading on the SMB factor. We expected this as we have removed the short positions of typically large acquirer companies. The fact that we see no decrease suggests that the loading on SMB is not driven by the short positions, but rather the long positions in target companies and the overweight in small cap due to equal weighting.

Overall we can say that the hedge has very desirable features for a merger arbitrage portfolio for the period we have investigated. Even if the the total risk increases, the hedge effectively reduces market risk and increases both total and abnormal returns.

Table 14: **Regression Results - EWMA NH & EWMA: 1996-2015**
This table provides output of the (CAPM), (FF3) (FF5) OLS regressions on the EWMA No hegde portfolio and the EWMA with hedge for the same period. The regressions are based on monthly log returns.

	Dependent variables: EWMA NH and EWMA					
	EWMA NH			EWMA		
	(CAPM)	(FF3)	(FF5)	(CAPM)	(FF3)	(FF5)
α	0.006***	0.006***	0.005***	0.010***	0.010***	0.009***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
β_{Mkt}	0.638***	0.599***	0.606***	0.474***	0.445***	0.482***
	(0.038)	(0.039)	(0.045)	(0.056)	(0.057)	(0.066)
β_{SMB}		0.230***	0.267***		0.216***	0.251***
		(0.054)	(0.062)		(0.080)	(0.092)
β_{HML}		−0.020	−0.020		0.030	−0.063
		(0.054)	(0.080)		(0.080)	(0.120)
β_{RMW}			0.089			0.133
			(0.090)			(0.133)
β_{CMA}			−0.071			0.120
			(0.112)			(0.167)
Observations	237	237	237	237	237	237
R^2	0.541	0.576	0.579	0.236	0.260	0.264
Adjusted R^2	0.539	0.570	0.570	0.233	0.250	0.248
Note:						*p<0.1; **p<0.05; ***p<0.01

5.3 Predictive modeling

5.3.1 Logistic regression

Table 15: **Logistic regression: 2001-2012**
This table reports the results from the logistic regression. The parameter estimates are the estimated change in log odds of deal success related to a change in the co-variates. The regression is based on data on all mergers from 2001 to 2012. The different deal characteristics are calculated as described in section (4.3).

	Estimate	Std. Error	Z value	Pr(>| Z |)
Intercept	-0.6279	0.6318	-0.99	0.3203
**Announced Deal Value	0.0862	0.0298	2.195	0.0037
***Nature of bid	2.6028	0.2011	12.94	0.0000
***Relative Acq to Target	0.2303	0.0483	4.77	0.0000
Payment type	0.0573	0.0872	0.66	0.5115
Has Contingency Payment	2.3170	1.6070	1.44	0.1494
Net Debt Tar	-0.0000	0.0000	-0.06	0.9503
**Percent Owned	-0.0177	0.0063	-2.82	0.0047
*Percent Sought	-0.0115	0.0057	-2.03	0.0426
***Target Instit Owner	-0.6484	0.0492	-13.19	0.0000
*Target Roc Wacc Ratio	0.0033	0.0015	2.22	0.0265
*Debt to equity	-0.0488	0.0239	-2.04	0.0409
***Price run up	0.0128	0.0029	4.46	0.0000
***Same industry sector	0.8210	0.1390	5.91	0.0000
*Same sub industry	-0.3832	0.1489	-2.57	0.0101
Bid Premium	0.0015	0.0019	0.80	0.4254
Null deviance:	2895.2	3299 DoF		
Residual deviance	2293.8	3280 DoF		

* Statistical significance at the level of 0.05
** Statistical significance at the level of 0.01
*** Statistical significance at the level of 0.001

The results from the logistic regression are the estimated relationship between the 16 predictor variables and the outcome of a bid in the period from 2000 until 2013. For references on the different factors used in the regression see section (2.4) and (4.3).

It is to no surprise that the nature of the bid and the relative size of the acquirer is the most significant predictors of deal success. This is consistent with earlier conducted studies, which also have found these as the most significant parameters predicting deal outcome. In our model the probability of successful deal outcome increases with more than 58% when the bid is friendly, compared to hostile. If there is an increase in the relative size of the acquirer to target by a factor of one, the probability of success increase by 21%. Furthermore we reveal a negative relationship between percent sought and deal success, which also is consistent with previous research.

Further, we observe a positive relationship between price run up in target and deal success. This is also a variable significant at a 99.9%level. The finding corroborate previous research. We explain the results by arguing that before a merger is actually announced, investors willing to place a bet on merger rumors will position themselves in the stock. Consequently, an increase in the amount of neutral owners could decrease the uncertainty regarding shareholder approval.

A relationship we have not seen identified earlier is the negative relationship between institutional ownership and the probability of deal success. We see that institutional holdings decrease the probability of deal success. We think this results is quite intuitive. Since large institutional shareholder possess a great number of shares and hence have more power and influence on the board it is conceivable to think that only they will have the capability to deteriorate a deal on their own. Hence greater risk of deal not going trough. Just as the preceding parameters this is also relationship significant at a 99.9% level

Following Global Industry Classification Standard (GICS) [7] companies can belong to industry groups, industries, sub-industries and sectors. When it comes to sectors, a company can belong to one of ten different sectors. If we look at the relationship between companies in same sectors and deal success we find evidence suggesting a positive relationship. If the acquiring firm and the target firm is in the same sector the probability of a successful deal outcome increase by 35%. It is conceivable that acquiring a firm in the

[7]Global Industry Classification Standard, developed in 1999 by MSCI and Standard & Poor's (S&P)

same sector will make implementation of target firm more straightforward compared to a firm from another sector.

Additionally we look at the relationship between deal success and companies in the same sub group. When it comes to sub groups, a company can belong to one of 156 different sub industries. For this relationship the parameter estimate is negative, which means that the probability of deal success decrease if acquirer and target are in the same sub-group. Intuitively, a consolidation within the same sub-group would likely decrease competition within that sub-group. Consequently, this could lead to problems related to regulatory clearances, which could call off the deal.

Percent sought states the amount of outstanding shares to be tendered for a bid to go trough. This relationship is negatively correlated with deal success. This implies that if the acquiring firm seek less of the outstanding shares the probability of deal success increase, which is trivial. This results is also consistent with findings in earlier studies. Not that intuitive, there is a negatively relationship between percent owned and deal success. Which implies that initial holdings in the target decrease the probability of deal success. We cannot find any intuitive explanations for this result. The last significant variable in this regression is the positive relationship between ROIC & WACC ratio and deal success. Which indicates that deals are more likely to be completed when the target firm is more profitable.

Even though consistent with earlier research it is interesting to note that there is no relationship between bid premium and probability of deal success. This is an essential result relating to risk neutrality. If we take into consideration the risk neutral model mentioned in section (4.3) one would expect the bid premium be associated with a lower probability of deal success as a high bid premium should imply great downside risk. But because downside risk is modelled as bid premium minus deal spread, this relationship is ambiguous.

As described in section (4.3) we run McFadden, Cox & Snell and Tjur tests to assess the prediction models fit. The results from these test are shown in Table (16) below.

Table 16: **Results from pseudo R^2 and goodness of fit test: 2001-2012**

McFadden	0.2077
Cox and Snell	0.1666
Tjur	0.2476

A value larger than 0.20 in a McFadden test indicates excellent prediction power, Domencich & McFadden (1996). The Tjur and the Cox & Snell test also indicates that the models estimation of probabilities are a good match with the actual probabilities.

We have also calculated VIF values to detect multicolinearity. Results are in Table (17) below.

Table 17: **VIF: 2001-2012**

	VIF
Announced Deal Value	2.77956
Nature of bid	1.043273
Relative Acq to Target	2.69586
Payment type	1.150035
Has Contingency Payment	1.008916
Net Debt Tar	1.084369
Percent Owned	5.385808
Percent Sought	5.644722
Target Instit Owner	1.316763
Target Roc Wacc Ratio	1.017141
Debt to equity	1.080322
Price run up	1.185544
Industry sector	1.846521
Industry sub group	1.781407
Bid Premium	1.18193

In section (4.3) we refer to conflicting research regarding recommended maximum VIF values. In previous research, the recommended maximum VIF varies from 4 to 10. From the table we can see that both Percent owned and Percent sought is in the range of violating these maximum. Both variables have VIF values above 5. Which means that their standard errors are larger by a factor of around 5 compared to if there were no inter correlations between the respective variable and the other variables. If we consider the correlation matrix presented in Table (29) (Appendix) we see that the correlation is -0.89. Such a high negative correlation is as expected. This is due to the fact that percent owned puts a upper bound on percent sought. This is probably one of the reasons for the mildly high VIF values. Combining this with the fact that we are interested in the accuracy of the prediction models rather than the precise effect of each variables, we do not see these modestly high VIF values as a concern.

5.3.2 Batch Learning

As described in section (2.4) we perform an out of sample test to gauge the forecasting power of the logistic regression. This is done by performing an out sample test. Based on a training set from 2001 until 2012 we estimate the probability of deal success on each deal from 2013 to 2015. We consider a deal to be successful if the estimated probability is above 50%. If the estimated probability is below 50% we considered it to fail and subsequently we would not invest in such a deal. Table (18) below is a summary of the forecasts.

Table 18: **Summary of the predicted outcomes based on the logistic regression: 2013-2015**

	Successful deals	Failed deals	Total deals	%
Correct forecast	700	72	772	89.04%
Incorrect forecast	38	57	95	10.95%
Total forecast	738	129	867	100%

This result gives us a clear indication that the model performs quite well and provides precise predictions of deal outcome. Among deals being predicted as successful the model predicts 95% of the deals correctly. When it comes to failed deals the model predicted 72 out of 129 failed deals, this amount to hit rate of 56%. Overall the model gets a hit rate of impressively 89.04%. Compared to the merger arbitrage market, which possess a success rate of 85.12% this is a increased hit rate of about 4%. Such a hit rate is in favour of great forecasting power and chosen variables working as good proxies for deal success.

Albeit great forecasting power, the model incorrectly predicts 6.5% of the deals to fail. Abandoning such deals is of similar art as type 1 error. A inccorrect rejection of a successful deal entails the risk of forsaking deals with great return. We evaluate this risk by calculating the return of the predicted portfolio and compare the return to the return on a CAMA portfolio for the same period. These results are visualised on the next page in Figure (10). Keep in mind that each tick on the x-axis represent mid year.

Figure (10) indicates that the predicted model consistently outperforms the CAMA portfolio over the whole period. In 2015 the merger arbitrage market in general performs bad. The main source of the sharp decline seen in April 2015 are few deals failing and thus generating some abnormal losses. One of the largest positions incurs a one day negative return of over 20%. This illustrates the hefty risk involved in merger arbitrage. Conceivably, the most favorable feature of the model are the ability to spot these hazardous deals. In the end these deals plays a major part in the total return on both CAMA and the predicted portfolio. At the end 2015 the predicted portfolio has achieved a return which is about 25% greater than CAMA. This indicates that the model does a great job at identifying the outcome of risky deals which in the end has an massive impact on the total return.

In Table (19) below we have summarized the monthly data for the CAMA and the predicted portfolio. In the end the predicted portfolio achieves a statistically significant greater return as well as lower standard deviation compared with the CAMA portfolio.

Table 19: **Portfolio statistics and T-test on difference in monthly returns: 2013-2015**

	CAMA	Predicted
Return	0.64%	1.09%
STD	2.02%	1.61%
T-score	2.79	
P-value	0.0065	

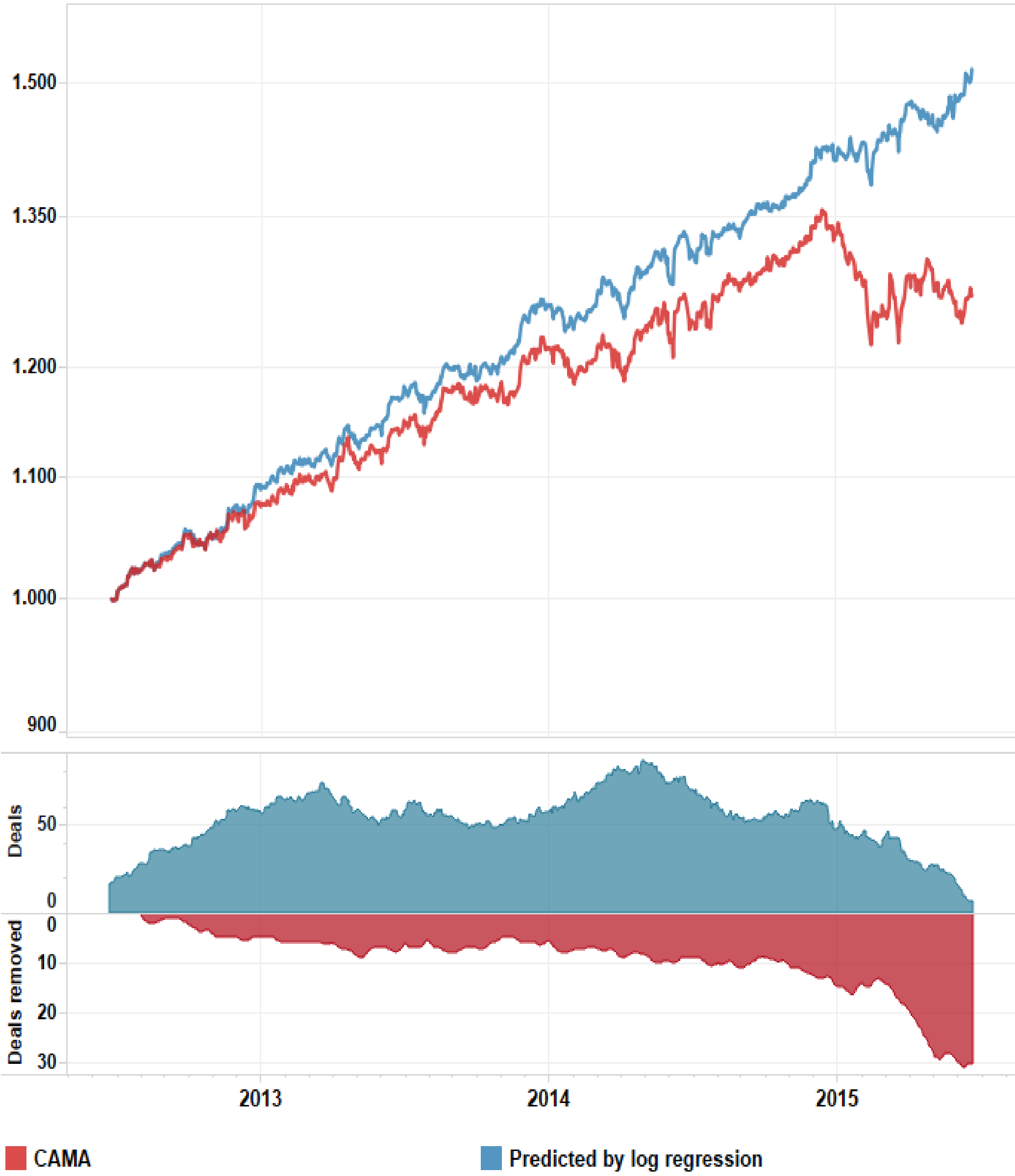

Figure 10: **Predicted vs CAMA log graph:**
Log scale plot of predicted total return index and CAMA total return index from 2013-2015. Bottom graph shows the total amount of deals the prediction model are invested in, and total amount of deals excluded, at each point in time

In the bottom graphs of fig (10) we have included total deals invested by the predicted model and number of deals excluded. This number is almost above 50 for the whole period. If we assume non perfect correlation between deal returns this means that the portfolio is in fact considerably diversified. Relating to the large discrepancy in the total return on these portfolios, it is interesting to look at number of deals excluded and included. In the bottom graph, we have plotted number of excluded deals by the prediction model at each point in time. Number of excluded deals are stable and around 10 over the whole period, however, towards the end of 2015 there is a increase in deals excluded with an all time high of 30 excluded deals. In our sample, a lot of deals incurs large losses in this period, however the predicted portfolio does not invest in these. As a result, the predicted portfolio does not suffer from the large losses in this period.

Table 20: **Prediction model stress test of forecast: 2013-2015**
This table provides the results from the stress test for different cut off values and it's given hit rate. Successful deals are number of successful deals predicted correctly, and failed deals are number of failed deals predicted correctly for each cut off point.

Cut off	0.5	0.6	0.7	0.8	0.9
Successful deals	95%	89%	87%	80%	46%
Failed deals	56%	58%	65%	67%	78%
Total deals	89%	85%	84%	78%	50%

Table (20) above is a summary of a cut off stress test performed on the batch based training set. A cut off of 0.5 resulted in investing in 95% of the successful deals and excluding 56% of the failed deals. The total amount of correct forecast declines steady along with increased certainty. At the 90% cut off the hit rate decreases drastically. The model predicts only 42% of the successful deals. It invests in only 60% of the deals and the repercussion leads to correctly exclude 78% of the deals. At this amount of exclusion it is natural to get a high hit rate among the unsuccessful deals. Additionally, it invest in only 46% of the successful deals, which is dramatically lower than the 0.8 cut off. This must imply that the model can model the probability of deal success with high certainty up to about 80%, but well above this level it is not that effective. It excludes a lot of successful deals and the improved hit rate in unsuccessful deals is a a pure mathematical property and thus an illusion.

Table 21: **Prediction model stress test of forecast: 2013-2015**
Returns are annualised log returns. Standard deviation are annualised daily standard deviation. AVG. Deals refers to average deals in portfolio at each day, correspondingly AVG. Deals Removed refers to average number of excluded deal in the portfolio at each day. Each columns represent its given cut off value

	CAMA	*PREDICTED*				
Cut off		0.5	0.6	0.7	0.8	0.9
Return	8%	13.9%	12.4%	11.8%	11.5%	8.4%
Std	7%	5.5%	5.9%	6.3%	6.5%	7.8%
Deals removed		15%	17%	20%	27%	59%
AVG. Deals	63	53	51	50	45	24
AVG. Deals Removed		9	11	13	17	39

There is obviously a possibility that the returns among the different cut off levels variate, and since we are not only interested in the cut off that gives the greatest forecasting power, but to evaluate which cut off that generates the greatest risk return payoff we have performed such a test. In table (21) above we have summarized the results from a cut off return stress test. In terms of risk and return the 0.5 cut off seems inevitable best. It generates a return of 13.9% and a standard deviation of 5.6%, which is well above CAMA's performance. Same as forecasting power, the performance of the predicted portfolio steadily declines towards the 0.9% cut off. At this cut off level, both the return and standard deviation are less attractive. Intuitively, we can argue that a cut off of 90% demands a great deal of certainty from the model, which means that a lot of deals with greater risk return are excluded, thus lower return. Unlike return, there is a positive relationship between cut off value and standard deviation. It can be argued that the meager amount of deals bought leads to increased standard deviation due to greater exposure to the risk in each deal as well as a less diversified portfolio. Convincingly and to our own serendipity it seems to be evident that the best cut off is 0.5 in this sample.

5.3.3 Robustness

We are also interested in conducting the robustness of the logistic regression model. The error margin of forecasts which we calculated above indicates a robust model. However, a more precise approach will be to evaluate the consistency of our results over different data samples. We have done this by doing a series of logistic regression on different sub samples of the data. The results from these regressions are presented in Table (22) below.

To capture the effect of the financial crisis we have divided our data set between the period before the outbreak of the financial crisis and a period including the financial crisis and it's aftermath. The first regression in Table (22) present a regression based on the pre financial crisis data. When evaluating this regression both percent sought and owned are insignificant. This is also the case for target ROC-WACC ratio and same sub industry. Comparing this to the subsequent period the results changes. Now percent sought, percent owned and target ROC-WACC ratio becomes significant. During the financial crisis we saw an increased rate of failed deals, which in turn increase the data on failed deals in the model. This could lead to increased significance of the parameter estimate. It could also be argued that during the financial crisis there was an increased focus on profitability, which could lead to a greater loading on these factor.

It is not clear to us what leads percent sought and percent owned to become significant when comparing these two regression. Further, if we look at percent sought and percent owned in the last two regression, they do not become significant at a 95% level, when we exclude each other. Additionally, when we evaluated multicolinearity these two variables had the largest VIF and also obtained a correlation of about -0.87. This is in favour of these factor not withstanding a robustness test.

To summarize the results, we conclude that the most significant parameter estimates in Table (15) withstand our robustness tests. The parameters which are significant on a 99.9% level stay significant on the same level trough the four different regressions.

Table 22: **Robustness regressions: 2001-2015**
This table provides the results for different logistic regression. The first and second model report the results from regression where we divided our data set in half, based on calendar time. Hence the first regression relates to the 50% first data points, and the second to the other half. In the two last regression we have excluded the varibles most likely to be affected by multicollinearity. Those regression are based on full sample from 2001-2016

	< 50%	> 50%	Excluded Percent sought	Excluded Percent Owned
Constant	−1.606**	0.646	−1.872***	−1.808***
	(0.793)	(0.988)	(0.318)	(0.345)
Ann. Deal Value	0.088**	0.101**	0.085***	0.089***
	(0.044)	(0.042)	(0.033)	(0.030)
Nature of bid	2.841***	2.135***	2.625***	2.659***
	(0.227)	(0.533)	(0.204)	(0.201)
Relative Acq to Tar	0.175***	0.215***	0.167***	0.195***
	(0.044)	(0.050)	(0.034)	(0.032)
Payment type	−0.074	−0.188	−0.052	−0.127
	(0.121)	(0.120)	(0.092)	(0.084)
Has Cont. Payment	−0.111	0.250	0.702	0.045
	(1.112)	(0.783)	(1.048)	(0.642)
Net Debt Tar	−0.00001	−0.0001	−0.00000	−0.00002
	(0.00002)	(0.00004)	(0.00002)	(0.00002)
Percent Owned	−0.003	−0.029***	−0.002	
	(0.008)	(0.009)	(0.003)	
Percent Sought	−0.004	−0.021***		−0.016*
	(0.007)	(0.008)		(0.006)
Tar Instit Owner	−0.534***	−0.479***	−0.538***	−0.484***
	(0.086)	(0.040)	(0.046)	(0.034)
Tar Roc Wacc Ratio	−0.002	0.004***	0.004***	0.004***
	(0.003)	(0.001)	(0.002)	(0.001)
Debt to equity	−0.069**	−0.039	−0.051**	−0.051**
	(0.033)	(0.032)	(0.024)	(0.022)
Price run up	0.011***	0.015***	0.010***	0.012***
	(0.004)	(0.004)	(0.003)	(0.003)
Same Sector	1.118***	0.481***	0.848***	0.769***
	(0.195)	(0.171)	(0.143)	(0.127))
Same Sub group	−0.321	−0.144	−0.346**	−0.234*
	(0.209)	(0.187)	(0.153)	(0.137)
Bid Premium	−0.0004	−0.002	0.001	−0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Observations	1,933	1,935	3,121	3,867

Note: *p<0.1; **p<0.05; ***p<0.01

5.3.4 Online Machine Learning

As described in section (4.3) we are interested in testing the abnormal returns based on our continuously updated trading algorithm (CUPA). Table (23) below summarise the forecast made by CUPA. We can see that results concur with the results from the batch learning model. For the entire period CUPA predicted almost 40% of the failed deals accurately and 97% of the successful deals accurately. This yields an 87.27% in total accuracy in forecasts. By comparison the merger arbitrage market in the same period had a success rate of 84.07%. This means that the model would have increased the hit ratio with about 3.2% points.

Table 23: **Summary of the predicted outcomes based on PAMA: 2002-2015**

	Successful deals	Failed deals	Total deals	%
Correct forecast	2774	209	2983	87.27%
Incorrect forecast	337	98	435	12.73%
Total forecast	3111	307	3418	

This table present the correct forecast in % of total successful and failed deals

	Successful deals	Failed deals
Correct forecast	97%	38%
Failed Forecast	3%	62%

Market Outcome

Successful deals market	2872
Failed deals market	546
Success rate	84.07%

If we look at Figure (11) we clearly see that PAMA consistently outperformed the market in terms of investing in successful deals. The only period it does not do so is a major period during the financial crisis and two minor periods in 2007 and 2012.

Figure 11: **PAMA and merger arbitrage markets success rate:** The uppermost graph plots a six months lagged moving average of deals success-rate given the algorithm and the moving average success rate of deals in the merger arbitrage market. The bottom graph visualizes the discrepancy between those two.

One reason for the poor performance during the financial crisis may be linked to a combination of structural changes to the merger environment and an unprepared algorithm. In such a crisis as the one we saw in 2008 there is a distortion in pricing and valuation, liquidity and financing becomes scare and consequently there's a jump in the number of failed deals. Such an event will probably distort predicting power among the variables. As the crisis moves along, the model learns and start to predict which deals that will fail. In fact, the all time high discrepancy between market hit rate and algorithm hit rate occurs shortly after the financial crisis. Also in favour of constantly improved algorithm is the increased average hit ratio in the last three years, which in fact is 3% higher than the first three years. This is a natural consequence of a larger training-set. However, this does not mean that the model outperform the market. To evaluate if the algorithm increased returns, we simulate a portfolio based on the prediction model and then calculated the return on such a portfolio.

In Table (24) below we have summarized the characteristics of the deals in the full sample, the deals predicted by the algorithm and the deals excluded by the algorithm. We can see that the algorithm bought almost every friendly deal. Only 0.48% of the deals were hostile, which means that over 86% percent of the hostile deals are excluded by the algorithm. This is not surprising. If we look at our batch based model a friendly deal was the most significant predictor of success.

There is also a large discrepancy in institutional holdings between included deals and excluded deals. The algorithm excludes almost every deal with large institutional ownership. This results is consistent with what we have argued before, regarding large institutional owners influence on the board and their capability to deteriorate a deal on their own. Another interesting finding corroborating with the batch based model and previous research is the large price run up seen in included deals, and the correspondingly low price run up in the deals excluded.

As expected there is also large discrepancy between the algorithm portfolio and the excluded portfolio when we look at average same sector deals. In the algorithm portfolio about 65% of the deals are from the same sector whereas only 46% for the excluded deals. This confirms the results from the batch learning and previous research.

Table 24:
Results from Online Machine Learning Technique: 2002-2016
Each column present average values of the factors in their corresponding portfolio

	Full Sample	Included	Excluded
Announced deal value(Mill)	1985.48	1976.28	2086.98
Friendly	96.14%	99.52%	61.89%
Hostile	3.86%	0.48%	38.11%
Size of Acq to Target	137.91	139.91	134.35
Cash	70.01%	69.77%	73.49%
Stock	18.21%	18.61%	13.78%
Cash and Stock	11.85%	11.61%	12.72%
Has Contingency Payment	0.70%	0.71%	0.65%
Percent Owned	4.70%	4.33%	8.42%
Percent Sought	94.11%	94.73%	87.88%
Deal Status	84.07%	87.27%	32.24%
Price run up	20.55%	21.48%	11.18%
Same Sector	63.60%	65.35%	45.93%
Same Subgroup	30.78%	31.05%	28.01%
Different Sector	36.40%	34.65%	51.07%
Different Subgroup	69.22%	68.95%	71.99%
Bid Premium	33.70%	33.84%	32.26%
Institutional holdings in target (%)	5.99%	1.36%	52.96%
N	3418	3111	307

In earlier studies there is evidence in favour of a negative relationship between percent sought and the probability of deal success. Our results are somewhat counter intuitive in this matter. We see that average percent sought is higher in the algorithm portfolio compared to both the full sample and the excluded sample. By looking at the significance level of this variable in the batch based regression we reason this to be due to other variables being more significant. If we look at the percent owned, the average ownership pre-announcement are much larger among the excluded deal. This corroborate the findings in the batch based model. The argument that initial holding would increase the probability of deal success trough acquirers influence on shareholders, management and board is not valid in neither our results or the most recent studies.

One of the most surprising discoveries in Table (24) is probably the acquirer to target ratio. In the batch based model, this ratio came out as one of the most significant parameters. However, if we look at the average ratios among the invested and the excluded deals, the average ratio is just a tad higher in the invested deals. This pattern could not be generalized to a larger pattern.

In Figure (12) on the next page we have plotted the total log return for the whole period from 2002 until 2015. From the very start until the start of the financial crisis the CAMA portfolio outperforms the PAMA, it does so despite the fact that PAMA is removing a whole lot of deals and on average holds a portfolio with a higher success rate. This confirms our thoughts related to buying deals with lower return. The results does also confirm what we discussed above about the algorithm learning a lot about deal failures during the financial crisis. After the crisis the model consistently outperforms the CAMA portfolio from mid 2008 until mid 2015. There is also, as in the batch based model, a large loss to the CAMA portfolio around mid 2014, and as in the batch based model, the predicted portfolio does not suffer from this loss.

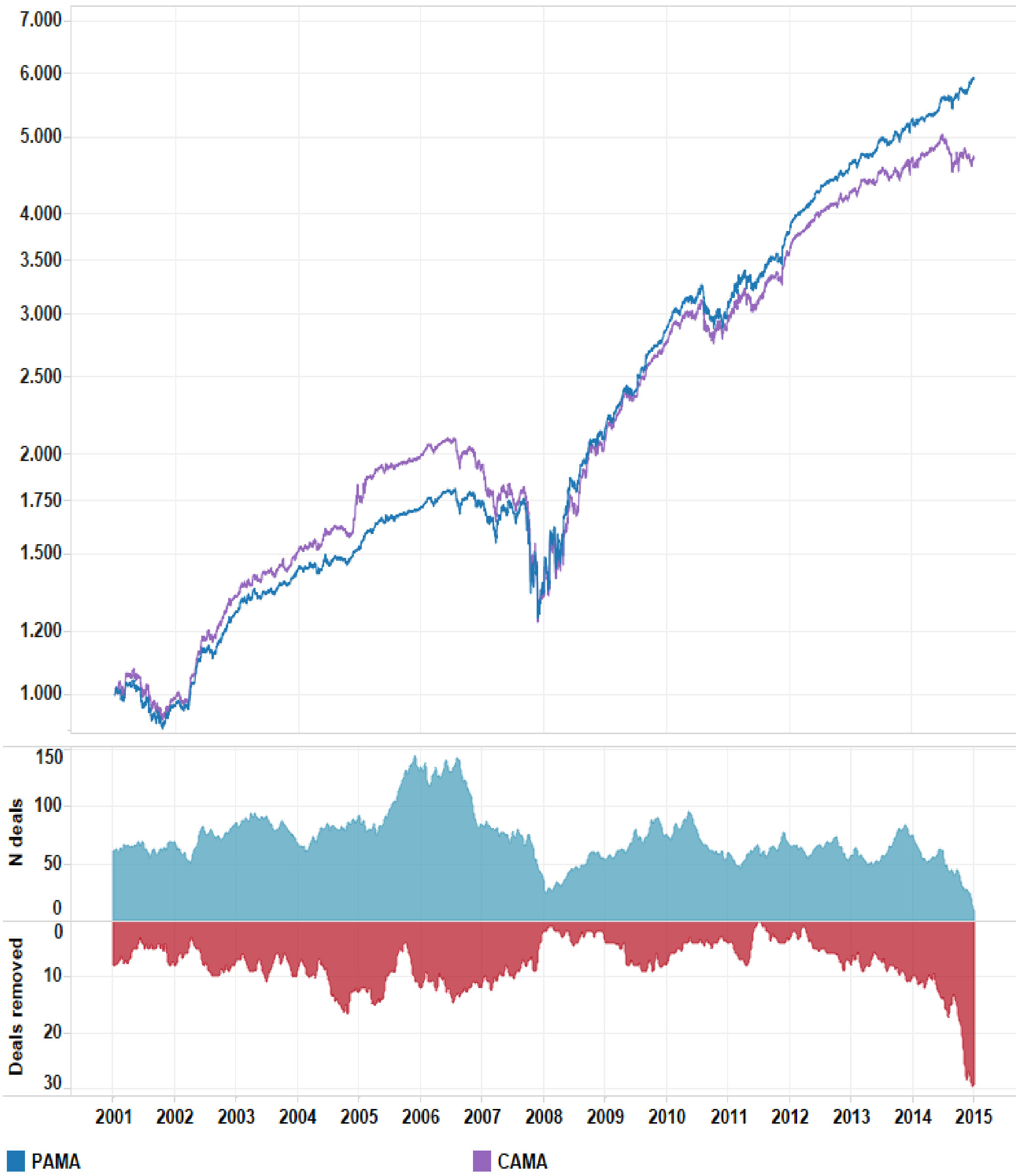

Figure 12: **PAMA vs CAMA log graph:**
Log scale plot of the algorithm portfolio total return index and CAMA total return index from 2002-2015. Bottom graph shows the total amount of deals excluded by the prediction algorithm as well as the number of deals in the the algorithm portfolio at each point in time.

Table 25: **Improved Portfolio: 2002-2015**
This table summarise the development of the CAMA portfolio and the CUPA based PAMA portfolio.

	CAMA	PAMA	Diff	Diff %
Portfolio value [8]	4032	5935	1902	47.17
Annual Return %	9.41	12.38	2.69	27.72
Annual σ %	12.76	10.80	-1.96	-18.14
Sharpe	0.76	1.15		

T-test on difference in monthly returns

T-score	2.07
P-value	0.038

If we look at the descriptive statistics the algorithm portfolio has generated an annual return of 12.38%, which is 2.69% percentage points larger than CAMA and significant on a 0.05 level. An attractive feature about the algorithm is the rejection of deals with extreme negative returns. In the end this leads to a much less volatile return. By means of volatility it obtains a 2.96% points lower standard deviation compared to CAMA. Consequently the Sharpe ratio of the algorithm portfolio ends at 1.07 which is much higher than CAMA that ends at 0.69.

To assess some of the short term risk to a merger arbitrage strategy we can study the short term returns. Daily maximum and minimum returns to both portfolios are almost identical. With one day maximums of about 16%, and one day minimum of -17% and -20% respectively. If we look at the the largest five day accumulated losses CAMA accumulates a bit larger losses than PAMA. The maximum five day accumulated losses for CAMA and PAMA are -21% and -19%, respectively.

Table 26: **PAMA Portfolio Regression: 2002-2015**
This table provides output of the (CAPM), (FF3) and (FF5) OLS regressions on the CUPA based portfolio, as described in Section (4.1). The regressions are based on monthly returns

	Dependent variable:					
	EWMA			**PAMA**		
	CAPM	FF3	FF5	CAPM	FF3	FF5
α	0.007***	0.007***	0.007***	0.010***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
β_{Mkt}	0.415***	0.369***	0.355***	0.352***	0.317***	0.290***
	(0.046)	(0.048)	(0.057)	(0.044)	(0.046)	(0.054)
β_{SMB}		0.249***	0.252***		0.227***	0.220**
		(0.087)	(0.091)		(0.083)	(0.086)
β_{HML}		−0.047	0.005		−0.114	−0.046
		(0.087)	(0.098)		(0.083)	(0.094)
β_{RMW}			−0.046			−0.101
			(0.126)			(0.120)
β_{CMA}			−0.181			−0.205
			(0.145)			(0.137)
Observations	168	168	168	168	168	168
R^2	0.329	0.361	0.367	0.280	0.314	0.324
Adjusted R^2	0.325	0.349	0.348	0.276	0.301	0.304
Note:						*p<0.1; **p<0.05; ***p<0.01

By means of the regression presented in Table (26) above there is a clear indication that the CUPA based portfolio outperforms the CAMA portfolio. By comparison, the first thing to notice is the enhanced alpha. On a yearly basis the alpha is about 3.6% larger in PAMA compared to CAMA. In addition PAMA has a significantly lower loading on the market than CAMA. CUPA removes about 10% of the deals, resulting in a 16% decrease in the average market beta compared to CAMA. The removed deals seemed to carry a disproportional part of the market risk. Removing high beta deals should in theory also decrease the return if CAPM holds. This is clearly not the case. An increase in returns, combined with a decrease in market beta yields a double positive effect on alpha. The only additional factor the CUPA portfolio loads significantly on is the SMB factor. If we compare the SMB factors in both CAMA and PAMA we see that they are not significantly different from each other, this suggest that the CUPA based portfolio does not invest more heavily in small companies than CAMA.

5.4 Transaction Cost

In Table (27) the annualized excess returns for the PAMA and CAMA-portfolio has been calculated for different assumed trading costs. We see that trading cost definitely have an impact on the annual return. This is not strange as the strategy is rebalanced fairly often. With that being said, we have significant abnormal returns even with the most conservative trading cost in this test.

Table 27: **Trading Cost - Stress Test: 2002-2015**

Trading Cost (bps)	5	10	15	20	25
PAMA	12.8%	12.4%	12.0%	11.5%	11.1%
CAMA	9.9%	9.4%	9.0%	8.5%	8.0%
Diff	2.9%	3.0%	3.0%	3.0%	3.1%

Table 28: **Shorting Cost - Stress Test: 2002-2015**

Shorting Cost (bps)	50	100	150	200	250
PAMA	12.6%	12.4%	12.3%	12.1%	12.0%
CAMA	9.6%	9.4%	9.3%	9.1%	8.9%
Diff	3.0%	3.0%	3.0%	3.0%	3.0%

Table (28) shows the annualized excess return for the PAMA and CAMA-portfolio with different assumed costs of shorting. We can see that changes in the shorting costs does not affect the return a lot. This relationship will depend on the number of stock and cash & stock deals in our portfolio as this dictates the amount of shorting needed. The improvement in return is also fairly stable. This suggests that our PAMA does not involve a lot more shorting than CAMA.

6 Conclusion

After evaluating US data in the period 1996 to 2015 we conclude that the merger arbitrage strategy historically contained significant market risk with a market beta between 0.45 to 0.49 depending on model choice. As we could not observe any significant non-linearity in this risk relationship with the market, we conclude that the segmented market risk pattern observed by Mitchell & Pulvino (2001) is not valid for a post millennium US merger arbitrage portfolio. Based on this we consider linear asset pricing models adequate for calculating abnormal returns.

Our CAMA portfolio produced annual excess log returns of 12.0% from 1996 to 2015. This number is in excess of both the risk free rate and transaction cost. The portfolio had a yearly standard deviation of 14.0%. In comparison the market had an annual excess log return of 5.5% and a yearly standard deviation of 16.0% for the same period. This corresponds to Sharpe ratios of 0.85 and 0.34 for the CAMA portfolio and the market respectively. Applying CAPM, FF3 and FF5 yields annual abnormal returns between 8.0% and 9.4%. These alphas are significantly greater than zero on a 99% confidence level. We conclude that the strategy is superior both in terms of Sharpe ratio and alpha. Due to the ambiguous results from studies for earlier time periods, we cannot confidently say if merger arbitrage profitability has changed over the last years.

By estimating a logistic regression we have investigated the predictability of 16 deal specific factors on deal outcome on merger data from 2001 to 2012. Significant predictors include announced deal value, nature of bid, relative market capitalization, percent owned, percent sought, target institutional owners, target ROC to WACC ratio, same industry sector and same sub industry. All of these factors are well documented in various studies, except for target institutional owners.

Due to lack of deal spread data, we cannot observe directly if this predictability is priced in. We therefore investigate if an out of sample portfolio based on these predictions can outperform the CAMA portfolio for the same period. This portfolio runs from 2013 to 2015. We invest in every deal with a predicted probability greater than 50%. This leaves us investing in 85% of the available deals. The predicted portfolio yields an annual excess log return of 13.0% and a yearly standard deviation of 5.6%, by comparison CAMA yields a return of 7.7% and standard deviation of 7.0%. The return of the predicted portfolio are greater than that of CAMA on a 99% confidence level.

Finally, we test the performance of a merger arbitrage portfolio based on a continuously updated prediction algorithm. The algorithm uses all information in prior completed deals to predict the deal outcome. The PAMA portfolio runs from 2002 to 2015 and yields an annual log excess return of 12.38% and a yearly standard deviation of 10.8%. For comparison, CAMA yielded a return of 9.41% and a standard deviation of 12.8%. This corresponds to Sharp ratios of 1.15 and 0.76 for PAMA and CAMA respectively. The PAMA return is greater than CAMA on a 95% confidence level. Applying CAPM, FF3 and FF5 yields alphas from 10.8% to 12.0% and betas from 0.29 to 0.35. The PAMA portfolio is superior to the CAMA portfolio both in terms of Sharpe ratio and abnormal returns, hence we conclude that factor predictability is not sufficiently priced into market prices.

Overall, we conclude that several factors can predict deal success in a matter not currently priced in by equity market. This leaves room for arbitrageurs to further enhance an already exceptional strategy with prediction models and algorithms.

7 Limitations & Future Research

The biggest unanswered question in our opinion is the effect of equally weighted returns, contra, the more standard, value weighted returns. To what extent this increases transaction costs and reduces the capacity of the strategy is hard to estimate. Getting more accurate data for market values is thus recommended as a point of emphasis for future research.

There is also unanswered questions related to the source of abnormal returns documented in this paper. This is not something we have emphasized particularly. This is of course a challenging topic to investigate. However we think that looking for more complex relationships can prove worth while. This could include adding more factors to the models, or evaluating portfolio data from merger arbitrage portfolios.

Additionally we think that future research should include other markets. An increase in number of deals could increase the capacity of the strategy. Further it would be interesting to include other markets to evaluate the diversification effects, if any. It would also be interesting to investigate if predictors are consistent across borders.

Regarding the prediction models there is certainly more sophisticated methods available. A potential approach would be to apply unsupervised machine learning in neural networks. This approach could exploit the available data in a much greater fashion. It would also be of considerable interest to investigate continues variables and how they affect the probability of deal success. This could potentially be variables such as time since announcement, development in deal spread and so on.

The merger arbitrage strategy suffers from some quite large accumulated losses. In combination with leverage this could potentially have a major impact on both returns and perseverance of investors. Considering this, the effects of risk management such as draw-down control would naturally be of interest to evaluate.

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9 Appendix

Table 29: CorrelationMatrix

Ann. deal value	1.00	-0.01	0.20	-0.15	-0.02	0.29	-0.18	0.18	0.00	0.03	0.22	-0.11	0.09	0.08	-0.14
Nature of bid	-0.01	1.00	-0.04	-0.02	0.00	0.00	-0.06	0.06	-0.07	0.00	-0.01	0.05	0.04	0.00	0.01
Relative Acq to Tar	0.20	-0.04	1.00	-0.28	-0.02	0.09	0.05	-0.05	0.04	0.03	0.07	-0.21	0.06	0.18	-0.16
Payment Type	-0.15	-0.02	-0.28	1.00	0.00	-0.09	0.08	-0.11	0.05	0.00	-0.09	0.11	-0.28	-0.27	0.06
Has Cont. Payment	-0.02	0.00	-0.02	0.00	1.00	-0.01	-0.01	0.01	0.00	0.00	0.01	0.00	0.02	-0.02	0.01
Net Debt Tar	0.29	0.00	0.09	-0.09	-0.01	1.00	-0.03	0.02	0.01	-0.01	0.17	-0.05	0.04	0.02	-0.05
Percent Owned	-0.18	-0.06	0.05	0.08	-0.01	-0.03	1.00	-0.89	-0.02	0.01	0.03	-0.07	-0.07	-0.04	-0.05
Percent Sought	0.18	0.06	-0.05	-0.11	0.01	0.02	-0.89	1.00	-0.05	0.00	-0.04	0.09	0.10	0.06	0.05
Target Instit Owner	0.00	-0.07	0.04	0.05	0.00	0.01	-0.02	-0.05	1.00	-0.02	0.01	-0.01	-0.07	-0.04	0.01
Target Roc Wacc	0.03	0.00	0.03	0.00	0.00	-0.01	0.01	0.00	-0.02	1.00	-0.01	-0.01	0.03	0.02	-0.03
Debt to equity	0.22	-0.01	0.07	-0.09	0.01	0.17	0.03	-0.04	0.01	-0.01	1.00	-0.06	0.11	0.09	-0.07
Price Run up	-0.11	0.05	-0.21	0.11	0.00	-0.05	-0.07	0.09	-0.01	-0.01	-0.06	1.00	0.02	-0.04	0.62
Same sector	0.09	0.04	0.06	-0.28	0.02	0.04	-0.07	0.10	-0.07	0.03	0.11	0.02	1.00	0.50	0.00
Same sub group	0.08	0.00	0.18	-0.27	-0.02	0.02	-0.04	0.06	-0.04	0.02	0.09	-0.04	0.50	1.00	-0.02
Bid Premium	-0.14	0.01	-0.16	0.06	0.01	-0.05	-0.05	0.05	0.01	-0.03	-0.07	0.62	0.00	-0.02	1.00

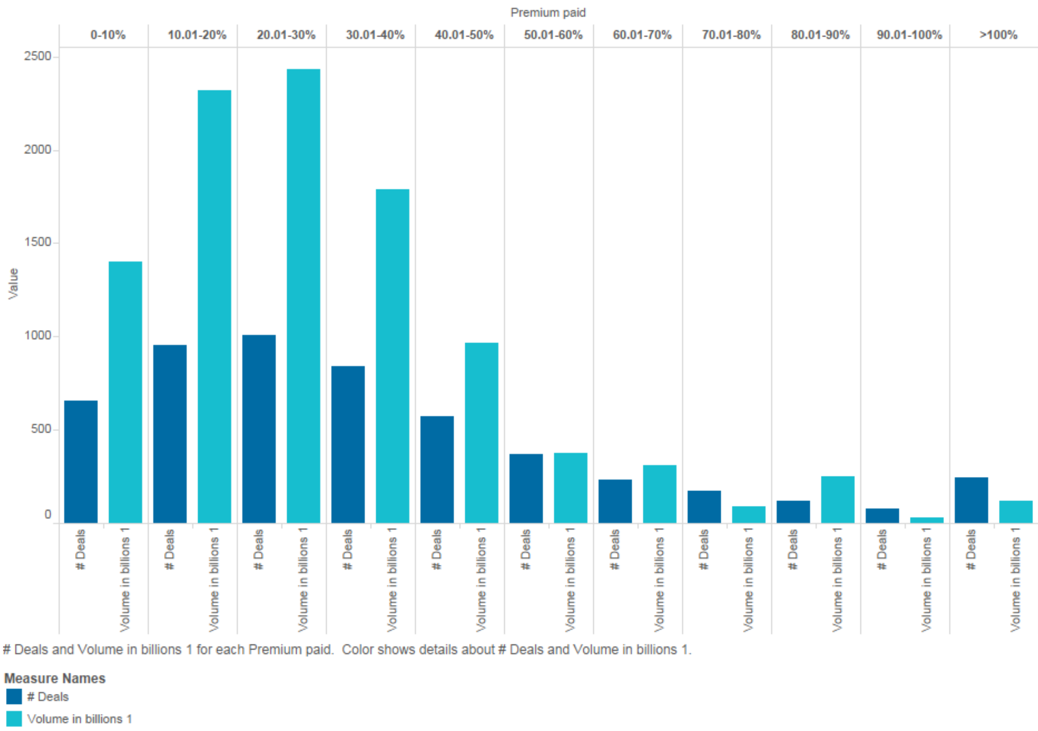

Figure 13: Summary of premium paids

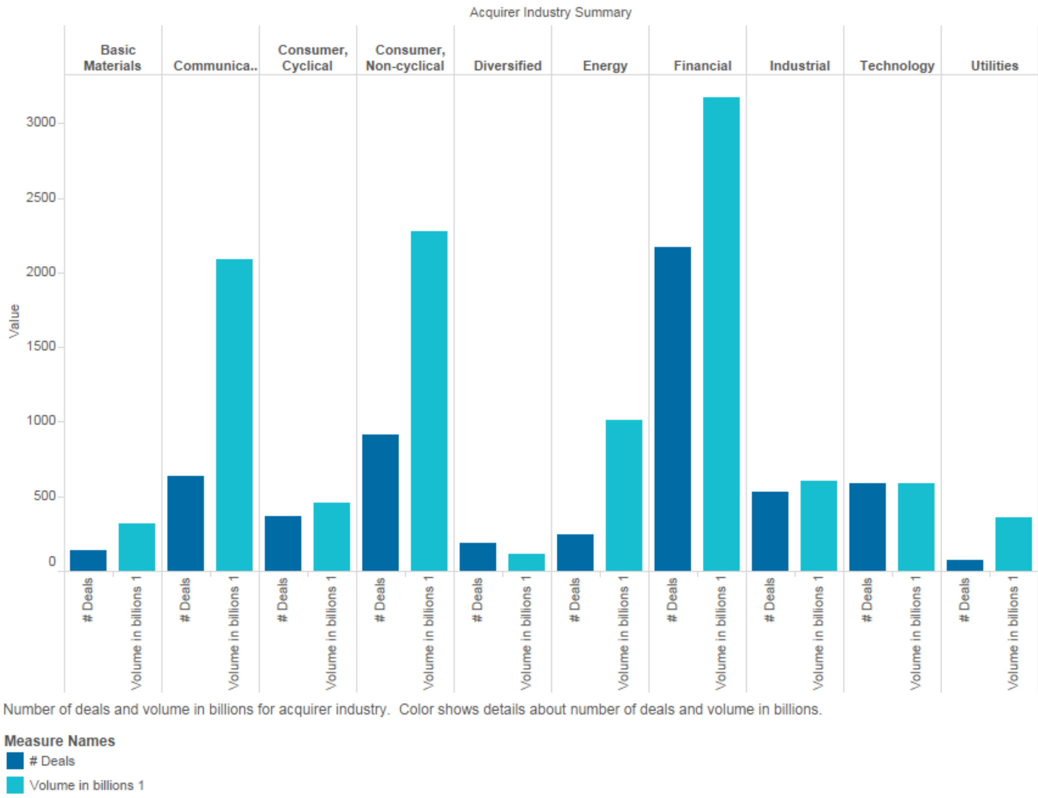

Figure 14: Acq. Industry Summary

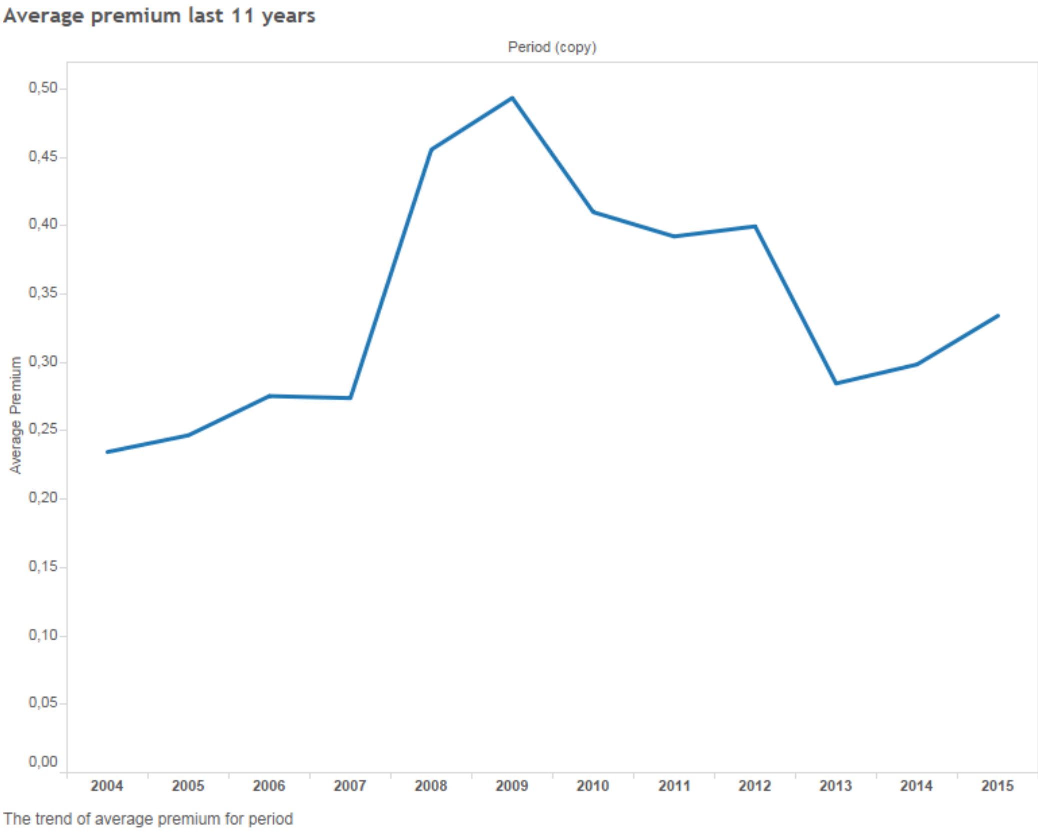

Figure 15: Average premium paid