# Market efficiency and cumulative abnormal returns in M&A

Radboud Universiteit

Master's Thesis Economics

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| Date: | 17-08-2021 |

# Abstract

This study examines the relationship between market efficiency and cumulative abnormal returns around announcement dates of M&A deals. Previous research in M&A found many determinants of M&A success, however the relation with market efficiency has never been researched. This study obtains M&A data of six analyzed markets covering a period from 2002 to 2020. An event study is conducted to calculate the cumulative abnormal returns for 11,123 M&A deals. To determine the value for market efficiency, the model of Delgado-Bonal (2019) is used. Fixed effects regressions and quantile regressions are applied to test the relationship. The results show a significant negative effect between market efficiency and cumulative abnormal returns during the [1, 5] event window. This implies that more efficient market result in lower cumulative abnormal returns after the announcement date of an M&A deal. However, the quantile regressions show significant positive effects for the event windows [-5, 5] and [1, 5].

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# 1. Introduction

Mergers and acquisitions (M&A) have been the favorite growth strategy for companies around the world and will be in the future (Das & Kapil, 2012). In fact, the majority of foreign direct investments occurs through M&A (Stiebale & Reize, 2011). In 2020, a total of 45,652 M&A deals were completed worldwide with a total value of over $2,835 billion (IMAA, 2021). M&A deals can potentially benefit for shareholders by improving shareholders' value due to, among others, increasing market power, economies of scale and reducing costs. Although the goal of an acquisition is to benefit from it, in practice the majority of M&A deals tend to fail, where existing research find failure rates between 45% and 82% (Angwin, 2007).

Since the total value of the M&A market is extremely high, a lot of research has been conducted to understand the effects of M&A and what the determinants of M&A success are. However, one possible factor that could influence M&A deals, which has not been researched in existing empirical research, is market efficiency. In Finance, efficient capital markets are often used as a starting theory. The theory behind this is called the Efficiency Market Hypothesis (EMH). Fama (1970) defined markets as efficient when the prices "fully reflect" the available information. Therefore, a distinction between three forms of market efficiency is created – weak, semi-strong, and strong. In the weak form prices should incorporate all the existing historical financial information. Therefore, the MTH implies that prices will follow a random walk, which means that future prices are not predictable, and investors cannot obtain abnormal profits. The semi-strong form assumes that prices reflect all information on the market, so all historical information. Next to that, prices should change rapidly, without biases, to incorporate new public information. The strong form assumes that prices incorporate all available information, which means that private information is incorporated in the prices as well.

Despite the fact that studies conducted research on the determinants of M&A success extensively, there remains a lot unknown in this field. Moeller et al. (2004) find a significant negative effect between bidder size and cumulative abnormal returns around the announcement date. Next to that, their research find that higher deal size increases bidder announcement returns, which is consistent with the research of Asquith et al. (1983). Servaes (1991) find a significant negative effect between equity paid acquisitions and abnormal returns. However, Chang (1998) and Fuller et al. (2002) find that deals that are paid with stocks are less negative or even positive when the target is privately held. Additionally, many other deal and acquirer characteristics have been research, including Tobin's *q*, leverage, free cash flow, antitakeover provisions, operating industries, and many more (Lang et al., 1991; Sarvaes, 1991; Stulz, 1990; Morck et al., 1990; Loughran & Ritter, 2004).

Many studies were elaborated to test the different types of Efficient Market Hypothesis and to find the determinants of M&A success. However, interestingly, there is no research on the effect that efficient or inefficient markets might have on M&A deals. Therefore, this research focusses on the relationship between market efficiency and M&A success. To capture this relation, the following research question is formulated:

*"What is the effect of market efficiency on the cumulative abnormal returns around announcement dates for M&A deals?"*

In this research, M&A success is measured by cumulative abnormal returns. The cumulative abnormal returns are calculated using an event study with an event window starting 5 days prior to the announcement date of the M&A deal and ends 5 days after. The estimation window is set as [-210, -10] days. In addition, various other event windows are used to be able to test all hypotheses. To measure market efficiency, the model of Delgado-Bonal (2019) is used. This model uses approximate entropy (ApEn) to find whether there are existing patterns in data series. Their study develops the ApEn by defining a measure to be able to compare time series using a maximum entropy approach. This measure indicates a total predictability of the market when the value of the ratio is zero, and a value of one or greater than one implies randomness.

To be able to conduct this research, M&A deal information is collected from Zephyr for a time period of 2002 until 2020. In total, 11,123 M&A deals are identified executed by 1,298 firms where the acquirer is listed in either IBEX 35 (Spain), FTSE 100 (UK), NASDAQ (USA), S&P 500 (USA), Hang Seng (Hong Kong), or Nikkei 225 (Japan). Additionally, stock price data is obtained from Thomson Reuters Eikon.

This research contributes to the existing research by conducting a research that investigates a potential relationship between M&A and market efficiency, which has not been researched before. Therefore, it helps to fill a gap in existing literature. Additionally, it contributes to a further use of the Delgado-Bonal (2019) model to measure market efficiency. Since many M&A deals turn out to be a failure, it is important to understand all factors that affect M&A success. By knowing the relation between market efficiency and cumulative abnormal returns, firms can prepare themselves and assess whether an acquisition in an efficient or inefficient market might payoff. Optimally, the knowledge of this relation could result in more successful mergers and acquisitions. Therefore, this research is relevant because it adds a new piece to the puzzle.

The findings of this paper show a significant negative relation between market efficiency and cumulative abnormal returns for an event window of [1, 5] with a fixed effects OLS regression. This implies that more efficient markets experience lower cumulative abnormal returns between the first and fifth day after the announcement date of the M&A deal. When a quantile regression is performed, partly to control for outliers, a significant positive relation between market efficiency and cumulative abnormal returns for the event windows [-5, 5] and [1, 5] are found.

The remainder of this paper is structured as follows. Section two presents an overview of the existing literature on the topic of M&A and market efficiency. Section three contains the hypotheses are formulated, which are tested in this research. Section four focuses on the data that is needed to perform the regressions. In section five the methodology will be further explained. The results of the paper are presented in section 6. Finally, section six concludes and discusses the limitations.

# 2. Literature review

In this chapter existing relevant literature on M&A and market efficiency is listed.

## 2.1 M&A

Mergers and acquisitions have become one of the most researched topics in finance. However, the findings on M&A research are very diverse and sometimes contradicting each other. There are two motives why companies merge or acquire other companies, which are disciplinary and non-disciplinary acquisitions (Morck et al. 1988). Manne (1965) and Palepu (1986) mention that shareholders will gain because of the disciplinary actions taken against managers who perform poorly, which is known as the agency theory.  On the other side, mergers and acquisitions can have some disadvantages too; it can hamper shareholder value, and synergies might be overestimated by the managers. As a result, companies need to pay too much for the target firm (Roll, 1986).

Disciplinary acquisitions are acquisitions where the acquirer can benefit from the acquisition by replacing an inefficient management with an effective management team. The gains from disciplinary acquisitions will be higher when the target firm has more agency problems. Non-disciplinary acquisitions try to gain synergies by acquiring profitable firms. Those synergies could result from increased market power, economies of scale, reduction in costs, new products, or other joint benefits. By combining the strengths of both companies, additional revenues can be realized, or costs could be reduced (Ross et al. 2009). Abnormal returns for non-disciplinary acquisitions are likely to be lower than for disciplinary acquisitions because the target firms' management is more efficient (Morck et al. 1988).

In the history of Finance, we see periods of large number of mergers, which are called merger waves. The causes of these merger waves are largely debated in existing literature. When merger waves are discussed, economists usually refer to five waves between 1890 to 2000. Rhodes-Kropf & Viswanathan (2004) show that during the periods where large amounts of mergers occur, many more mergers are paid by stocks instead of money. They argue that it is difficult to determine the real value of such an acquisition. They believe that even fully rational participants make mistakes. When a market is overvalued, targets are more likely to overvalue the offer of the acquirer. So, market overvaluation increases the chances that a merger occurs. Harford (2005) finds that shocks cause industry merger waves, which supports the neoclassical explanation of merger waves. For this, sufficient capital liquidity must be present to cause those merger waves.

Results of existing research show that merger and acquisitions earn abnormal returns around the announcement dates of M&A deals. Abnormal returns are defined as the excess return of a stock compared with the expected return. Bruner (2002) presents an overview of existing research related to abnormal returns. This research concluded that target firm shareholders enjoy significant positive returns for M&As. However, this is totally different for the acquirer, where the results are contradicting. The results of the acquirer firms show that 20 studies report negative returns for buyer firms' shareholders, and 24 studies report positive returns. Typically, the buyer is substantially larger than the target. Hence, a large percentage gain for the target might not be that large for the buyer's shareholder. Bruner (2002) also reports that almost all the studies, which research the combined returns of buyer and target, report positive combined returns.

The results that show positive returns for target firms are in line with disciplinary acquisition theory. Lang et al. (1989) find that shareholders gain the most when an acquirer with a good management acquires a target with an inefficient managed firm. Ghosh & Lee (2000) also find that higher abnormal returns for targets are associated with negative earnings forecast revisions, which indicates that disciplinary acquisitions are more likely to have higher abnormal returns.

Many existing research identified what possible determinants could be of the abnormal returns around announcement dates. The study of Masulis et al. (2007) find that more antitakeover provisions are associated with significantly lower announcement-period abnormal returns. Berger & Ofek (1995) find a negative relation between diversification and the profitability of an acquisition. This result indicates that synergies will be gained the most when a buyer acquires a target which is operating in the same business. Maquieria et al. (1998) also find a positive and significant return to buyers for deals between firms in a related business. Rau & Vermaelen (1998) find that companies with high book-to-market ratios are associated with post-acquisition underperformance, and companies with a low book-to-market ratio are associated with positive significant abnormal returns. Additionally, they find that hostile takeovers are associated with positive significant returns to bidders. This indicates that hostile takeovers might pay off for the acquirer. Asquith et al. (1987) find that paying the acquisitions with stocks is associated with significant negative returns around deal announcements. Another determinant of profitability of M&A deals is regulation. Asquith et al. (1983) find that returns for merging firms were significantly higher before than after the implementation of the Williams Amendment in 1969, which required mandatory disclosure of information regarding cash tender offers.

Moeller et al. (2004) find that bidder size has a negative effect on the cumulative abnormal returns around the announcement date. This effect could be evidence for supporting the managerial hubris hypothesis of Roll (1986), because they find that larger acquirers pay higher premiums which results in worse synergies. An alternative explanation for the negative effect could be that large firm size could function as takeover defense, because acquiring larger targets should take more resources.

Another variable that often has been researched in existing literature is the effect of Tobin's *q* on cumulative abnormal returns. In prior studies there are contradictory results for the effect of Tobin's *q* on cumulative abnormal returns. The studies of Lang et al. (1991) and Sarvaes (1991) find a positive relation between Tobin's $q$ and tender offer acquisitions. However, Moeller et al. (2004) find a negative relation in their study.

Two other variables, which are related to the acquirer of the M&A deal, that are frequently used in studies to find the determinants of cumulative abnormal returns are leverage and free cash flow. Leverage refers to the amount of debt a firm uses to finances their assets. Higher usage of debt helps to reduce future free cash flows and managerial discretion (Stulz, 1990). Next to that, leverage could incentivize managers to improve the firm performance, since financial distress often leads to resignation of the managers. Jensen (1986) came up with the free cash flow hypothesis, which means that managers with larger free cash flows have more resources to engage in empire building. On the other hand, those higher free cash flows can also indicate good firm performance in recent years, which could be due to high quality managers who involve in better acquisitions for their company.

Fuller et al. (2002) find that buying public firms result in significantly negative abnormal returns, while buying private firms result in significantly positive results. Next to that, Moeller et al. (2004) find similar results in their research. However, they also find that the highest abnormal returns are generated by acquisitions of the acquirer's subsidiaries. Therefore, many studies control for the ownership status of the target.

In many existing research the effect of the method of payment of an M&A deal is researched. Acquirers generally experience significantly negative abnormal returns when the acquisition is paid with equity (Servaes, 1991). Myers and Majluf (1984) discussed that this is mainly due to the adverse selection problem in equity issuance. This implies that the difference in knowledge between the acquirer and target is the cause of more negative abnormal returns in equity paid acquisitions. However, Chang (1998) and Fuller et al. (2002) find that deals that are paid with stocks are less negative or even positive when the target is privately held. One explanation for this effect can be that private companies are closely held, and by buying the target with stocks, the likelihood of blockholder formation increases. Blockholder formation allows for greater monitoring of the management of the acquirer, which increases the value. Next to that, acquisitions paid with cash result in high tax implications for the target's owners. Therefore, they could agree on a discounted acquisition price when the deal is fully or partly financed with stocks if this eventually results in at least equal returns to the target's owners. This discounted price will be reflected in the higher cumulative abnormal returns for acquisitions which are financed with stocks.

Another variable which is often controlled for in existing research is (relative) deal size. Asquith et al. (1983) and Moeller et al. (2004) find that higher deal size increases the bidder announcement returns.

Morck et al. (1990) find that diversifying acquisitions usually destroy shareholder value and benefit self-interested managers. Those managers can reduce firm risk by diversifying, which often does not result in increasing shareholder value. Also, Shleifer & Vishny (1989) find that it could be more costly for firms to replace manager when they acquire unrelated targets that fit the strengths of the manager. In this way the manager can secure their own position.

Finally, existing research finds that acquisitions between two high tech companies are expected to have a negative effect on the returns (Loughran & Ritter, 2004). The reasoning for this is that it is difficult for two high tech firms to integrate because of the importance of human capital and the skills of the employees at these firms (Masulis et al. 2007).

Adnan & Hossain (2016) researched what the time period is around the announcement date of merger announcements for the cumulative abnormal returns. This study uses a time period of 5 days prior to the announcement date of the merger, and 5 days after the announcement date. They find that prior to the announcement of a merger both the target and acquiring companies cumulative abnormal return show an upward trend. This might be for the reason of information leakage before the merger.

## 2.2 Market efficiency

Markets are defined as “efficient” when prices “fully reflect” available information (Fama, 1970). Fama (1970) defined three different forms of market efficiency. First, the weak form, is where historical prices is the information set. In the semi-strong form of market efficiency all publicly available information reflects the price changes of new equilibrium levels. Last, the strong form of market efficiency states that all market information, public or private, tests whether investors or groups have access to limited information relevant for price formations. Beaver (1981) argues whether all information is universally available at zero cost for all individuals. When this is not the case, there could be doubted whether markets are efficient.

In empirical research, the weak-form of market efficiency is often tested. In these studies, the goal is to see whether it is possible to predict future prices with historical returns, or to determine which factors affect market efficiency. As mentioned above, prices fully reflect all available information in an efficient market. When more information is available, the prices will be more efficient. Therefore, information availability is an important factor that influences market efficiency.

Existing research suggest that market liquidity is closely linked to financial market efficiency. In a liquid market large trading volumes can be immediately and quickly executed with minimal effects on prices (Hodrea, 2015). The research of Hodrea (2015) finds a direct link between liquidity and market efficiency, which concludes that liquidity can be seen as an important determinant of market efficiency. This relation can be explained by the fact that high degree of liquidity cannot be absorbed in the price by market makers. This results in arbitrage opportunities for those who are able to detect the price deviation from the fundamental values, which helps to get back to fundamental values quicker. Therefore, high degree of liquidity facilitates arbitrage opportunities that will cause low predictability of returns, which results in high market efficiency. On the other side, high levels of illiquidity results in less arbitrage opportunities, which results in larger deviations from the random walk hypothesis, so lower market efficiency.

Trading volume is often used as a proxy for liquidity, which indicates the degree of absorption capacity of the market (Pagano, 1989). High degree of trading volume facilitates arbitrage opportunities. Additionally, high trading volumes often signals that investors show interest in a company. This stimulates the incorporation of new public information in the prices (Cammer & Bloom, 1989). Therefore, when the trading volume increases, the number of market participants are most likely to increase too, and new public information is incorporated into the stock prices. This should result in more efficient markets.

Research analysts collect important information about companies and write and publish research reports. These research reports create new public information, which will be incorporated in the stock prices (Kim et al., 1997). Investors use this information in their investment decisions, which results in more efficient markets according to Gurun et al. (2016). Therefore, higher levels of analysts coverage results in more publicly available information, which implies that markets are more efficient.

There is existing research on market efficiency measures. Griffin et al. (2010) provided a framework with the traditional measures of market efficiency. The efficiency measures they selected are all extensively used to measure stock market efficiency in the United States. The efficiency measures they examine are: firm return autocorrelations, portfolio return autocorrelations, and delay with respect to market returns. Existing research argue that efficient prices follow a random walk, and this is tested by using autocorrelation and variance ratios. Solnik (1973) find more departures from a random walk in Europe than in the United States by examining autocorrelations of stocks. Delay is the other measure, which is an $R^2$-based measure of the sensitivity of current return to past market information. Griffin et al. (2010) also find that weak-form efficiency measures for emerging markets are at least as efficient as for developed markets.

Existing research uses different measures to test for market efficiency. Lo and MacKinlay (1988) test the random walk hypothesis by using variance ratios, where there is examined how closely the price of a stock adheres to the random walk benchmark. Variance ratios are used to test whether prices exhibit autocorrelation. When there is autocorrelation, future prices can be predicted with past prices. Their research find evidence that stock prices do not follow random walks in weekly stock returns. This indicates that there is predictability in weekly stock returns and that markets are not efficient. A possible limitation of the variance ratio is that the tests can suffer from test-size distortions or low power, especially when the samples are small (Al-Khazali et al., 2007).

Another measure that is used in existing research to test for market efficiency is the Hurst exponent (Peters, 1994). In the research of Eom et al. (2008), for example, the Hurst exponent is used to calculate the degree of efficiency in financial time-series. This research finds that there is a strong positive relationship between the degree of efficiency and the predictability, which means that a market index with a lower degree of efficiency has a higher level of predictability. However, the research of Grech & Mazur (2004), and confirmed by Kristoufek (2010), the Hurst exponent method only provides significant results when there are long and stable trends in the market.

A third measure for market efficiency is approximate entropy (ApEn), which was developed by Pincus (1991). With approximate entropy patterns in evolving data series are measured. This statistical measure looks at the level of randomness of data series by counting patterns and their repetitions. Low levels of this statistic indicates that there are many repeated patterns, and high levels of this statistic indicate randomness and unpredictability. Using ApEn in finance has some limitations, where the biggest limitations is that the algorithm is a relative measure. However, Delgado-Bonal (2019) solved the problems by combining Monte Carlo simulations, bootstrapping of the sequences and the selection of the MaxApEn value. To be able to compare the results between different series, he created the Pincus Index (PI) measure. This measure measures the distance between MaxApEn(original) and MaxApEn(Monte Carlo). This measure indicates a total predictability of the market when the value of the ratio is zero, and a value of one or greater than one implies randomness.

## 2.3 Combining M&A and market efficiency

M&A and market efficiency are not combined in existing research as far as I know. However, it could definitely be interesting to see what the effect of market efficiency is on M&A topics. When a market is efficient, market prices should “fully reflect” available information according to Fama (1970). When all information is known by all individuals, abnormal returns around announcement dates of M&A deals should not be possible, especially not before the announcement date. When a market is efficient, the expected value of abnormal returns is zero (Fama, 1998). However, when a market is inefficient when not all information is incorporated into the prices. Therefore, market inefficiencies are due to information asymmetries. So, there can be concluded that highly inefficient markets have extremely large abnormal returns. The higher the efficiency of the market, the lower the abnormal returns should be. Therefore, there is expected that more efficient markets are associated with less abnormal returns.

As discussed in section 2.2, there are various factors that determine market efficiency. By knowing what the effects of M&A deals are on those determinants, there can be reasoned what the effect of an M&A deal is on the market efficiency. Smith et al. (1997) find that the volatility and trading volume are higher for the target firm after the announcement of an M&A deal. Even though this result is not researched for the target firm in their research, there is expected that the trading volume is increased for the target firm as well, because new information generally results in an increase in trading activity (Bhole et al., 2020). Since trading volume is often used as a proxy of liquidity, the same applies for liquidity. When the degree of liquidity increases, it facilitates arbitrage opportunities that will cause low predictability of returns. To conclude, when there is M&A activity, the trading volume and the degree of liquidity are expected to increase. This ensures higher market efficiency, which results in lower cumulative abnormal returns.

Additionally, the relation between M&A deals and analyst coverage is also interesting to cover. Tehranian et al. (2007) find that analysts who covered the target firm often retain coverage of the merged firm. This implies that the analyst coverage of the target firm increases after the M&A deal. As discussed before, an increase of analyst coverage will increase the market efficiency because of additional publications of new information. Therefore, M&A activity results in higher levels of analyst coverage, which increases market efficiency, which results in lower cumulative abnormal returns.

Merger waves might be related to market efficiency. Rhodes-Kropf & Viswanathan (2004) find that mergers are more often paid by stocks during the higher periods of merger waves. According to existing literature, those stock paid mergers are associated with significant negative returns, because it is difficult to value the offer and overvaluation of the market result in more overvaluation of the offer. Prices should “fully reflect” available information in efficient markets. However, when there is much overvaluation, there can be argued whether all information is available to all market participants.

For managers of firms, it can be beneficial to know the possible effects of market efficiency on deal returns. The question they can ask themselves is: should we engage in M&A activity when markets are inefficient, or is it better to invest in efficient markets? The major factor for inefficient markets is asymmetric information, where one person might have more information than the other. When the manager of the acquirer knows that he or she possesses information which is not available to everyone, the manager could make value increasing acquisitions. However, the same applies vice versa, where the acquirer could lack information and overvalues the target firm. For the manager it could be useful to know in what market they work and what the risks are. Because of the asymmetric information, extra research could be beneficial to prevent value destroying deals in inefficient markets.

## 3. Hypotheses

Based on the existing research that is presented above, three hypotheses are formulated. First, based on existing empirical research there is expected that total efficient markets are expected to have zero abnormal returns (Fama, 1998). When markets are inefficient, prices do not incorporate all available information. This could be because there are information asymmetries in the market. Therefore, more inefficient markets are expected to have larger cumulative abnormal returns.

Moreover, based on the existing research and the relation between market efficiency and cumulative abnormal returns, there is expected that there is a negative relationship between efficient markets and cumulative abnormal returns. Therefore, the following hypothesis will be tested:

*H1: There is a negative effect between efficient markets and cumulative abnormal returns.*

The second hypothesis is based on the effect of market efficiency on cumulative abnormal returns before the announcement date. When an M&A deal has not been announced, this information should not be incorporated in the prices. In less efficient markets, information asymmetry can lead to information leakage, which could result in cumulative abnormal returns before the announcement date of M&A deals (Adnan & Hossain, 2016). Therefore, the following hypothesis will be tested:

*H2: There is a negative effect between efficient markets and cumulative abnormal returns before announcement dates of M&A deals.*

The third hypothesis relates to the effect between market efficiency and cumulative abnormal returns after the announcement date of an M&A deal. Existing empirical research finds factors that influence the efficiency of the market. First, the liquidity of the market, which is often measured by trading volume, is seen as an important factor of market efficiency. Hodrea (2015) finds a direct link between liquidity and market efficiency, which concludes that liquidity can be seen as an important determinant of market efficiency. Since M&A activity generally results in an increase of trading activity (Bhole et al., 2020), market efficiency is expected to increase too.

Next to that, analyst coverage positively affects market efficiency too. Also, analysts who covered the target firm prior to the M&A deal often retain coverage of the merged firm. So, there is expected that analyst coverage increases after an M&A deal (Tehranian et al., 2007). Therefore, there is expected that market efficiency increases after an M&A deal.

So, because the markets are expected to be more efficient after the announcement, there is expected that the negative effect between market efficiency and cumulative abnormal returns after the announcement is lower than between market efficiency and CARs before the announcement date in this sample. Therefore, the following hypothesis will be tested:

*H3: There is a less negative effect between efficient markets and cumulative abnormal returns after announcement dates of M&A deals than between market efficiency and CARs before M&A deals.*

# 4. Data

In this section, the data sources and variables used in this research, to be able to test the hypotheses, are discussed. First, the overall sample and data sources which are used to obtain the data are covered. Thereafter, the dependent, independent, and control variables of the regressions are discussed.

## 4.1 Data collection

To perform the analysis of this research, M&A deal and firm specific data of multiple indexes for the period from 2002 to 2020 is obtained. In this study, the method of Delgado-Bonal (2019) to measure market efficiency is followed. Therefore, the following indexes are used: Spain (IBEX 35), UK (FTSE 100), USA (NASDAQ and S&P 500), Hong Kong (Hang Seng), and Japan (Nikkei 225). The initial sample consists of all M&A deals on the Zephyr database of the above-mentioned indexes for the period 2002-2020. The data source used to obtain stock prices, index prices, and firm specific data is Thomson Reuters Eikon (hereafter: Eikon). Since Eikon only includes index price data starting from 2002, the data period of 2002-2020 is used.

M&A deal data is obtained from Zephyr. 11,123 M&A deals are identified made by 1,298 firms between 2002 and 2020. M&A deals that are used meet the following criteria: (1) the merger or acquisition is completed, (2) the acquirer is listed in one of the mentioned indexes, (3) the announcement dates are known, (4) ISIN codes of the acquirer are known. The Hang Seng index is not included in the Zephyr database. For this index Hong Kong stock exchange data has been used. Since this study was intended to focus on the M&A deals of firms that are listed in the Hang Seng index, the acquirers are most likely to be large firms. Therefore, there is a need to control for small firms from the deals in the Hong Kong stock exchange. To control for small firms, M&A deals where the acquirer's share value is below $5, so called penny stocks, are removed from the sample. Finally, the deals where no cumulative abnormal returns can be calculated for, due to missing data on stock prices, are deleted from the sample.

## 4.2 Dependent variable

The dependent variable examined in this research is cumulative abnormal returns. The cumulative abnormal returns are calculated by using an event study. Event studies are useful to measure the impact of a specific event on the value of a firm (MacKinlay, 1997). For this research, the specified event is the announcement date of the M&A deal. Therefore, the event date is set as the announcement date of the M&A deal. To be able to calculate cumulative abnormal returns, the daily stock and index returns are obtained from Eikon. Section 5.1 of this research elaborates further on calculating cumulative abnormal returns.

For the second and third hypotheses, the cumulative abnormal return variable is adjusted. For the second hypothesis the cumulative abnormal returns are calculated in the days prior to the M&A

deal, for which the dependent variable CAR_before is created. The third hypothesis tests the effect of market efficiency on announcement dates of M&A deals after the event date. Therefore, the variable CAR_after is created.

## 4.3 Independent variable

In this research there is examined what the effect of market efficiency is on the cumulative abnormal returns around announcement dates of M&A deals. Therefore, to test the hypotheses, market efficiency is considered as the independent variable. In existing research, different measures are used to measure market efficiency. For this research, market efficiency is measured similarly as proposed by the study of Delgado-Bonal (2019). The research of Delgado-Bonal (2019) creates a statistical measure of randomness, where lower numbers of the measure indicate randomness, and higher numbers of this measure indicate higher levels of predictability. Section 5.2 of this research discusses the measurement of market efficiency more extensive.

In section 2.2 market efficiency measures which are used in existing empirical research are discussed. Often used measures are variance ratio (Lo and MacKinlay, 1988), the Hurst exponent (Peters, 1994), and approximate entropy (Pincus, 1991). All measures have their own limitations, but Delgado-Bonal (2019) improved the ApEn measure by creating a statistical measure instead of the relative measure. Therefore, this measure can be used to directly compare indexes. Because the major limitations of ApEn are addressed by the model of Delgado-Bonal (2019), this measure is used in this research.

Following the study of Delgado-Bonal (2019), the sample is partitioned into four sections, which are: Q1 (January 2002 – October 2006), Q2 (October 2006 – July 2011), Q3 (July 2011 – April 2016), and Q4 (April 2016 – December 2020). For each index a market efficiency measure is calculated for each time period.

## 4.4 Control variables

In existing research multiple variables are considered to influence cumulative abnormal returns. To improve the regressions of this research, these variables are added to the regression models. By adding variables which are related to the dependent variable, the estimation of the predictor coefficient will be more precise. In this research, the control variables which are added can be categorized into either bidder characteristics or deal characteristics. The category bidder characteristics includes variables that are related to the acquirer in the M&A deal. The category deal characteristics includes variables that are related to the M&A deal itself.

Firstly, for bidder characteristics, firm size is added as a control variable to the regression model. In existing research on cumulative abnormal returns, firm size is frequently used and found to have a negative effect on the cumulative abnormal returns around the announcement date (Moeller et al. (2004). Firm size has been defined as the log transformation of the total assets.

Secondly, following the study of Masulis et al. (2007), Tobin's Q is added to the regression models. Tobin's *q* is defined as the ratio of an acquirer's market value of assets over the book value of assets and is calculated by: (market capitalization + total liabilities) / (equity capital and reserves + total liabilities).

Finally, for bidder characteristics, leverage and free cash flow are added in the regression models. FCF is calculated by: (operating income before depreciation – interest expense – income taxes – capital expenditures) / total assets.

All bidder characteristics are measured at the fiscal year-end prior to the pre-announcement stock price runup date of the merger or acquisition, which is -210 days from the announcement date.

For deal characteristics, multiple control variables are added to the regression models. Firstly, following the study of Masulis (2007), relative deal size is added as a control variable. Relative deal size is defined as the ratio of deal value to bidder market value of equity. Next to that, a control variable is added which measures whether the M&A deal is so called diversifying or not. For both the acquirer and target the Fama-French industries they work in are collected. For this control variable, a binary variable is created for diversifying acquisitions that is equal to one that do not share a Fama-French industry, and zero otherwise. Additionally, a control variable is added that checks whether both the acquirer and target are from high tech industries. This control variable equals one if both companies of the deal operate in high tech industries and zero otherwise.

Fuller et al. (2002) find that buying public firms result in significantly negative abnormal returns, while buying private firms result in significantly positive results. Masulis et al. (2007) created three indicators for target ownership, which are *public, private,* and *subsidiary*. In the Zephyr database it is not possible to identify whether the target firm is a subsidiary, so in this study the target ownership only has two indicators, which are *public* and *private.* Additionally, there is also controlled for the method of payment, since existing research, amongst others, Myers and Majluf (1984) and Sarvaes (1991), find that the method of payment does affect abnormal returns. For method of payment three indicator variables are created; stock deal, all-cash deal and unknown, where stock deal equals one when deals are financed entirely or partly with stocks and zero otherwise. All-cash deals equal one when the deal is fully financed with cash and zero otherwise. For M&A deals where the method of payment is unknown, the unknown indicator variable equals one.

Finally, to fully capture the effects of target ownership and method of payment, an interaction between the two indicators for ownership and the three method-of-payment indicators is created. Therefore, the following categories that are created are: *public all-cash deal, public stock deal, private all-cash deal,* and *private stock deal.*

## 4.5 Descriptive statistics

Table 1 presents the distribution of M&A deals over all indexes and periods. In total there are 11,123 deals completed and included in the sample that fit the requirements of this research. Nearly half of the deals are completed in the S&P 500 index, whereas the peak period with the most completed deals was the second period, from October 2006 until July 2011. The least number of deals are completed in the IBEX 35 index, and during the fourth period, which was from April 2016 until December 2020.

***Table 1.*** *Number of M&A deals in each time period per index*

| **Index** | **(1)** | **(2)** | **(3)** | **(4)** | **Total** |
|---|---|---|---|---|---|
| S&P 500 | 1,344 | 1,402 | 1,518 | 1,123 | **5,387** |
| NASDAQ | 392 | 442 | 478 | 351 | **1,663** |
| Nikkei 225 | 332 | 390 | 343 | 339 | **1,404** |
| IBEX 35 | 150 | 88 | 90 | 78 | **406** |
| FTSE 100 | 345 | 308 | 298 | 179 | **1,130** |
| Hang Seng | 280 | 331 | 214 | 308 | **1,133** |
| **Total** | **2,843** | **2,961** | **2,941** | **2,378** | **11,123** |

Table 2 presents the descriptive statistics of dependent, independent, and control variables which are used in this research. In the table the number of observations, the mean, the standard deviation, the min, and max values are shown. Considering the dependent variables, the mean of CAR is just about 0.1862, which means that the average cumulative abnormal return for an M&A deal in our sample is positive. Compared to the research of Masulis et al. (2007) the average CAR of this research seems to be slightly higher, where the mean of CAR has a value of 0.215. The average CAR in the five days before the announcement date (CAR_before) is just about 0.0896, and (CAR_after) has a mean of 0.0202. So, this implies that the average of all deals is also positive for both these variables.

In this sample, the mean of the market efficiency measure is around 0.9521. This measure indicates total predictability when this value is zero and imply randomness when the value is one or greater than one. Therefore, there can be concluded that the markets on average show randomness. The minimum value of market efficiency is 0.9128, which means that the markets are the most predictable there and therefore the market is the least efficient. Since this is the first study that uses this measure, it is not possible to compare these results.

For the variables relative deal size, firm size, Tobin's Q, leverage, and free cash flow some observations are missing. The missing values for relative deal size are mainly caused by the unknown deal values. Since many deal values are not made public, the relative deal size cannot be calculated. For the other variables there are only a little number of observations missing due to missing data in the databases. For the missing values the dummy variable adjustment method is used before doing the regressions to execute credible regressions.

***Table 2.*** *Descriptive statistics of all variables*

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| CAR | 11,123 | 0.1861926 | 6.524163 | -89.73807 | 144.6597 |
| CAR_before | 11,123 | 0.0896488 | 3.795726 | -69.49133 | 78.44574 |
| CAR_after | 11,123 | 0.0202474 | 4.600116 | -51.07198 | 119.3926 |
| Market efficiency | 11,123 | 0.9520822 | 0.0305326 | 0.9128176 | 1.107822 |
| Relative deal size | 5,722 | 0.1106596 | 0.7582935 | 0.000000756 | 48.40237 |
| Diversifying | 11,123 | 0.5731367 | 0.4946443 | 0 | 1 |
| High Tech | 11,123 | 0.314034 | 0.4641508 | 0 | 1 |
| Public | 11,123 | 0.142947 | 0.3500346 | 0 | 1 |
| Private | 11,123 | 0.857053 | 0.3500346 | 0 | 1 |
| Stock deal | 11,123 | 0.0895442 | 0.2855405 | 0 | 1 |
| Cash deal | 11,123 | 0.2992898 | 0.4579675 | 0 | 1 |
| Unknown payment | 11,123 | 0.6111661 | 0.4875074 | 0 | 1 |
| Public * Stock deal | 11,123 | 0.0451316 | 0.2076023 | 0 | 1 |
| Public * Cash deal | 11,123 | 0.0795649 | 0.2706305 | 0 | 1 |
| Private * Stock deal | 11,123 | 0.0444125 | 0.206019 | 0 | 1 |
| Private * Cash deal | 11,123 | 0.2197249 | 0.4140788 | 0 | 1 |
| Firm size | 11,085 | 9.945236 | 0.8501051 | 5.708421 | 12.41224 |
| Tobin's Q | 10,907 | 2.259507 | 2.593545 | 0.1828 | 114.5989 |
| Leverage | 11,005 | 0.2401097 | 0.1846946 | 0 | 4.052 |
| Free Cash Flow | 10,855 | 0.0698665 | 0.0805498 | -2.7813 | 2.1828 |

# 5. Methodology

In this section the techniques to test the effect of market efficiency on CARs around announcement dates are discussed. An event study is conducted to perform the quantitative analysis. In the first section the method of measuring CARs will be discussed, which is followed by an in-depth explanation of the Delgado-Bonal model to measure market efficiency. Last the regression model is discussed.

## 5.1 Measuring Cumulative Abnormal Returns

Event studies are useful to measure the impact of a specific event on the value of a firm (MacKinlay, 1997). In this study, the announcement of a merger or acquisition deal is defined as the event, and the Cumulative Abnormal Returns are used to measure the effects of the event. So, event studies make it possible to measure the effect of M&A deals on CARs.

Adnan & Hossain (2016) find that prior to the announcement of a merger both the target and acquiring companies cumulative abnormal return show an upward trend. This could indicate information leakage and therefore the event window is set at [-5, 5], that refers to the time period of 5 days before the announcement date until 5 days after the announcement date. Next to that, there is controlled for the bidder's pre-announcement stock price runup with a 200-day estimation window of [-210, -11] from the event date.

To calculate the abnormal returns, the daily returns for firm i is calculated, which is calculated using the following formula:

$$R_{i,t} = (P_t - P_{t-1})/P_{t-1}$$

Where return indicates the daily return of one individual stock return, and $P_t$ is the closing share price on day t. The pre-announcement period, also known as the estimation window, is used to calculate the normal return for the firm during this period. This normal return indicates what the return should be for the firm when the event did not happen. The normal return is calculated as follows:

$$N\left(R_{i,t}\right) = \alpha_i + \beta_i R_{mt}$$

Where $R_{mt}$ is the return of the market during the estimation window, and $\alpha$ and $\beta$ are calculated in Stata. When $N(R_{i,t})$ is calculated, the abnormal return for the firm can be calculated by:

$$AR_{i,t} = R_{i,t} - N(R_{i,t})$$

Where $AR_{i,t}$ is the abnormal return. With this calculation the abnormal return per day is calculated, but since the cumulative abnormal return must be calculated, these daily abnormal returns should be summed up together, which is calculated as follows:

$$CAR_{i,s,e} = \sum_{t=s}^{e} AR_{i,t}$$

Where $CAR_{i,s,e}$ is the cumulative abnormal return, s is the starting day of the event window and e is the ending day. Thus, s will be 5 days prior to the event and e will be 5 days after.

## 5.2 Measuring market efficiency

Event studies make it possible to measure the effect of M&A deals on CARs. When those effects are measured, the next question arises, which is: what are the determinants of the effects? Prior studies focused on this question and found some determinants, however, this study explores whether market efficiency is a determinant as well. In 2019, Alfonso Delgado-Bonal created a new measure to quantify the randomness of stock markets. In this section a detailed explanation of their model, and how this model is applied in this study, is described.

Randomness has been defined and quantified by using algorithms like Approximate Entropy (ApEn). However, ApEn cannot be applied directly to make comparisons between financial data. Delgado-Bonal (2019) developed the ApEn to be able to allow comparisons between time series. In the model the first step is to calculate the original MaxApEn for each window, then calculate 100 MaxApEns of the shuffled version of the returns for each window, and finally calculate the so called Pincus Index to be able to compare the series.

Markets are predictable when prices follow the same patterns and are random when there are no patterns and thus market participants are unable to predictable the continuation of the market prices. Approximate Entropy is a statistical measure that measures the randomness by indicating potential patterns and counting the repetitions. A low ApEn value indicates the existence of patterns, which means that there is predictability in the market. High values of ApEn indicate randomness and unpredictability. For the ApEn algorithm, the parameters will be selected first, where *m* is the length of the compared patterns, and *r* is the tolerance or effective filter. First, the idea of the algorithm is showed for symbolic chains, which is illustrated in figure 1. For symbolic chains *m* is only necessary, where *m* is the parameter that determines the size of the template window that is compared. Usually, $m = 2 \; or \; 3$, so in this research $m = 2$ is used and the only possible symbols are {red, green, purple}.

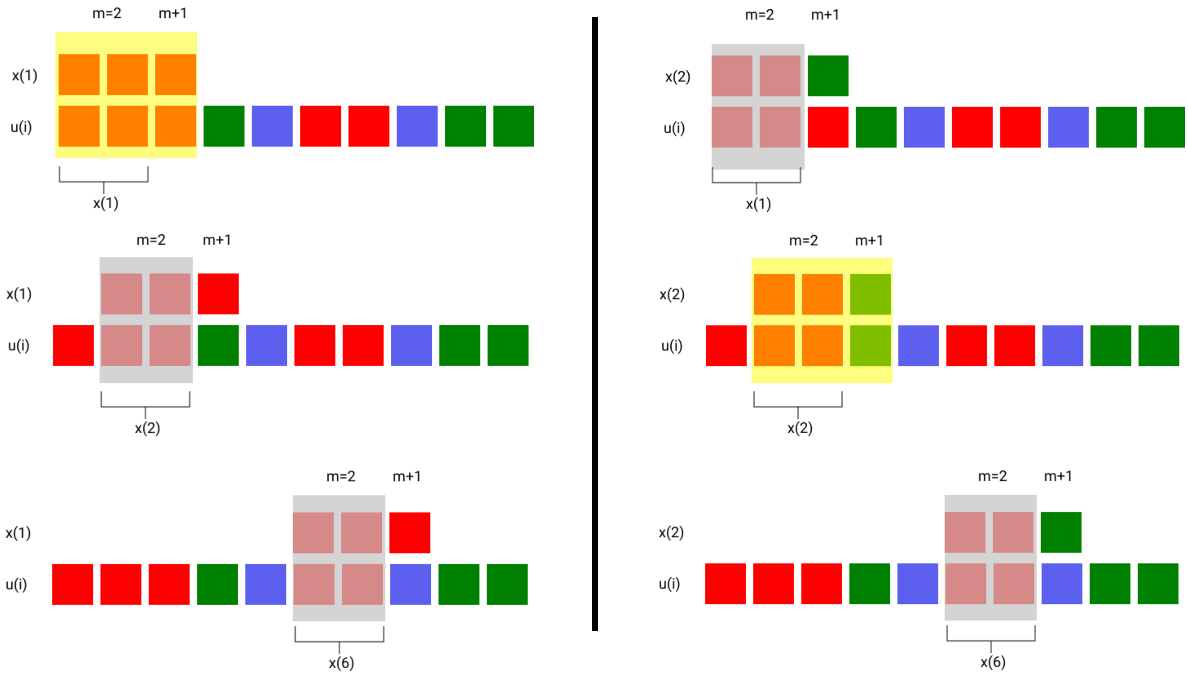
The illustration of figure 1 starts at the left top corner. Here the first subsequence of size *m* is $x(1) = [red, red]$. The objective is to count how many times the sequence $[red, red]$ occurs in the series, and how many times the next position $(m + 1)$, is equal to the sequence. In this instance, the third box must be $(red)$. We start the illustration with vector $x(1) = [red, red]$ in the data series *u*. The first box of the series is $(red)$, which is similar to our template. Since the first box is similar to our template, we continue with the next box, which is also $(red)$. This makes a possible vector because all *m* components are similar. Now the next box is checked, which is $m + 1$. The figure shows a $(red)$ box, which matches the template factor and makes a match.

Following this process, the template vector is compared to target factor $x(2)$. Again, the first box is $(red)$, just like the second box which is also $(red)$. This means that there is a possible vector again. However, in this case the box $m + 1$ is $(green)$ which is not a match. This process is continued by comparing $x(1)$ with $x(3)$ and all other boxes. This results in three possible and one match vector for $x(1)$.

This process is continued for $x(2)$ on the right side of figure 1, and this process continues until all vectors are used as a template. Then the Approximate Entropy can be calculated by:

$$ApEn(m,r,N) \cong -\left(\frac{1}{N-m}\right)\sum_{i=1}^{N-m} \log \frac{\sum_{j=1}^{N-m}[number\ of\ match_i]}{\sum_{j=1}^{N-m}[number\ of\ possible_i]}$$

***Figure 1.*** *ApEn illustration where* $m = 2$.




*Note. From "Quantifying the randomness of the stock markets," by A. Delgado-Bonal, 2019, Scientific reports, 9, p. 3, original title: Illustration of the ApEn algorithm for symbolic chains with embedding dimension of m=2, (https://www.nature.com/articles/s41598-019-49320-9.pdf). CC BY-NC 4.0. Figure is slightly changed to make it more compact.*

The ApEn calculates the ratio between the number of match and the number of possible vectors. When the number of matches is high, the ratio $\frac{match}{possible}$ will be closer to one, which will give a logarithm close to zero. As described before, a low ApEn value indicates existence of patterns and predictability. When the number of matches is low, the negative value of the logarithm will be higher, which results in higher ApEn values, indicating randomness.

The illustration of figure 1 is valid for symbolic chains or in situation where the alphabet is well defined like a dice {1, 2, 3, 4, 5, 6} for example. However, for this study data has been used where the alphabet is unknown and therefore the noise filter $(r)$ is used. The same idea which is illustrated in figure 1 implies for alphabets which are unknown. The objective is to count possible and match vectors to be able to calculate Approximate Entropy. First, the template vector is determined. Then, the range in which the price should move is determined by the noise filter. Finally, the possible and match vectors are indicated.

The noise filter $r$ determines the probability of finding existing patterns. To avoid the problem of which $r$ should be selected, Delgado-Bonal (2019) uses the maximum value of ApEn (MaxApEn) to compare sequences. In this study the method of their paper is followed, therefore iterations are performed for each value of $r$ from 0.01 to 0.99 in steps of 0.01 and selecting the maximum value. This maximum value eliminates the arbitrariness in the choice of $r$ by providing a hierarchy to classify the randomness of each period. Unfortunately, the MaxApEn value is not sufficient for comparing different time series, because ApEn is a relative measure, and the data of different series might not be the same.

To counter this problem, an absolute measure of randomness is needed. Pincus & Kalman (1997) say that it is possible to create a measure by defining the *def* function as the difference between the maximum theoretical randomness and the ApEn value, when the maximum entropy is known. To be able to create an absolute measure for stock markets, we need to know all possible future prices, i.e., know the alphabet. Since we do not know the alphabet, we can bootstrap sample (Efron & Tibshirani, 1993). With bootstrapping the maximum randomness could be calculated by shuffling the data a sufficient number of times to obtain representative values of the randomness. With this approach of using Monte Carlo simulations, the value which maximizes ApEn ($MaxApEn_{original}$) for each period is calculated. Additionally, the data has shuffled 100 times and determined $MaxApEn_{shuffled}$.

To compare the results between different series, the distance between $MaxApEn_{original}$ and $MaxApEn_{shuffled}$ is measured and the ratio MaxApEn(original)/MaxApEn(Monte Carlo) is calculated. This measure is called the Pincus Index (PI), where the low values of the ratio imply the same as low ApEn values and vice versa. The median value (50% percentile) is used to calculate the Pincus Index, and the 5% and 95% percentile are used to calculate extremes[1].

The measure for market efficiency is calculated in the software package R. The R-codes which are used are based on the codes of Alfonso Delgado-Bonal, which have been edited by Sascha Füllbrunn. The codes are received from Sven Nolte.

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[1] Note. Section 5.2 is mostly retrieved from the paper of Delgado-Bonal (2019). Textual changes have been made, but the majority of this section is retrieved from: *"Quantifying the randomness of the stock markets," by A. Delgado-Bonal, 2019, Scientific reports, 9, p. 1-6, (https://www.nature.com/articles/s41598-019-49320-9.pdf). CC BY-NC 4.0.*

The results of the median value of the Pincus Index are listed in table 3. The highest Pincus Index is for IBEX 35 in the first period, which is from January 2002 until October 2006. This implies that the market is the most efficient in the first period of the IBEX 35. However, the lowest Pincus Index value is for the NASDAQ during period four. This indicates that the least market efficiency period is the fourth period of the NASDAQ index. Overall, the IBEX 35 index presents relatively high values for the Pincus Index, being above 1.00 for all periods. This signifies that the IBEX 35 index is a market efficient index. On the other side, the Pincus Index values of the S&P 500, NASDAQ, and FTSE 100 are valued below 1.00 for all periods. This indicates that the markets in these indexes are not that efficient.

***Table 3.*** *Market efficiency values*

| **Index** | **(1)** | **(2)** | **(3)** | **(4)** |
|---|---|---|---|---|
| S&P 500 | 0.958732 | 0.934119 | 0.937612 | 0.914550 |
| NASDAQ | 0.931492 | 0.941228 | 0.960547 | 0.917591 |
| Nikkei 225 | 1.004808 | 0.912818 | 0.956178 | 0.993274 |
| IBEX 35 | 1.107822 | 1.088464 | 1.043534 | 1.054910 |
| FTSE 100 | 0.932946 | 0.969341 | 0.974506 | 0.977050 |
| Hang Seng | 1.005835 | 0.933283 | 0.971151 | 0.982419 |

## 5.3 Regression model and statistical method

Based on the variables discussed before, the following regression model is estimated:

$$CAR_{i(t-5,t+5)} = \alpha_i + \beta_1 MARKEff_{it} + \beta_2 RDSIZE_{it} + \beta_3 DIVERSIFYING_{it} + \beta_4 HIGHTECH_{it} + \beta_5 PUBLIC * STOCK_{it} + \beta_6 PUBLIC * CASH_{it} + \beta_7 PRIVATE * STOCK_{it}\ \beta_8 FSIZE_{it} + \beta_9 TOBIN's\ Q_{it} + \beta_{10} LEVERAGE_{it} + \beta_{11} FCF_{it} + \mu_{it} \quad (1)$$

Additionally, to test hypothesis 2 the dependent variable of the regression model is changed. Therefore, the following regression models are estimated:

$$CAR\_before_{i(t-5,t-1)} = \alpha_i + \beta_1 MARKEff_{it} + \beta_2 RDSIZE_{it} + \beta_3 DIVERSIFYING_{it} + \beta_4 HIGHTECH_{it} + \beta_5 PUBLIC * STOCK_{it} + \beta_6 PUBLIC * CASH_{it} + \beta_7 PRIVATE * STOCK_{it}\ \beta_8 FSIZE_{it} + \beta_9 TOBIN's\ Q_{it} + \beta_{10} LEVERAGE_{it} + \beta_{11} FCF_{it} + \mu_{it} \quad (2)$$

Next to that, to test the third hypothesis the dependent variable of the regression model is changed. The following regression model is estimated:

$$CAR\_after_{i(t+1,t+5)} = \alpha_i + \beta_1 MARKEff_{it} + \beta_2 RDSIZE_{it} + \beta_3 DIVERSIFYING_{it} + \beta_4 HIGHTECH_{it} + \beta_5 PUBLIC * STOCK_{it} + \beta_6 PUBLIC * CASH_{it} + \beta_7 PRIVATE * STOCK_{it}\ \beta_8 FSIZE_{it} + \beta_9 TOBIN's\ Q_{it} + \beta_{10} LEVERAGE_{it} + \beta_{11} FCF_{it} + \mu_{it} \quad (3)$$

Where,

CAR = the cumulative abnormal returns over the event period

CAR_before = the cumulative abnormal return before the event date

CAR_after = the cumulative abnormal return after the event date

$\alpha$ = constant variable

MARKEFF = market efficiency measure calculated with the Delgado-Bonal model

RDSIZE = relative deal size target

DIVERSIFYING = target active in other

HIGHTECH = both firms from high tech industry

PUBLIC * STOCK = interaction between public ownership target and stock paid deal

PUBLIC * CASH = interaction between public ownership target and all cash paid deal

PRIVATE * STOCK = interaction between private ownership target and stock paid deal

FSIZE = firm size, calculated by the log transformation of the bidder's total assets

TOBIN's Q = Tobin's q of the bidder

LEV = leverage

FCF = free cash flow

Next to that, t refers to time and i refers to firm. The dependent variable of this model is the abnormal returns, which is measured by calculating the cumulative abnormal returns around announcement dates of M&A deals.

In prior research studies on the determinants of cumulative abnormal returns around announcement dates, panel data regression is the method to analyze the data which is frequently used. For this study, first an F-test is conducted to determine whether an OLS regression, or a fixed effects regression model should be used. When the F-test is not significant, OLS cannot be used.

To determine whether the fixed effects model or the random effects model is appropriate to use, the Hausman test is performed. The Hausman test checks whether there is a significant difference between the coefficients of the variables of both models. The null hypothesis for the Hausman test is: the coefficients of the fixed effects model and the coefficients of the random effects model are similar. When this hypothesis is accepted, the random effects model and the fixed effects model both can be used. When the Hausman test is significant, only the fixed effects model is used.

# 6. Results

This section presents the results which are found in the regressions. The results, which are displayed in tables, are analyzed and discussed. First, the correlation matrix is discussed to check for multicollinearity. Second, the hypotheses are tested.

To ensure that no multicollinearity issues occur with the dataset, a correlation matrix between the variables which are used in the regression models is constructed in appendix 1. Liu et al. (2014) indicate that multicollinearity issues are indicated when the absolute correlation of 0.7 or higher. In appendix 1 a couple values exceed the 0.7. First, we see a value of over 0.8 between the variables *all cash deal* and *Private Cash deal*, and *all cash deal* and *unknown payment*. To avoid multicollinearity, the variables *Private Cash deal* and *unknown payment* are excluded from the regression equations. Next to that, there is also a high correlation of 0.72 between *public* and *public cash,* and a high correlation of -0.72 between *Private* and *Public cash.* Since *Public cash* is an interaction term between the variables *Public* and *all cash deal*, and *private* and *public* will not be included in the same regression as the interaction term, there is not a possible multicollinearity issue. Finally, there is also a -1 correlation between *public* and *private*. Both are binary variables, where they are either 0 or 1. So, when *public* is 0, *private* is 1 and vice versa. Therefore, the *private* variable is excluded from the regression models.

Since the Hausman test is significant at the 1% level for both CAR, CAR_before and CAR_after, the random effects model is rejected, and a fixed effects regression of all models is performed. The tables with the results of the regressions are presented below in table 4, table 5, and table 6.

## 6.1 Regressions

The results of the fixed effects regression of model (1) are presented in table 3, where the *Cumulative Abnormal Returns (CAR)* with an event window of [-5, 5] is used. This table first includes the regression results without using control variables, which presents the relationship between *CAR* and *Market efficiency*. The baseline model includes the control variables. However, it excludes the interaction between the method of payment and the ownership status of the target firm. Finally, the results of model (1) are presented, which include the interactions. In table 4, the results of the fixed effects regression of model (2) are presented, where the *CAR* with an event window of [-5, -1] is used in order to measure the abnormal returns before the announcement of the M&A deal. In table 5, the results of model (3) are presented, where the *CAR* with an event window of [1, 5] is used to measure the abnormal returns after the announcement of the M&A deal. Both tables 5 and 6 are used to test the second and third hypothesis.

Hypothesis 1 is formulated as: *There is a negative effect between efficient markets and cumulative abnormal returns.* This implies that a negative coefficient for variable Market Efficiency is expected.

As can be concluded from table 4, the coefficients of market efficiency in the regression without control variables, the baseline regression, and the regression of model (1) are all negative, which indicates a negative effect between the cumulative abnormal returns and market efficiency. However, all these results are insignificant. This implies that there is no significant effect between cumulative abnormal returns and market efficiency found. Therefore, hypothesis 1 cannot be accepted.

Considering the control variables of model (1), the regression shows some interesting results. First, the relative deal size shows a 1% significant negative effect on cumulative abnormal returns. This implies that higher relative deal size results in a decrease of CAR. Asquith et al. (1983) and Moeller et al. (2004) find that higher deal size increases the bidder announcement returns. So, the results of the regression of model (1) regarding relative deal size are contradictory to the results of prior studies. Second, a positive effect between diversifying deals and cumulative abnormal returns with a significance level of 10% is found. Morck et al. (1990) find that diversifying acquisitions usually destroy shareholder value and benefit self-interested managers. However, in the results of the regression of model (1) there can be concluded that diversifying does benefit for cumulative abnormal returns. A reason for a different result between Morck et al. (1990) and the regression of model (1) could be the timeframe. Diversifying could have been value destroying 30 years ago, but might be creating value now. Third, a negative effect between the interaction term Public * Stock deal and CAR is found with a 1% significance level. This implies that listed targets which are paid with stocks experience more negative cumulative abnormal returns. Sarvaes (1991) find that acquirer's generally experience significantly negative abnormal returns when the acquisitions is paid with equity. So, the results of the regression of model (1) do support that finding. Finally, a significant negative effect between firm size and CAR is found in the regression. This finding is consistent with the results of Moeller et al. (2004), who find that bidder size has a negative effect on the cumulative abnormal returns around the announcement date.

The within R-squared of model (1) without any controls is 0.0000, which implies that 0 per cent of the variation in the cumulative abnormal return is explained by the variable market efficiency. When the control variables and interactions are added, the within R-squared increases to 0.0036. The between R-squared of model (1) is 0.0132, which means that 1.32 per cent of the variation in the cumulative abnormal returns is captured by the model. The overall R-squared is a weighted average of the within R-squared and the between R-squared and has a value of 0.0001. Based on this, there can be concluded that the model has a low goodness of fit and explanatory power.

***Table 4.*** *Fixed effects regression of model (1)*

| CAR | No control | Baseline | Model (1) |
|---|---|---|---|
| Market efficiency | -1.540727 | -3.657737 | -3.426721 |
| | (2.80032) | (2.887451) | (2.888985) |
| Relative deal size | | -0.879036*** | -0.9142312*** |
| | | (0.307182) | (0.3074733) |
| Diversifying | | 0.2435231* | 0.2469515* |
| | | (0.127472) | (0.127452) |
| High Tech | | -0.0864324 | -0.0922731 |
| | | (0.2169931) | (0.217081) |
| Public | | -0.5638424*** | |
| | | (0.1943144) | |
| Stock deal | | 0.024309 | |
| | | (0.2548347) | |
| All cash deal | | 0.4825033*** | |
| | | (0.1459281) | |
| Public * Stock deal | | | -0.8689313*** |
| | | | (0.3029421) |
| Public * Cash deal | | | 0.0966615 |
| | | | (0.215346) |
| Private * Stock deal | | | 0.2445381 |
| | | | (0.3230704) |
| Firm size | | -0.4047748* | -0.441544** |
| | | (0.217373) | (0.2168386) |
| Tobin's *q* | | 0.0230068 | 0.0227449 |
| | | (0.0324524) | (0.0324691) |
| Leverage | | -0.4197089 | -0.3757281 |
| | | (0.620856) | (0.6209295) |
| Free cash flow | | 1.770186 | 1.701398 |
| | | (1.183549) | (1.183769) |
| _cons | 1.653091 | 7.527506* | 7.758062** |
| | (2.666626) | (3.851827) | (3.849204) |
| Number of observations | 11,123 | 11,123 | 11,123 |
| Number of groups | 1,298 | 1,298 | 1,298 |

| | | | |
|---|---|---|---|
| $R^2$ within | 0.0000 | 0.0043 | 0.0036 |
| $R^2$ between | 0.0003 | 0.0152 | 0.0132 |
| $R^2$ overall | 0.0000 | 0.0001 | 0.0001 |

*Note. *, **, **** Denote significance at the 10%, 5%, and 1% levels, respectively.

Hypothesis 2 is formulated as: *there is a negative effect between efficient markets and cumulative abnormal returns before announcement dates of M&A deals.* This implies that a negative coefficient between CAR_before and market efficiency, and CAR_after and market efficiency is expected. In table 5 the results of the fixed effects regression of model (2) are presented, where the effect of market efficiency on cumulative abnormal returns in the period [-5, -1] is tested. The coefficients in the table are positive for the regression where no control variables are used, the baseline regression, and the regression for model (2). This implies that higher market efficiency results in higher cumulative abnormal return, which was not expected. However, these results are not significant. Therefore, hypothesis 2 cannot be accepted.

Regarding the control variables, the results of the fixed effects regression of model (2) only show one significant effect. The interaction term between private ownership and deals paid with stocks has a positive relation with a significance level of 5%. Chang (1998) and Fuller et al. (2002) find that deals that are paid with stocks are less negative or even positive when the target is privately held. The results of model (2) support the findings of these papers.

The within R-squared of model (2) is 0.0008, which implies that 0.08 per cent of the variation of the cumulative abnormal returns is explained by the variable market efficiency. Next to that, the between R-squared is 0.0096, and the overall R-squared is 0.0022. There can be concluded that the goodness of fit and the explanatory power of this model are low.

***Table 5.*** *Fixed effects regression of model (2)*

| CAR_before | No control | Baseline | Model (2) |
|---|---|---|---|
| Market efficiency | 0.1788688 | 0.0303891 | 0.0841035 |
| | (1.764238) | (1.822045) | (1.822551) |
| Relative deal size | | -0.2009085 | -0.2110762 |
| | | (0.1938385) | (0.1939733) |
| Diversifying | | -0.0578177 | -0.0576201 |
| | | (0.0804376) | (0.0804047) |
| High Tech | | 0.0794257 | 0.078166 |
| | | (0.1369274) | (0.1369482) |

| | | | |
|---|---|---|---|
| Public | | -0.233716* | |
| | | (0.1226166) | |
| Stock deal | | 0.373791** | |
| | | (0.1608063) | |
| All cash deal | | 0.1159712 | |
| | | (0.0920838) | |
| Public * Stock deal | | | 0.0728216 |
| | | | (0.1911147) |
| Public * Cash deal | | | -0.0826591 |
| | | | (0.1358537) |
| Private * Stock deal | | | 0.4181568** |
| | | | (0.2038129) |
| Firm size | | -0.0003754 | -0.0097695 |
| | | (0.1371671) | (0.1367953) |
| Tobin's *q* | | 0.0195683 | 0.0193777 |
| | | (0.0204782) | (0.0204836) |
| Leverage | | 0.1690192 | 0.1798416 |
| | | (0.3917737) | (0.391721) |
| Free cash flow | | 0.4242114 | 0.4052698 |
| | | (0.746845) | (0.7467952) |
| _cons | -0.080649 | -0.0567469 | 0.0054675 |
| | (1.680009) | (2.430587) | (2.428318) |
| Number of observations | 11,123 | 11,123 | 11,123 |
| Number of groups | 1,298 | 1,298 | 1,298 |
| $R^2$ within | 0.0000 | 0.0010 | 0.0008 |
| $R^2$ between | 0.0011 | 0.0095 | 0.0096 |
| $R^2$ overall | 0.0000 | 0.0023 | 0.0022 |

*Note. *, **, **** Denote significance at the 10%, 5%, and 1% levels, respectively.

Hypothesis 3 is formulated as: *There is a less negative effect between efficient markets and cumulative abnormal returns after announcement dates of M&A deals than between market efficiency and CARs before M&A deals.* For this hypothesis, the cumulative abnormal returns in the period of [1, 5] from the announcement date is measured. In table 6 the results of the fixed effects regression of model (3) are presented. From the table there can be concluded that there is a significant negative effect of market efficiency on the cumulative abnormal returns after the announcement date. This implies that more efficient markets experience significant lower cumulative abnormal returns between the first and the fifth day after the announcement date of the M&A deal, which was expected. However, the relation between market efficiency and the CAR_after variable is larger than the relation between market efficiency and CAR_before. Therefore, the third hypothesis cannot be accepted.

***Table 6.*** *Fixed effects regression of model (3)*

| CAR_after | No control | Baseline | Model (3) |
|---|---|---|---|
| Market efficiency | -3.151771 | -4.04254** | -3.97847** |
| | (1.928511) | (1.989759) | (1.990218) |
| Relative deal size | | -0.6500868*** | -0.6892843*** |
| | | (0.2116808) | (0.211818) |
| Diversifying | | 0.2387584*** | 0.2371237*** |
| | | (0.0878417) | (0.0878015) |
| High Tech | | -0.1624531 | -0.1614126 |
| | | (0.1495312) | (0.1495468) |
| Public | | -0.0856976 | |
| | | (0.1339031) | |
| Stock deal | | 0.0070115 | |
| | | (0.175608) | |
| All Cash deal | | 0.1345203 | |
| | | (0.1005599) | |
| Public * Stock deal | | | 0.0375445 |
| | | | (0.2086964) |
| Public * Cash deal | | | -0.0141521 |
| | | | (0.1483516) |
| Private * Stock deal | | | -0.2103006 |
| | | | (0.2225628) |
| Firm size | | -0.0157207 | -0.0394465 |
| | | (0.1497929) | (0.1493798) |
| Tobin's *q* | | 0.0118906 | 0.0123024 |
| | | (0.0223631) | (0.0223679) |
| Leverage | | -1.178418*** | -1.15891*** |
| | | (0.4278354) | (0.4277575) |

| | | | |
|---|---|---|---|
| Free cash flow | | 0.5612625 | 0.5248578 |
| | | (0.81559) | (0.815497) |
| _cons | 3.020993* | 4.191822 | 4.405591* |
| | (1.83644) | (2.654315) | (2.651712) |
| Number of observations | 11,123 | 11,123 | 11,123 |
| Number of groups | 1,298 | 1,298 | 1,298 |
| $R^2$ within | 0.0003 | 0.0033 | 0.0031 |
| $R^2$ between | 0.0000 | 0.0571 | 0.0580 |
| $R^2$ overall | 0.0000 | 0.0038 | 0.0042 |

*Note. *, **, **** Denote significance at the 10%, 5%, and 1% levels, respectively.

Regarding the control variables of model (3), some significant effects are found. For both baseline regression and model (3) regression the relative deal size indicates a significant negative effect towards CAR_after with a significance level of 1%. These results contradict with the results of model (1). However, the results of model (3) are in line with the findings of Asquith et al. (1983) and Moeller et al. (2004), who find that higher deal size increases the bidder announcement returns. Next to that, a significant positive effect between diversifying deals and cumulative abnormal returns is found. The significant positive effect is consistent with the results from model (1), but again contradicts with Morck et al. (1990) who find that diversifying acquisitions usually destroy shareholder value. Finally, a significant negative effect between leverage and CAR_after is found. This implies that larger levels in leverage result in lower cumulative abnormal returns after the announcement date. Since a positive effect for leverage was expected, the significant negative effect is remarkable. According to Stulz (1990) higher usage of debt helps to reduce future free cash flows, and leverage could incentivize managers to improve the firm performance. However, the results of model (3) show differently.

The values of R-squared presented in table 6 are found to be higher than that of the fixed effects regression of model (1). Therefore, model (3) has a higher goodness of fit and explanatory power.

## 6.2 Quantile regressions

The OLS regressions in the previous section give some interesting insights in the determinants of cumulative abnormal returns around announcement dates of M&A deals. However, outliers have not been considered in the dataset, nor in the regressions. Mills et al. (1996) find that outliers do affect CAR tests, and that the results of an OLS regression in the presence of outliers is extremely unreliable. Therefore, it is important to account for outliers. One possible method to account for outliers is winsorizing the dataset, which transforms the dataset by limiting extreme values. With this method the minimum and/or maximum extreme values are replaced by the lowest or highest values which are not replaced. The total desired winsorized percentage can be specified and selected, and varies for each dataset. Winsorizing the data might treat some outliers and could potentially improve the accuracy of the inferences, but the removal of these outliers may also delete important information from the analysis and even add unambiguously incorrect observations (Sorokina et al., 2013).

Another, more effective, method to deal with outliers is by performing quantile regressions. Quantile regressions can produce, even in the presence of extreme outliers, good and reliable estimates (John, 2015). The quantile regression is introduced by Koenker and Bassett (1978) and estimates the conditional median of the target, instead of the mean which is estimated in OLS. Least Square methods have some assumptions about variance of errors, whereas quantile regressions make no assumptions about the distribution of residuals. Therefore, the median regression estimator minimizes the sum of absolute errors and are more robust against outliers compared to OLS regressions.

To account for outliers, quantile regressions for model (1), model (2), and model (3) are performed and presented in table 7. As can be concluded from the results of the quantile regressions, for the market efficiency variable significant positive relations are found for model (1) and model (3), which are contradicting the results of the OLS regressions. First, in model (1), where the effect of market efficiency is tested for an event period of [-5, 5], there is an insignificant negative effect found between market efficiency and cumulative abnormal returns. In the quantile regression, a significant positive effect is found. This implies that when markets become more efficient, the cumulative abnormal returns increase as well. Second, in model (3), the OLS regression results present a significant negative relation between market efficiency and CAR_after, which was expected. However, in the quantile regression a significant positive result is shown. These results are contradicting, and these different results are probably due to the effect outliers have in this research.

Considering the control variables of the quantile regressions, some significant results are shown in table 7. First, relative deal size has a significant positive effect for model (1) and model (3), but a significant negative effect for model (2). This implies that cumulative abnormal returns are positively influenced when the deal is larger for the event window [-5, 5], and [1, 5]. This is consistent with existing empirical research (Asquith et al., 1983; Moeller et al., 2004). However, in model (2), with an event window of [-5, -1] a significant negative effect for relative deal size is found. Next to that, a significant negative effect between diversifying deals and cumulative abnormal returns before the announcement date is presented in table 7. A negative relation between both variables was expected in this research, since Morck et al. (1990) find that diversifying deals often result in destroying shareholder value.

***Table 7.*** *Quantile regressions*

| CAR, CAR_before, CAR_after | Model (1) | Model (2) | Model (3) |
|---|---|---|---|
| Market efficiency | 2.219988* | -0.5627733 | 1.296028* |
| | (1.171977) | (0.7604462) | (0.763729) |
| Relative deal size | 0.5358491*** | -0.0920262* | 0.1047315** |
| | (0.075143) | (0.0487571) | (0.0489676) |
| Diversifying | -0.0656797 | -0.1623986*** | 0.080243 |
| | (0.0827572) | 0.0536976 | (0.0539294) |
| High Tech | -0.0263919 | -0.0213368 | -0.0709631 |
| | (0.0916231) | (0.0594503) | (0.059707) |
| Public | | | |
| Stock deal | | | |
| All Cash deal | | | |
| Public * Stock deal | -0.8581758*** | -0.1272685 | -0.2773468** |
| | (0.196754) | (0.1276653) | (0.1282164) |
| Public * Cash deal | -0.2618449* | -0.1293577 | -0.0281777 |
| | (0.1498314) | (0.0972192) | (0.0976389) |
| Private * Stock deal | 0.2024888 | -0.0551258 | -0.3913959*** |
| | (0.2017763) | (0.1309241) | (0.1314893) |
| Firm size | -0.1852964*** | -0.0537019* | -0.0477701 |
| | (0.0498632) | (0.0323541) | (0.0324938) |
| Tobin's *q* | 0.0229386 | 0.0286143*** | 0.0262953** |
| | (0.0167131) | (0.0108444) | (0.0108913) |
| Leverage | -0.5508285** | -0.1227817 | -0.3455443** |
| | (0.2258471) | (0.1465426) | (0.1471752) |
| Free cash flow | 0.8872733 | 0.1292184 | 0.6213883* |
| | (0.5448028) | (0.3534993) | (0.3550254) |
| _cons | -0.1244001 | 1.181841 | -0.7901021 |
| | (1.255229) | (0.8144643) | (0.8179803) |
| Number of observations | 11,123 | 11,123 | 11,123 |
| Pseudo $R^2$ | 0.0028 | 0.0014 | 0.0015 |

*Note. *, **, **** Denote significance at the 10%, 5%, and 1% levels, respectively.

The results from the quantile regressions also show a significant negative effect between the interaction of public target firm and stock deal for model (1) and model (3). This effect was expected, since stock paid acquisitions generally result in significantly negative abnormal returns for acquirers (Sarvaes, 1991). Also, a significant negative effect between the interaction term private target firm * stock deal and CAR_after is found. This result contradicts with the findings of existing research, which argue that deals paid with stocks could be positive for targets which are privately held (Chang, 1998; Fuller et al., 2002). Significant negative relations are found for firm size in model (1) and model (3), and significant positive relations for model (2) and model (3) of Tobin's *q*. Finally, model (1) and model (3) show a negative effect for leverage and model (3) shows a positive effect for free cash flow.

Finally, the pseudo R-squared value of the quantile regressions show that model (1) predicts the outcome the best. Since the pseudo R-squared cannot be compared to an OLS R-squared, it is not possible to conclude whether the OLS regressions better predict the outcome than the quantile regressions based on the R-squared values.

# 7. Conclusion

This research contributes to existing empirical research on the determinants of cumulative abnormal returns around announcement dates for M&A deals. Existing research focused on many determinants and found evidence that some determinants have effect on cumulative abnormal returns. However, previous research did not test the effect of market efficiency. This research focusses on the effects of market efficiency on the cumulative abnormal returns.

The effect of M&A announcements on acquiring firms was measured by cumulative abnormal returns. To measure the abnormal return, the returns of the acquirer are compared to the returns of the index. An event window of [-5, 5] days was used to calculate the cumulative abnormal return. Market efficiency was measured by the Pincus Index, which provides a way to quantitively compare values in time series. For market efficiency, an algorithm is used that detects predictable patterns in stock market data. This predictability is expressed as the Pincus Index.

This research finds that market efficiency has a significant negative effect on cumulative abnormal returns for an event window of [1, 5]. Higher market efficiency, which means that there are less predictable patterns in the data, result in lower cumulative abnormal returns in the first five days after the announcement of the M&A deal. This result supports hypothesis 3, where a negative relation between market efficiency and cumulative abnormal returns after the announcement date was expected. However, the fixed effects regression of model (1) and model (2) do not show a significant effect. Therefore, no support is found for the first and the second hypothesis. Since there is no existing literature examining the relation between market efficiency and cumulative abnormal returns, there is no opportunity to compare the results of this paper to other findings regarding market efficiency.

Concerning the control variables, the regressions of this study conclude some similar and contradictory findings as existing literature. For both model (1) and model (3) the relative deal size has a significant negative effect on cumulative abnormal returns. This result is contradictory to the finding of Asquith et al. (1983) and Moeller et al. (2004) who find that higher deal size increases the bidder announcement returns. Next to that, significant positive effects are found in both model (1) and model (3) for diversifying deals. This implies that deals which are diversifying have a positive effect on cumulative abnormal returns. This result contradicts the finding of Morck et al. (1990) who find that diversifying acquisitions usually destroy shareholder value. Also, model (3) shows a significant negative effect of leverage on cumulative abnormal returns. This was not expected since higher usage of debt prevents higher free cash flows (Stulz, 1990). This study also finds results that are consistent with the results of earlier empirical research. First, model (1) shows significant negative effects between the interaction term public ownership * stock paid deal and CAR, and between firm size and CAR. Second, Model (2) indicates a significant positive relation between the interaction term private ownership * stock paid deals, which Chang (1998) and Fuller et al. (2002) also find in their studies.

When the results from the OLS regressions are compared to those of the quantile regressions, there can be concluded that some results are contradicting. Quantile regressions are performed to control for possible outliers in the sample. In the results of the quantile regressions positive relations between market efficiency and cumulative abnormal returns are found, which indicates that cumulative abnormal returns increase, when market are considered to be more efficient. From a theoretical point of view, this result is unusual and contradicts the expectations of this research. Despite this, existing literature finds that CAR tests are affected by outliers, and that OLS regression in the presence of outliers are extremely unreliable (Mills et al., 1996). Based on literature, quantile regressions are considered to give good and reliable estimates, even when there are outliers (John, 2015). Therefore, quantile regressions might be the better option.

This research is subject to several limitations. First, although various determinants are considered as control variables in this model, the R-squared of all regressions are low. M&As are quite complex processes and there are many determinants which influence the cumulative abnormal returns. Therefore, future research might include more and different variables in their models. Second, robustness checks could have been added to the regressions to identify whether the same results are found. For example, simpler variables to measure market efficiency could have been added to compare the results with the results of the regressions which are executed in this research. Finally, this research focusses on the short-term effects of M&A deals, which is the [-5, 5] event window. However, the long-term effect of market efficiency on M&A deals is interesting too. Interesting questions that can be questioned are: do the long-term effects cancel the short-term effects out? Or will the effects only be strengthened in the long-term? Such questions can be worthwhile to answer in future research.

Despite the limitations of this research, the research could be seen as a good starting point for research that tests the effects between market efficiency and cumulative abnormal returns. By using the model of Delgado-Bonal (2019) to measure market efficiency, there is room for a lot of different approaches for future research. Future research could extend the sample by adding more indexes and expand the time period which is used for this study. By expanding the time period, periods which are identified as merger waves could be added and there can be tested what the effects of merger waves are.

## 8. References


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# Appendix 1

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) car | 1.000 | | | | | | | | | | | | | | |
| (2) marketeff | 0.005 | 1.000 | | | | | | | | | | | | | |
| (3) rdsize | 0.072 | 0.004 | 1.000 | | | | | | | | | | | | |
| (4) Diversifying | 0.003 | -0.010 | 0.005 | 1.000 | | | | | | | | | | | |
| (5) Hightech | 0.002 | -0.138 | -0.024 | 0.157 | 1.000 | | | | | | | | | | |
| (6) Public | -0.021 | 0.027 | 0.051 | 0.091 | -0.028 | 1.000 | | | | | | | | | |
| (7) Private | 0.021 | -0.027 | -0.051 | -0.091 | 0.028 | -1.000 | 1.000 | | | | | | | | |
| (8) Stockdeal | 0.008 | 0.071 | 0.119 | 0.042 | -0.050 | 0.324 | -0.324 | 1.000 | | | | | | | |
| (9) Allcashdeal | 0.022 | 0.074 | -0.021 | 0.017 | -0.010 | 0.229 | -0.229 | -0.205 | 1.000 | | | | | | |
| (10) Unknown | -0.025 | -0.111 | -0.050 | -0.041 | 0.039 | -0.405 | 0.405 | -0.393 | -0.819 | 1.000 | | | | | |
| (11) PublicStock | -0.035 | 0.019 | 0.093 | 0.076 | -0.036 | 0.532 | -0.532 | 0.693 | -0.142 | -0.273 | 1.000 | | | | |
| (12) PublicCash | 0.011 | -0.002 | -0.003 | 0.052 | 0.012 | 0.720 | -0.720 | -0.092 | 0.450 | -0.369 | -0.064 | 1.000 | | | |
| (13) PrivateStock | 0.046 | 0.079 | 0.071 | -0.018 | -0.033 | -0.088 | 0.088 | 0.687 | -0.141 | -0.270 | -0.047 | -0.063 | 1.000 | | |
| (14) PrivateCash | 0.018 | 0.083 | -0.021 | -0.015 | -0.018 | -0.217 | 0.217 | -0.166 | 0.812 | -0.665 | -0.115 | -0.156 | -0.114 | 1.000 | |
| (15) fsize | -0.082 | -0.050 | -0.114 | -0.004 | 0.002 | 0.107 | -0.107 | -0.100 | -0.064 | 0.118 | 0.040 | 0.075 | -0.178 | -0.119 | 1.000 |
| (16) tobinq | 0.048 | -0.080 | -0.019 | 0.034 | 0.144 | -0.058 | 0.058 | 0.005 | -0.011 | 0.007 | -0.040 | -0.036 | 0.048 | 0.012 | -0.201 |
| (17) leverage | -0.044 | 0.075 | -0.013 | -0.017 | -0.199 | 0.021 | -0.021 | 0.019 | 0.030 | -0.040 | 0.038 | -0.002 | -0.011 | 0.035 | 0.115 |
| (18) fcf | -0.011 | -0.182 | -0.096 | 0.055 | 0.190 | -0.062 | 0.062 | -0.158 | -0.026 | 0.117 | -0.072 | -0.012 | -0.147 | -0.020 | 0.008 |

| Variables | (16) | (17) | (18) |
|---|---|---|---|
| (16) tobinq | 1.000 | | |
| (17) leverage | -0.121 | 1.000 | |
| (18) fcf | 0.254 | -0.083 | 1.000 |