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# The stock market reaction to Green M&As

*An empirical analysis of companies listed in the US and UK*

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# Abstract

This thesis seeks to investigate the relationship between shareholder value and acquisitions with a environmental-friendly ("Green") perspective. By examining the shareholders reaction to the announcement of Green acquisitions, we investigate whether there are significant abnormalities in the security stock prices. We believe that the increasing focus towards corporate social responsibility (CSR) and environmental social governance (ESG) during the last decade makes the investigation of shareholders reaction to Green acquisitions an interesting topic to study.

To the best of our knowledge, little research within the field of Green M&As have been conducted, and we believe that the ongoing shift and increasing focus towards CSR and ESG encourages research within this field. By performing an event study and a cross-sectional analysis, we aim to contribute to research by investigating differences between Cumulative abnormal returns (CARs) for shareholders observing a Green acquisition and for shareholders observing a non-Green acquisition.

We perform this study by analyzing a total of 40 Green deals from US and UK during the last decade, as well as a corresponding matched sample with 40 Non-Green deals.

Our results suggests that the acquisition of a Green target company does not create significant value for the acquiring shareholders. When comparing our Green sample to the Non-Green sample, we find that without controlling for firm and deal-specific characteristics, the Green sample yield a higher, significant mean in CAR. However, when adding firm and deal-specific characteristics as explanatory variables through our cross-sectional analysis, we find that the differences in CAR instead is explained by deal- and firm-specific characteristics. Put differently, our results suggest that investors do not value Green acquisitions higher than Non-Green acquisitions in terms of equity valuations. We also observe that the acquisition of a company in another sector destroys shareholder value during our event window. Lastly, our study supports previous research by showing that acquiring shareholders, on average, does not experience significant value creation through acquisitions.

***Keywords*** – M&A, Green, Cleantech, Renewables, NHH

# Acknowledgements

This thesis concludes our indiviual work as masterstudents at NHH with a major in Financial Economics.

During our thesis, we aimed to increase our knowledge within the field of Mergers and Acquisitions as well as shareholders perception of clean technology. Therefore, we ended up with conducting an event study with emphasis on Green acquisitions.

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# Abbreviations

| | | |
|---|---|---|
| AR | = | Abnormal return |
| AAR | = | Average abnormal return |
| CAR | = | Cumulative abnormal return |
| CAAR | = | Cumulative average abnormal return |
| CSR | = | Corporate social responsibility |
| ESG | = | Environmental social governance |
| FiT | = | Feed-in tariff |
| M&A | = | Merger & Acquisition |

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# 1 Introduction

During the last decade the cleantech and renewable energy industry has seen substantial growth in financial investments. According to UNEP (McCrone et al., 2019), \$ 2.6 trillion has been invested in cleantech and renewable energy during the period 2010 - 2019, which is more than treble the amount invested in the previous decade. The majority of investments has been in the sub-sectors of wind and solar, accounting for \$ 1.3 trillion and \$ 1 trillion, respectively. Investments in biomass and waste-to-energy are the third largest, amounting to \$ 115 billion during the period. At the start of 2010, wind and solar only accounted for 4 % of the global energy capacity, while now at the end of 2019 these renewable technologies account for over 18 % (McCrone et al., 2019).

Given the immense increase of financial investments in cleantech and renewable energy, it is interesting to research to what extent this affect mergers & acquisitions (M&As) within this field. The motivation behind our thesis is to analyze the perspective of shareholders of firms that perform "Green" acquisitions. According to Pernick and Wilder (2007), cleantech refers to any product, service, or process that delivers value using limited or zero non-renewable resources and creates significantly less waste than conventional alternatives. We deem this definition of cleantech as an accurate and appropriate definition of "Green" technology. Thus, any reference to a Green deal will refer to deals performed within the cleantech industry. We provide a discussion on the keywords we applied to our text search in chapter 5.

Our thesis is structured as follows: In chapter 2 we present a review of relevant literature and previous empirical findings. In chapter 3 we discuss the motivation behind our hypothesis by relating it to previous research. In chapter 4 we provide a discussion of how we performed the event study and cross sectional study. In chapter 5, we discuss how we created our data sample. In chapter 6 we provide the results from our analysis based on our hypotheses. We provide a discussion on the robustness and limitations of our analysis in chapter 7, before arriving at our conclusion in chapter 8.

# 2 Literature overview

In this section we will review some theoretical concepts relevant for our thesis. First, we will start by giving a brief overview of mergers and acquisitions and the motivational factors behind them. Then we will discuss the dynamics of the cleantech and renewable energy sector, before reviewing empirical findings on how these dynamics affect the field of M&A.

## 2.1 Mergers and Acquisitions

Mergers and acquisitions (M&A) are a vital part of what's often referred to as "the market of corporate control". According to Berk and DeMarzo (2017), a merger is a combination of two companies in which the assets and liabilities of the selling company (target) is absorbed by the buying company (acquirer), while an acquisition is when an acquiring firm purchases all the stocks or existing assets from a target firm in either cash or assets of equivalent value. M&A's can be classified into three types, horizontal, vertical and conglomerate (Gaughan, 2017). A horizontal merger occurs when two or more competitors combine, which could lead to a combined increase in market power. A vertical merger is when two or more companies in different stages a supply chain combine, in order to increase synergies effects and gain more control of the supply chain process. Lastly, a conglomerate merger occurs when two or more companies that are not competitors and do not have a buyer-seller relationship, engage in a merger.

Periods of high merger activity is usually referred to as "merger waves". These waves are characterized by cyclic activity, meaning periods of high level merger activity followed low-activity periods with few merger deals. In the U.S., six merger waves has occurred in history.

| | |
|---|---|
| First wave, 1897-1904 | Second wave, 1916-1929 |
| Third wave, 1965-1969 | Fourth wave, 1984-1989 |
| Fifth wave, 1992-2001 | Sixth wave, 2004-2007 |

Mitchell and Mulherin (1996) identified that "merger waves" tend to be caused by a combination of economic, regulatory, and technological shocks. Economic shocks come in the form of an economic expansion that motivates companies to expand to meet a rapidly growing aggregate demand in the economy. M&As can serve as a faster way of expansion than internal, organic growth by allowing the acquirer to seize synergy opportunities. Regulatory shocks, on the other hand, might occur when regulatory barriers are eliminated, which ex-ante may have prevented corporate combinations. Ovtchinnikov (2013) found that industry deregulation tends to occur when industries experience poor performance. Technological shocks might occur in many forms as technological change can result in dramatic changes altering existing industries and can even create new industries(Gaughan, 2017). Harford (2005) finds in his studies that various shocks in technology are not enough to bring out a merger wave by themselves. By looking into specific industry merger waves, rather than the overall level of activity, he found that capital liquidity is also a necessary condition for a wave to take place and that misevaluation and market timing efforts by managers are not a direct cause of wave, though they could be a cause in some specific deals (Harford, 2005). Rhodes-Kropf et al. (2005) contradicts this when finding that misevaluation and valuation errors do motivate merger activity by comparing market-to-book ratios to true valuations.

## 2.2 Merger strategy and motivation to acquire

According to Gaughan (2017), one of the most fundamental motives for engaging in mergers and acquisitions is growth. If a company wants to expand, they face the choice between internal, organic growth and growth through M&A. Expanding through internal growth may be a slow and uncertain process compared to expanding through acquisitions. As many growth opportunities are dependent on acting within a limited window of opportunity, internal growth increases the risk of competitors responding quicker and seizing desired market shares Gaughan (2017). Growth through M&As could thus reduce the risk of being blindsided by competitors and limit the time it takes to realize the desired advantage.

Horizontal mergers that result in an increase in market share may have a significant impact on the combined firm's market power, dependent on the size of the merging firms and the level of competition in the industry (Gaughan, 2017). Market power refers to the ability to set and maintain price above competitive levels, in other words the ability to set price excess the marginal cost and thereby gain the difference. Vertical integration through M&A involves acquiring a firm that is either backward or forward of the acquirer in the supply chain.[1]

Expanding into other geographical regions or countries is a common and practiced method of growth (Gaughan, 2017). In order to successfully expand into new geographical market a company needs to know the all the nuances of the new market, recruit new personnel and circumvent a broad specter of hurdles, such as language and customs barriers. According to Gaughan (2017), geographical expansion can be achieved quicker and with less risk through M&A than through internal development, as established companies already have the facilities, management and knowledge as well as other resources needed to successfully operate in the region. Cross-border acquisitions are a widely used method of entering foreign markets and creating growth opportunities (Gaughan, 2017). Utilizing the country-specific expertise of the target, such as distribution network and indigenous staff, may bring advantages that an internal expander might struggle to acquire. On the other hand, cross-border deals present some basic and obvious challenges that domestic deals lack. A successful business model from one country is not necessarily as successful in other countries and often need to be redeveloped and modified in order to fit country-specific market conditions (Gaughan, 2017).

A primary justification behind performing takeovers are the synergy effects they bring to the acquirer. Synergy is the value realized from the incremental cash flows generated by combining two firms (DePamphilis, 2019). Synergy is usually divided into two main types: operating and financial. Operating synergy is achieved by improving operation efficiency through economies of scope and scale by acquiring a customer, supplier or competitor or to enhance technical skills. Financial synergy refers to the acquirer's reductions in cost of capital due to an M&A. These synergies occur for instance if the merged firm have relatively uncorrelated cash flows or they can realize cost savings from lower securities issuance and transaction costs. Diversification is one method to obtain financial synergies, as acquiring a firm beyond the current industry category can help reduce the level of systematic risk and thereby lower cost of capital (Gaughan, 2017). Diversification can be divided into

[1]Backward integration is when acquiring a firm closer to the source of supply, such as a raw material producer. Forward integration is when acquiring a firm closer to the ultimate costumer, such as a transportation or marketing firm

related and unrelated diversification. Related diversification can be achieved by performing vertical mergers, such as acquiring a supplier or retailer. Unrelated diversification on the other hand, can be achieved through conglomerate mergers. Many studies have questioned the risk-reducing benefits from diversifying a company though conglomerate mergers, with dividing results. Elgers and Clark (1980) found evidence that conglomerate mergers provided superior gains relative to non-conglomerate mergers. The result showed positive wealth effects for both the shareholders of the target firm and the acquiring firm. Wansley et al. (1983) also provided evidence of positive wealth effects for both target and acquiring shareholders. However, they found that shareholder returns were larger in horizontal and vertical acquisitions than in conglomerate acquisitions, contradicting the result of Elgers and Clark (1980). A study conducted by Berger and Ofek (1995) found that diversification resulted in a loss of firm value averaging between 13 % and 15 %. Their results showed that the diversified firms over-invested in the diversified segments more than single-line firms, resulting in an overall loss in firm value.

When firms use M&As to adapt to changes in external environment, such as regulatory restrictions and technological innovation, they preform what is called strategic realignment. Sectors such as utilities, telecommunication, healthcare and financial services has been subject to a high degree of strategic realignment during recent years, as these sectors have been significantly deregulated (DePamphilis, 2019).

## 2.3 Energy transition and clean technology

As we are exclusively looking into M&A transactions in the cleantech and renewable energy sector, we find it important to understand the dynamics of the energy transition which is occurring and factors driving strategic investment in the industry.

Energy transition is the period which elapses between the introduction of a new primary energy source, or a prime mover, and its rise to claiming a substantial share of the overall energy market (Arent and Zinaman, 2017).[2] During the last 200 years there have been two major transitions within this field, the transition from biomass to coal, and the transition from coal to oil and gas. The third energy transition to renewable energy sources is currently unfolding (Arent and Zinaman, 2017). Historical transitions were driven by

[2]Substantial share refers to a 25 % market share

the opportunity to generate energy at higher rate and at a lower cost in order to sustain a growing global demand, while the low-carbon transitions we experience today are on the other hand "problem driven", with the main problem being greenhouse gas (GHG) emissions (Sovacool and Geels, 2016).

The transition toward newer and cleaner solutions, such as sources of renewable electricity, require significant changes in technology, political regulations, tariffs, and pricing regimes, as well as changes in the behavior of users and adopters (Arent and Zinaman, 2017). Sovacool and Geels (2016) argue that energy transitions are multidimensional, non-linear, non-deterministic, complex and highly uncertain. They suggest that energy transitions involve changes in three interrelated dimensions: 1) the tangible elements of clean technology and energy systems, 2) actors and social conduct, and 3) socio-technical regimes. The tangible elements refer to aspects of technology, infrastructure, production equipment, consumption patterns and market conditions. The dimension of actors and conduct refers to new strategies, changing investment patterns, changes in coalitions and capabilities of actors. The last dimension of socio-technical regimes regards formal regulations and policies, institutional norms and social practices.

### 2.3.1 Factors affecting the transition to clean technology

#### Cost reductions in cleantech

During the last decade, the global Leveraged Cost Of Electricity[3] (LCOE) produced from renewable energy technologies has been reduced drastically. Since 2009, the LCOE of solar photovoltaic has been reduced by 81 %, whilst LCEO of onshore wind and offshore wind has been reduced by 46 % and 44 %, respectively (McCrone et al., 2019) A range of specific factors has contributed to the cost reduction seen in clean technology. Through technological improvement and R&D, clean technology have incrementally increased efficiency and generated increased output per level of capacity.

As a result, methods for developing and operating renewable energy facilities has become more streamlined and efficient (Hearps and McConnell, 2011). Factors such as economies of scale and high competitiveness among manufacturers and developers also drive cost

[3]Leveraged Cost Of Electricity includes cost of product development and construction, lifetime expences of operating and maintence, feedstock cost and finance cost

reductions (McCrone et al., 2019). A final important factor is the downward trend in financial costs. A common feature of renewable projects, such as solar plants, wind turbine parks and waste management facilities, are that they require high upfront capital expenditure in order to develop operational facilities. The last decade has seen record-low interest rates on a global scale, which in turn has driven down the cost of both equity and debt (McCrone et al., 2019).

**Environmental policies**

Policy makers play a significant role in the ongoing transition from a fossil-fuel dependent system to a more sustainable and resource efficient system, by stimulating and accelerating development of new energy technologies (Åstrand and Neij, 2006). Investment opportunities in renewable energy have usually been at a disadvantage compared to conventional energy because of environmental externalities.[4] The wave of energy policies seek to correct for these externalities and make the risk-return equation more favorable for renewable energy investors by for instance implementing feed-in tariffs (FiTs) and renewable energy certificate (RECs) systems, or reducing the risk perspective by issuing loan guarantees (Wüstenhagen and Menichetti, 2012). Naturally, the outcome or effectiveness of an environmental policy is strongly influenced by the variation in risk-exposure the different policies imply for investors in the sector. Identifying and trying to reduce actual risk is the first step in creating an effective policy. However, maintaining long-term sustainability require policy makers to understand and manage different investors risk perceptions, as they act under bounded rationality (Simon, 1957). Surveying investors preferences and attitudes is one method of identifying which risks are perceived as particularly relevant and could serve as a guideline of how policy makers should weight their environmental polices (Wüstenhagen and Menichetti, 2012).

The amount of countries implementing renewable energy polices has increased severely during the last decade and according to a report from REN21 (2019), 169 counties have implemented some form of renewable energy policy before the end of 2018. FiTs are the most frequently used form of priced-based policy on a global scale, with already 111 countries having implemented such a policy as of 2018 (REN21, 2019). The principle of FiT policies is to offer guaranteed prices for electricity produced by renewable energy resources

[4]Environmental externalities refers to the economic uncompensated environmental effects of production and consumption that effect consumer utility and enterprise costs.

for a fixed period of time. These prices will generally be offered in a non-discriminatory manner for every kWh of electricity that is produced, but could be differentiated in relation to type of technology, size of installation, location of project, etc. (Couture and Gagnon, 2010).

Sawin and Flavin (2004) studied the effectiveness of different policies based on a broad specter of impact criteria, such as installed capacity, amount of energy generated, technological advancement, etc., and concluded that FiTs are the most influential energy policy and responsible for most of the measured additions in renewable capacity and generation of renewable energy. Bürer and Wüstenhagen (2009) performed a study on the effectiveness of energy policies from the perspective of cleantech investors and found that investors assess FiTs as the most effective policy for development in the industry. Further, Criscuolo et al. (2014) studied the effect of FiTs and RECs as incentives for cross-border M&A investments. Similar to Sawin and Flavin (2004) and Bürer and Wüstenhagen (2009), they found that FiTs also had the strongest effect on cross-border M&A in cleantech. However, they found that too high levels of FiTs had a negative impact on M&A. They hypothesized two explanations for this finding. First, some countries set high levels of FiTs as a compensation for poor profitability and limited capacity potential. Secondly, maintaining high levels of FiTs are not sustainable long-term, leading to a reduction in policy credibility (Criscuolo et al., 2014). Overall, there is a consensus that implementing FiTs reduce the investors risk-exposure to clean tech and renewable energy investments, thereby creating a more level playing field, guiding the market to value positive externalities of renewables.

**Change in institutional norms and conduct**

During the last decade, firms have faced an increasing pressure from different stakeholders to report more information about their environmental impact. Stakeholders such as investors, customers, governments, etc. are increasingly demanding companies to disclose more information on both their environmental and social performance and their conduct. As a result from the pressure stakeholders induce, the amount of firms voluntarily issuing corporate environmental and sustainability reports has increased considerably during the last decade (Lyon and Maxwell, 2011). The number of companies in the S&P 500 reporting on sustainability have increased from 20 % in 2011 to 86 % in 2018 (Kwon et al., 2018).

Environmental non-governmental organizations (ENGOs), as industry stakeholders, work toward increasing awareness of climate change and encouraging sustainable development. Through collective action, driving citizen pressure and scrutinizing firms performing bad on environmental measures, ENGOs have gained traction in influencing corporate behavior (King and Pearce, 2010). Testa et al. (2018) studied the influence of institutional pressure from different stakeholders and the effect they have on environmental corporate strategy. Their results showed that while institutional pressure from stakeholders generally strengthen proactive environmental practices, it can also encourage superficial adaptation (i.e. greenwashing).

Greenwashing is the process of signaling a false impression or provide misleading information about a firm's environmental conduct, in order to capitalize on the growing demand of environmentally friendly products and services (Marquis et al., 2016). Lyon and Maxwell (2011) views greenwashing as a form of selective disclosure, whereby firms seek to gain legitimacy by only disclosing positive environmental actions while concealing negative actions, creating a misleading positive impression of the firm's overall environmental performance. Research on corporate environmental disclosure suggest that companies that cause more environmental damage are subject to greater external pressure and are therefore more likely to comply with voluntarily disclosure of their environmental performance, e.g. less selective disclosure (Short and Toffel, 2007; Cho and Roberts, 2010). Marquis et al. (2016), performed a global study of 4,750 companies over 45 countries, finding evidence that environmental damaging companies are less likely to engage in selective disclosure due to exposure of scrutiny and global norms.

## 2.4 Efficient Market Hypothesis

The belief of market efficiency is the most important underlying theoretical concept of performing an event study. The Efficient Market Hypothesis (EHM) states that the current price of an asset or stock should fully reflect all the information available in the market. In other words, this means that prices only fluctuate when new relevant information becomes available in the capital market. If no new information is shared, the prices should remain unchanged. It is impossible to consistently predict when new relevant information will enter the market, which in turn implies that it's impossible to consistently outperform the market portfolio (Bodie et al., 2014).

Fama (1970) states that there are three versions of market efficiency:

- The weak form
- The semi-strong form
- The strong form

The weak form assert that stock prices reflects all information that can be derived by examining historic prices, trading volume and short interest. Trend analysis is inefficient as the benefit of analyzing historic prices is already reflected in the stock price.

The semi-strong form states that all publicly available information regarding the past and future prospects of a firms is reflected in its stock price.

Lastly, the strong form of the EMH states that all information that are relevant to a firm, both public and insider-information, is reflected in the stock price. The strong form of market efficiency is quite extreme and is not viewed as valid by scholars but used as a completing benchmark for the efficient market hypothesis. In our event study, we have assumed that the semi-strong form of market efficiency holds and that all public information is reflected in the stock prices of our chosen sample firms.

# 3 Hypotheses

In this section we will review empirical studies on M&A activity and shareholder returns, and develop our hypotheses. According to a study performed by Andriuskevicius (2017), the most frequent and established methodologies used to measure M&A performance is event studies, accounting studies and executive surveys. The most utilized methodology out of these three are event studies, which we will elaborate on in our methodology section.

Generally, existing research on M&A performance show evidence that M&A transactions produce a positive effect on target firms and empirically show positive wealth effects for target firm's shareholders. Studies such as Jensen and Ruback (1983), Andrade et al. (2001) and Campa and Hernando (2004) all find evidence that M&A activity generates positive gains for the target shareholder due to the high target premiums being paid by the acquiring firm. However, empirical research has not found clear consensus on the effects M&A transaction has on the acquiring firm and the acquiring firms shareholders. Literature on post-acquisition performance has shown different and even conflicting results due to different performance measures, both market based and accounting measures being applied by different researchers (Bettinazzi and Zollo, 2017).[5] Nevertheless, the majority of studies in the field of M&A performance indicate negative wealth effect for the acquiring firm (Jensen and Ruback, 1983; Andrade et al., 2001; Campa and Hernando, 2004; Zollo and Meier, 2008). Andrade et al. (2001) studied the effects of 3688 M&A transactions between publicly traded U.S. firms, and found a negative three-day average abnormal return for the acquiring shareholders, though not statistically significant on conventional levels. These findings are supported by Campa and Hernando (2004) similar study of M&A transactions within the European Union, they also find an insignificant negative abnormal return for acquiring shareholders.

**Empirical studies on M&A performance in cleantech and renewable energy**

Until recent years, relatively little research has been conducted on renewable energy M&As. Eisenbach et al. (2011) examined stock price reactions to M&A transactions in the renewable energy sector. They analyzed 337 completed M&A transactions that were

[5] Examples of market based measures are Tobin Q and stock return. Examples of accounting measures are return on assets (ROA), return on equity (ROE), return on sales (ROS), ect.

announced between 2000-2009, with emphasis on acquirer return rather than the wealth effects of target shareholder. Exclusively focusing on acquirer returns and neglecting target returns, allows M&A of non-public targets to be included in the sample. The study concluded that acquirers from both inside and outside the renewable energy sector earned positive abnormal returns when diversifying into renewable energy.

Basse-Mama et al. (2013) researched capital market reactions to announcement of corporate strategic M&A transactions in the cleantech industry, finding evidence of significant positive wealth effects. Their result also show that on average, cleantech firms earn a higher abnormal return than non-cleantech firms, indicating that the effect of related diversification are more powerful than the effect of unrelated diversification. Backed by previous research, we developed the following hypothesis:

***Hypothesis 1: The announcement of a Green M&A have an effect on the acquirer shareholder value***

Yoo et al. (2013) studied the effect M&A transactions in the renewable energy sector had on enterprise value, whilst unlike Eisenbach et al. (2011) also considering effects the various types of renewable energy M&A had on enterprise value. They separated the transactions on related and unrelated diversification and divided them into four groups: homogenous, heterogenous, heterogenous-renewable and heterogenous-other. Their results indicated that three out of the four groups experienced a positive effect on enterprise value. In line with Basse-Mama et al. (2013), homogenous M&A showed the biggest effect on enterprise value overall, whilst heterogenous-other M&A showed the second largest effect. Renewable energy M&A performed by established firms in different energy industries, were found to have negative effects, which indicates that strict regulations on the use of clean energy lead to energy companies incurring considerable costs. Commenting on their findings, they state that homogenous M&A efficiently increase market power and other financial synergies through horizontal integration. They also argue that the relative high abnormal returns found the group hetrogenous-other M&A, indicate that firms in cleantech and renewable energy are considered to have strong potential as investment products (Yoo et al., 2013). As we discussed in chapter 2.3, the development of cleantech and the transition into renewable solutions are affected by numerous factors which are rapidly changing the speed of this transition. Therefore, we deem it interesting to analyse if these factors affect the shareholder value of the acquiring firm performing a "Green" acquisition.

In this section we have reviewed empirical research on M&A performance both from a general perspective and specific research from the cleantech and renewable energy industry. General empirical studies suggest that M&A transactions destroy shareholder value for the acquiring firm, whilst research on M&A performance in cleantech and renewable energy indicate a positive wealth effect on the acquirer. Based on these factors and a overall assessment of empirical studies, we developed our second hypothesis.

***Hypothesis 2: Green acquisitions obtain a higher cumulative abnormal return for the acquiring firm than Non-Green acquisitions***

# 4 Methodology

In this section, we provide a discussion on how we performed our analysis, as well as how we tested our results for statistical significance and robustness. In order to derive the cumulative abnormal returns for each event, we applied the Event Study Methodology. Furthermore, we provide an explanation of how we structured a cross-sectional analysis with the results from our event study as the dependent variable.

## 4.1 Event Study Methodology

The event study methodology is a popular methodology in finance and accounting for investigating the relationship between security prices and economic events (Strong, 1992). By analyzing financial data, an event study seeks to measure the effect an event has on a firm's value by isolating the effect within an "event-window". Under the assumption of a semi-strong form of the Efficient Market Hypothesis (EMH), the market will immediately react to the event's impact on the firm's future cash flows and/or changes in risk, and thus be reflected in the firm's value (Fama, 1970). Through various researchers, the event study methodology have improved to include the removal of general market price movements and confounding events (MacKinlay, 1997).

According to MacKinlay (1997), there is no unique structure to event studies. However, event studies follow a general flow of analysis. Initially, one starts by identifying the event of interest, which in this thesis is the acquisition of a "Green" company by US and UK acquirers, within the period the event is thought to be reflected in the security prices. This period is referred to as the "event window". Moreover, one must determine the length of the event window. According to MacKinlay (1997), it is customary to expand the event window over a larger period than the specific period of interest.

Dann et al. (1977) found that securities reflect newly released, firm-specific information within 15 minutes of announcement, suggesting a short event window. It is important that the event window is of such length that it includes the significant impact of the event of interest. By keeping the event window short, the problem of confounding effects is also limited (McWilliams and Siegel, 1997). Additionally, MacKinlay (1997) argues that the period of interest should include at least the day prior to the event and the subsequent day of the event in order to capture the impact of announcements that occur after the markets close, as well as any effect that might occur after the security exchange closes. One could also suspect that the period before the event window could reflect content of interest in the case of leaked information and rumors. We deem this important for our study, as the announcements of acquisitions might occur both before and after the stock exchanges opening hours. Public companies are required to announce events such as acquisitions in a public release. Thus, we consider the announcement date to be the time of interest, and include one day before and after the announcement within our window[-1,1]. Additionally, we report the results over a five-day event window by expanding the window to include observations from two days before and prior to the event [-2,2].

Once the event has been identified, it is necessary to include selection criteria for the inclusion of an observation in the study (MacKinlay, 1997). These criteria will be further discussed in chapter 5: Data.

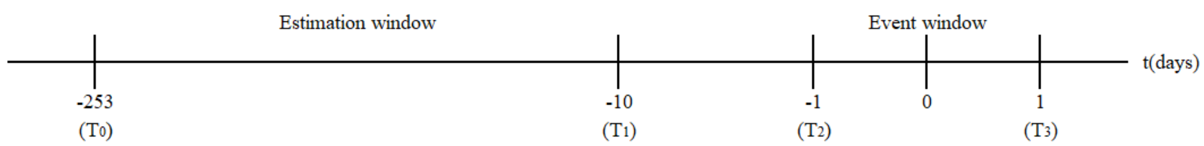
In order to measure the impact of an event on a firm, one must measure the abnormal return. Abnormal returns can be expressed as the difference between the actual, observed return of a firm's stock price during the event window and the normal, non-observed return of the firm's stock price during the event window. The normal, non-observed return is the expected return during the period of the event, without the occurrence of the event. For each firm $i$ and event date $t$, one can compute the abnormal returns as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t)$$

Where $AR_{i,}$, $R_{i,t}$ and $E(R_{i,t}|X_t)$ are abnormal, actual and normal returns respectively for time period $t$ (MacKinlay, 1997), with $x_t$ being the conditioning information for the normal return model. Furthermore, MacKinlay (1997) states that there are two common choices for modelling the normal return –*(1) the constant mean return model* and *(2) the market model.* The constant mean return model assumes that the price of the stock will continue to increase with the parameter obtained by averaging the return of the stock over a certain period. The market model, on the other hand, suggests that the price of a stock is dependent on the return of the market and that the normal return for stock $i$ can be computed by analyzing the relationship between the stock return and the return on the market $m$ over a certain period.

The next step is to define the estimation window. The estimation window should be short enough to only include the most recent changes in the stock prices, at best avoiding any changes in systematic risk, whilst being long enough to keep the variance of the returns at a low level (Strong, 1992), which provides a trade-off. MacKinlay (1997) uses an estimation window of 250 trading days, ending three days before the start of the event window to prevent biased estimates. The day of the event is defined at $t = 0$. We thus analyze data from 253 days prior to our event window starting at $t - 1$, ending at $t + 1$, omitting the last ten days of each return prior to the event window, as illustrated in the figure below.

**Figure 4.1:** Timeline




In order to model the normal performance (expected performance without the event occurring), there are, according to MacKinlay (1997) two groups the numerous approaches to calculate normal return can be categorized into: statistical and economic. In this study, we will apply the market model, a statistical model which relates the return of any given security to the return of the market portfolio (MacKinlay, 1997). The market model can be expressed as the return on any security $i$, illustrated in equation (4.1):

$$R_{i,t} = \alpha_{i,t} - \beta_i R_{m,t} + \varepsilon_{i,t} \tag{4.1}$$

$$E(\varepsilon_{i,t} = 0) \quad \text{and} \quad var(\varepsilon_{i,t}) = \sigma^2_{i,t}$$

$R_{i,t}$ is the return on security $i$ at time $t$, $R_{m,t}$ is the return on the market portfolio $m$ at time $t$, and $\varepsilon_{i,t}$ is the zero mean disturbance term. $\alpha_i$, $\beta_i$ and $\sigma^2_\varepsilon$ are the parameters of the market model (MacKinlay, 1997). These parameters are obtained by running an OLS regression. This illustrates an example of a one factor model, where the $\beta$-parameter returns the coefficient when regressing the return of security $i$ on the return of the market $m$. In order to capture the effect of security changes on a daily basis, we compute the continuously compounded returns for each security $i$ with the corresponding benchmark $m$. While Sharpe (1970) & Alexander and Bailey (1995) discusses the addition of other factors, MacKinlay (1997) argues that the gains from implementing multi-factor models for event studies are limited. This is because the gain in explanatory power is relatively small and does not reduce the variance of the abnormal return very much. In our study we thus proceeded with the market model. In addition, we provide the constant mean return-model and the market adjusted-model to provide a robustness-assessment of our results (see Appendix 1 for the methodology).

The abnormal return $AR_{i,t}$ for security $i$, at time $t$ is computed as the difference between the real, observed return for security $i$ and the normal, unobserved return estimated by the market model. This can be illustrated as in equation (4.2):

$$\widehat{AR}_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t}) \tag{4.2}$$

As explained, we use an event window over multiple days, and thus need to aggregate the abnormal returns for each security $i$ through each day $t$ throughout the event window [-1,1]. This returns the cumulative abnormal return (CAR) between periods $(T_2, T_3)$:

$$\widehat{CAR}_{i(T_2,T_3)} = \sum_{t=T_2}^{t=T_3} \widehat{AR}_{i,t} \tag{4.3}$$

By aggregating the abnormal returns for all the securities $i$, using OLS in accordance with equation (4.2) from each event period, the sample aggregated average AR for period $t$ is:

$$\overline{AR}_t = \frac{1}{N} \sum_{i=1}^{N} \widehat{AR}_{it} \tag{4.4}$$

Finally, the average abnormal returns can be aggregated through the event window by adopting the same intuition as in equation (4.3) such that:

$$\overline{CAR}_{(T_2,T_3)} = \sum_{t=T_2}^{T_3} \overline{AR}_t \tag{4.5}$$

## 4.2 Significance testing

In order to identify any differences between the cumulative abnormal return between Green acquisitions and Non-Green acquisitions, we must investigate for both sample sets whether the observed CAR for each firm $i$ is statistically different from zero. Furthermore, we will analyze whether the CAR for Green acquisitions is equal to the CAR for Non-Green acquisitions. For our results, we will have to employ tests such that the statistical power is of such level that we avoid a wrongly rejected null-hypothesis.

### 4.2.1 Tests

MacKinlay (1997) groups the significance tests into two groups: *parametric* and *non-parametric* tests. While the parametric methods rely on assumptions about the distribution of abnormal returns, non-parametric tests does not rely on any assumptions concerning the distribution of abnormal returns. According to MacKinlay (1997), sign test and rank test are common non-parametric tests for event studies, whilst also arguing that it is common to address parametric tests in order to analyze the robustness of any conclusion drawn. By supplementing either of the methods with the counterpart, we aim to increase the robustness of any conclusion drawn through our analysis.

In our analysis, we decided to investigate whether the $\overline{AR}$s and $\overline{CAR}$s were unequal to zero by conducting a cross sectional T-test (parametric), a standardization of this test introduced by Patell (1976), further developed by Boehmer et al. (1991). Lastly, we supplement our parametric tests with a generalized sign test (non-parametric). We deem it necessary to ensure robustness of our results, as we intend to finalize our thesis with a cross-sectional analysis with the results from our event study as the explanatory variable. We will elaborate further on the cross-sectional analysis later.

This leaves us with the following, generalized formulation of our first analysis:

$$H_0 : \overline{CAR}_{i,t} = 0$$

$$H_A : \overline{CAR}_{i,t} \neq 0$$

Where the null-hypothesis, denoted by $H_0$, is that the average cumulative abnormal return is equal to zero and the alternative-hypothesis, denoted by $H_A$, is that the cumulative abnormal return is unequal to zero. The event window is denoted by $t$, and the group of securities analyzed is denoted by $i$.

### 4.2.2 Cross-sectional t-test

When testing the null-hypothesis, we conduct a two-sided cross-sectional t-test. A cross-sectional t-test is assumed to have the following statistical properties (MacKinlay, 1997):

$$\overline{CAR}_{(T_2,T_3)} \sim N[0, var(\overline{CAR}_{(T_2,T_3)})] \tag{4.6}$$

Furthermore, this is used to test the null hypothesis and draw inferences about the cumulative average abnormal returns. For this to be valid, some considerations must be made as this model assumes no correlation across the abnormal returns for the different securities. In the event of overlap or clustering in the event window, one might suspect correlation between the abnormal returns. If there are no overlaps or clustering, MacKinlay (1997) argues that with the assumptions previously made about the distribution, the abnormal returns across the sample will be independent.

In practice, the residual variance for each security $\sigma^2_{\varepsilon_i}$, is unknown. This requires us to use an estimator to compute the variance of the abnormal returns. According to MacKinlay (1997), the sample variance measure of $\sigma^2_{\varepsilon_i}$ obtained from the market model regression in the estimation window is suitable for the test. This implies that our null-hypothesis can be tested with the following t-statistics:

$$t_{\overline{CAR}} = \sqrt{N}\frac{\overline{CAR}}{S_{\overline{CAR}}} \tag{4.7}$$

With $S_{\overline{CAR}}$ being the sample's standard deviation of the cumulative abnormal return for N number of firms.

### 4.2.3 Patell test

The Patell test is a communly used statistical test in event studies (MacKinlay, 1997). James Patell (1976) proposes an extension to the traditional test by standardizing each

$AR_i$ by applying the forecast-error corrected standard deviation to the calculation of the statistical parameter. The test statistic for abnormal returns can thus be calculated as in equation (4.8):

$$z_{Patell_t} = \frac{\overline{SAR}_t}{S_{\overline{SAR}_t}} \tag{4.8}$$

Where $SAR_{i,t}$ is computed as:

$$SAR_{i,t} = \frac{AR_{i,t}}{S_{AR_{i,t}}} \tag{4.9}$$

Thus, we obtain the following test statistic for testing $\overline{CAR}$:

$$z_{patell} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{CSAR_i}{S_{CSAR_i}} \tag{4.10}$$

Where $CSAR_i$ is computed as the sum of $SAR_{i,t}$ during the event window and $S^2_{CSAR_i}$ is computed as : $S^2_{CSAR_i} = L_2 \frac{M_i - 2}{M_i - 4}$. With $L_2$ and $M_i$ denoting the length of the event window and estimation window, respectively.

### 4.2.4 Standardized Cross-sectional test (BMP)

Boehmer et al. (1991) introduced an extension of the cross-sectional t-test. They argue that too often, the null-hypothesis is rejected wrongly, as the event-observations may have significant variance induced by the event. Thus, Boehmer et al. (1991) introduce an extension of the traditional cross-sectional test by introducing components of the method explained by Patell (1976). By employing a combination of data from the event window and estimation window, Boehmer et al. (1991) argue that their model is more robust than previous methods, as it considers the volatility induced by the event as a potential bias-issue. By aggregating each $AR_{i,t}$ and $CAR_{i,t}$ through events, one obtains the test statistic for $AR_t$ as expressed in equation (4.11).

$$Z_t = \sqrt{N} \frac{\overline{SAR}_t}{\sqrt{var(\overline{SAR}_t)}} \tag{4.11}$$

With the variance:

$$var(\overline{SAR}_t) = \frac{1}{N-1} \sum_{i=1}^{N} (SAR_{i,t} - \overline{SAR}_t)^2$$

Where $SAR_{i,t}$ denotes the standardized abnormal return for each event $i$ at time $t$. $\overline{SAR}$ is the average standardized abnormal return and $N$ denotes the number of events.

Furthermore, the test-statistics for $CAR_i$ is computed as in equation (4.12):

$$Z = \sqrt{N}\frac{\overline{SCAR}}{\sqrt{var(\overline{SCAR})}} \tag{4.12}$$

With the variance:

$$var(\overline{SCAR}) = \frac{1}{N-1}\sum_{i=1}^{N}(SCAR_i - \overline{SCAR})^2$$

Where $SCAR_i$ is the standardized cumulative abnormal return for each event i, $\overline{SCAR}$ is the average $SCAR_i$ across the sample. Finally, we computed the test-statistic as:

$$z_{BMP} = \sqrt{N}\frac{\overline{SCAR}}{S_{\overline{SCAR}}} \tag{4.13}$$

Please see appendix 1.3 for an explanation of the standardization of the forecast error terms.

### 4.2.5 Non-parametric test

To ensure robustness of the results from our parametric tests, we wish to conduct a non-parametric test, more specifically a sign test. Non-parametric tests have, as previously explained, no assumptions that rely on the distribution of the abnormal returns. Thus, we applied the Generalized Sign Test introduced by Cowan (1992). This test considers the fraction of positive CARs during the event period. In this test, the estimated proportion of positive returns during the event window is computed as:

$$\hat{p} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{L_1}\sum_{t=T_0}^{T_1}S_{i,t} \tag{4.14}$$

Where $L_i$ symbolizes the number of days during the event window. $S_{i,t}$ is characterized by a value of one in the case where the returns are positive and zero otherwise. We thus obtain the following test-statistic for the CARs:

$$Z = \frac{(w - N\hat{p})}{\sqrt{N\hat{p}(1-\hat{p})}} \tag{4.15}$$

With w denoting the number of observations with positive CARs.

## 4.3 Cross-Sectional Analysis

In our cross-sectional analysis, we use ordinary least squares (OLS) to estimate our parameters. Given our sample of N observations and M characteristics, we follow the method of MacKinlay (1997) and perform the following regression:

$$CAR_i = \delta_0 + \delta_{1x,li} + ... + \delta_{Mx,Mi} + \varepsilon_i \tag{4.16}$$

With $CAR_i$ being the $i^{th}$ cumulative abnormal return observation. The error term is assumed to have a mean of zero, uncorrelated with the $x$s, and the $\delta$s are the regression coefficients. We use the approach of White et al. (1980) when deriving our standard errors in order to provide heteroskedasticity-consistent statistics. This is motivated by MacKinlay (1997), as he argues that one should expect that heteroskedastic standard errors occurs when conducting an event study.

By conducting a cross-sectional OLS analysis, we aim to identify any explanatory variables that might explain the cumulative abnormal returns for each firm. We will thus provide a cross-sectional analysis with CAR for each firm as the dependent variable and apply a set of independent variables to identify any firm and deal-specific characteristics that might explain the dependent variable. These variables will be further discussed in chapter 5: Data.

# 5 Data

In this section, we will discuss how we collected data in order to perform our analysis. Throughout our study, we have used various sources to collect our data. We have used the Thomson Reuters SDC Platinum M&A Database to identify mergers and acquisitions, as it is recognized as a highly reliable database to use for research into M&A activity (Barnes et al., 2014). Furthermore, we have used the Thomson Reuters Datastream Database to collect firm-specific data and market-benchmarks.

## 5.1 Process

The sample in our study consists of mergers and acquisitions made in the US and UK from 2009 to July 2019. In order to test our hypothesis, we collected two samples based on different search criteria:

- Green: Acquisitions where the target firms are identified as “Green" companies.
- Non-green: Acquisitions where the target firms are not identified as “Green” companies.

A Green acquisition, as briefly discussed in the introduction, is defined as a deal where the target firm provides a product, service or process that delivers value using limited or zero non-renewable resources and creates significantly less waste than conventional alternatives (Pernick and Wilder, 2007). There are no available databases (Thomson Reuters SDC Platinum, Zephyr Bureu Van Dijk, Marketline) providing the option to select "Green" as a sector, since such firms not necessarily are bound by sector/industry specifications. In order to capture all acquisitions where the target firm are "Green", we applied a text search to the target (full) description through the SDC Platinum database. Some SIC/NAISC[6] sectors refers directly to some of our applied keywords, such as wind, hydro and solar power generation. But in order to capture all acquisitions of concerning a "Green" target, regardless the defined sector, we decided to not apply any restriction to the target sector in our sample. The keywords applied are in line with our definition of Green acquisition and suggested by the Zephyr Bureau Van Dijk database (See appendix

[6]SIC and NAISC are both widely used industry classification systems, assigning either a four-digit(SIC) or six-digit (NAISC) code to different industries in order to classify different sectors.

2).

A Non-Green acquisition can be any deal outside the scope of cleantech. Our goal was to match a sample of Green acquisitions with Non-Green acquisitions in order to identify differences through our analysis.

We applied deal-specific criteria in order to secure sufficient data from each deal in order to perform a valid analysis.

The period of interest was selected due to the recent focus towards ESG and sustainability. As we discussed in chapter 2.3, increasing pressure from stakeholders have lead to an increase of firms from the S&P 500 issuing corporate reports on environmental and social impacts from 20 % in 2011 to 86 % as of 2018 (Kwon et al., 2018). Thus, we concluded that a period consisting of the last ten years was suitable for our analysis. We considered the announcement date as the date of interest, as this is when the information becomes public, and thus when the information of relevance would be reflected in the security prices according to the EMH.

We chose to focus our analysis on UK and US, as these markets are broad, mature and represent major economies. This supports our assumption of semi-strong efficient markets. In addition, we consider these markets relatively liquid, reducing the risk of our sample suffering from thin trading.

In order to analyze any changes in shareholder value, we required the acquiring company to be publicly traded. This allowed us to analyze (abnormal) changes in the security prices, as discussed in chapter 4.

We required the percentage of shares owned post-transaction to be greater than 50.1 %, as we wish to observe the effect on shareholder value when the acquiring company controls the target company. Furthermore, we required the deal to be of at least $ 10 million USD.

Summarized:

1. Date announced: 01.01.2009 to 01.07.2019
2. Deal status: Completed
3. Acquirer nation: UK, US
4. Acquirer status: Publicly listed company.
5. Percent of shares owned after transaction: 50.1 % to 100 %.
6. Deal value: Minimum $ 10 million.

Originally, our search resulted in 213 results. However, we had to apply stricter filtering to ensure the robustness of our analysis. We started by removing the observations (deals) where the acquiring company was a financial institution/investor, as we believe that the prices of publicly traded mutual funds may be influenced by other factors than traditional, operational companies. We also removed observations where it was impossible to gather the necessary data to conduct our analysis.

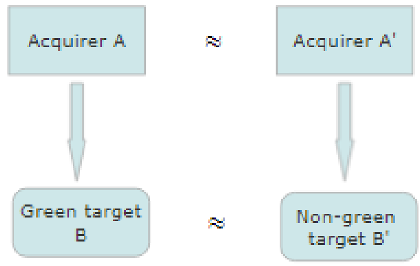
In order to limit the effect of greenwashing, we chose to exclude all observations where it was hard to understand if the target company operated within cleantech as their primary or major business. This was done by re-applying the keywords in a text search on the targets business descriptions, and thus analyzing to which extent our text search was relevant.

## 5.2 Matching

In order to test our second hypothesis (CAR green acquisitions $\neq$ CAR non-green acquisitions), we created a matching sample. The goal of our matching sample was to replicate the characteristics of our original sample, less the fact that the target company operates as a green company. To illustrate: we denote the original acquirers in our main sample A, and the acquirer in our matching sample A´. The green target is denoted as Green target B, whilst the matching target is denoted as non-green target B´.

In order to create a representative matching sample, we looked for certain characteristics of similar M&As to those in our main sample.

**Figure 5.1:** Matching




The first criteria we sat was that the acquiring company A must operate in the same country as A'. This criteria is sat to eliminate potential country specific differences in financial market conditions, as well as implications concerning environmental policies and stakeholder pressure as discussed in chapter 2.3.1. We included a dummy variable for cross-border acquisitions, as not allowing for the target company to be in different countries would narrow our matching universe too much. This also allowed us to control for cross-border acquisitions in our regression.

Next, we required that the companies must announce a deal in the same fiscal year as their green match. This requirement reduces the matching errors that might occur as the M&A market is highly cyclical and recognized by merger waves as discussed in chapter 2,1. Our analysis also benefits from this, as it allowed us to control for year fixed effects in our regression.

Third, we required that the companies must operate within the same industry. In order to identify the different industries, we chose to compare their SIC/NAICS codes. We required the companies to have at least the same starting three (four) digit SIC (NAICS) codes, to make the matching as real as possible, reducing the measurement errors of industry-specific characteristics.

To further improve our matching sample, we required the matching deal to have a similar relative deal size as the match in our original sample. This was done by choosing the deal with the closest relative deal size for company A' as company A. We measured the relative deal size as:

$$Relative\ size = \frac{Transaction\ value}{Total\ Assets_{Acquirer}}$$

Such that:

$$Relative\ size_{A,B} \approx Relative\ size_{A',B'}$$

In the case of higher deviation between observation A and observation A' than 30 %, we excluded the match from our sample. After our filtering, we ended up with a sample of green acquisitions that amount to 40, with 40 respective non-green matches.

## 5.3 Independent variables

In this sub-section, we describe the reasoning behind the independent variables included our analysis. We defined the independent variables by researching previous empirical studies on M&A performance in order to capture variables influencing our hypothesises.

### 5.3.1 Green dummy variable

A dummy-variable called Green is added in order to distinguish between green and Non-Green deals. The Green dummy variable is equal to one for all the events where a Green acquisition occurred, and zero otherwise. This is to be considered our main variable, as our goal through the cross-sectional analysis is to identify whether the cumulative abnormal returns can be explained by the difference in Green vs. Non-Green deals. Thus, any conclusions drawn through the analysis will rely on the inferences from this variable.

### 5.3.2 Relative deal size (DV/TA)

Relative deal size is included as a variable to adjust for firm-specific size of acquiring firm. Looking at M&A transactions from the perspective of relative deal value rather than deal value, we can capture the magnitude of the acquisition from an acquiring perspective. If a large firm acquirer a small firm, the direct implication of acquirer's total asset will lower than if a small firm acquirers another small firm. In line with previous literature on M&A performance, we apply relative size as an independent variable (Moeller et al., 2004; Eisenbach et al., 2011; Alexandridis et al., 2013). Relative deal size is calculated by comparing the deal value of the M&A transaction to total assets of the acquiring firm, collected from SDC Platinum and DataStream, respectively.

### 5.3.3 Market-to-book (M2B)

The market-to-book ratio is a variable identifying the market valuation prospect of the acquiring firm. A low market-to-book ratio (less than 1) indicate undervaluation in the firms stock and a low growth prospect, whilst a high market-to-book ratio indicate overvaluation and high growth prospects. The market-to-book variable adjust for differences in market perceptions. Based on previous research on M&A performance in renewable energy, we included the market-to-book variable. Eisenbach et al. (2011) find a negative relation between short-term abnormal returns and the market-to-book ratio of the acquiring firm. The market-to-book variable is retrieved from DataStream ten days before the announcement of a M&A deal, which is consistent with previous research.

### 5.3.4 Vertical acquisitions (Cross Industry)

The cross industry dummy variable specifies if the target firm belongs in a different industry than the acquirer, identified by three-digit SIC-code. We include the cross-industry variable to try to capture effects of diversification and strategic realignment as discussed in section 2.1 (Gaughan, 2017). Yoo et al. (2013) studies the effect of acquirer's sector in renewable energy M&A to identify diversification effects, and found that heterogenous M&A transactions had a large effect on enterprise value of the acquiring firm [7]. Since 57 of the acquisitions in our sample can be defined as heterogenous M&A transactions, we chose to include the cross-industry variable in an effort to capture unrelated diversification effects.

### 5.3.5 Cross-border acquisitions

Cross-border is added as dummy variable to control for differences of acquiring domestically or cross border. The sector of clean tech and renewable energy are influenced by numerous factors as discussed in section 2.2.1. Many of these factors (e.g. environmental policies, norms and conduct) are usually specific by country or region. United States and United

[7] Heterogenous M&A refers to an unrelated inter-relationship between acquirer and target, i.e. an "non-green" firm acquiring an "green" target

Kingdom have different approaches to the climate change issue. Whilst the UK are bound by EU-legislation on climate polices (at least until Feb. 2020.[8]) and are committed to the UN Paris agreement and Kyoto protocol, the US have not passed a major legislation on climate change in more than a decade (Erbach, 2015) and did withdraw from the Paris agreement in 2017. Since the majority of our sample consist of US acquirers, and that prior research has found evidence that environmental policies affect cross-border M&As (Criscuolo et al., 2014), we find it fitting to control for this effect in our sample. The cross-country is added as a dummy in the OLS returning 1 if target firm is located in another country than the acquirer.

### 5.3.6 Market Capitalization

We added the natural logarithm of each company's equity (ten days prior to the event) as an independent variable in order to identify whether the size of the firm (measured in the securities market valuations) affect the cumulative abnormal returns. We deem this an important variable, as we chose total assets as the benchmark for relative deal value during our sampling process. By including the market capitalization, we are able to control for the size of each firm during our cross-sectional study.

### 5.3.7 Deal value/Market capitalization

In addition to the relative deal size previously discussed (DV/TA), we include an alternative measurement of relative deal size where we apply the market capitalization (as previously described) as the denominator. The inclusion of this variable might also reduce the potential matching-errors that might occur through our sampling process. Additionally, we consider this a relevant measure of the magnitude of the deal size.

### 5.3.8 Year dummy variable

In order to control for year fixed effects, we apply a dummy-variable for each year during our sampling period. The literature review in chapter 2 suggests that the market of M&A is highly cyclical. As a result, our matching was dependent on years, as we believe that the inclusion of year-fixed effects in our regression can help us to increase the power of

[8] The date of Brexit, when the UK is leaving the European Union

our model.

## 5.4 Descriptive statistics

**Table 5.1:** Descriptive statistics

| Statistic | N | Mean | St. Dev. | Min | Pctl(25) | Pctl(75) | Max |
|---|---|---|---|---|---|---|---|
| CAR | 80 | 0.015 | 0.061 | −0.197 | −0.012 | 0.034 | 0.227 |
| DVTA | 80 | 0.140 | 0.268 | 0.002 | 0.024 | 0.127 | 1.573 |
| M2B | 80 | 2.867 | 2.948 | 0.580 | 1.470 | 3.160 | 21.970 |
| lnMCAP | 80 | 8.391 | 1.936 | 2.406 | 7.396 | 9.489 | 12.740 |
| DVMCAP | 80 | 0.084 | 0.221 | 0.001 | 0.008 | 0.071 | 1.829 |
| MCAPm | 80 | 25.915 | 64.466 | 0.011 | 1.630 | 13.212 | 340.983 |
| lnTA | 80 | 7.600 | 1.755 | 2.557 | 6.575 | 8.262 | 11.525 |

This table provides descriptive statistics for our variables of interest.

# 6 Analysis

In this section, we provide the results from our analysis on the hypothesis described in chapter 3 by presenting our event study. First, we examine whether there are any significant impacts from the announcement of acquisitions in our sample. Secondly, we provide our analysis on the relationship between the results derived through our event study and deal/firm specific factors.

## 6.1 Event study results

In our first hypothesis, we estimated whether the announcement of a green deal would result in a positive, cumulative abnormal return. Recall our initial hypothesis:

$$H_0 : \overline{CAR}_{Green} = 0$$

$$H_A : \overline{CAR}_{Green} \neq 0$$

To test our hypothesis, we applied the event windows and significance tests described in our methodology chapter. Two event windows were applied in order to ensure robustness to our initial results, and in order to investigate whether the effect of our event was fully absorbed during our initial event window [-1,1].

**Figure 6.1:** CAR-plot

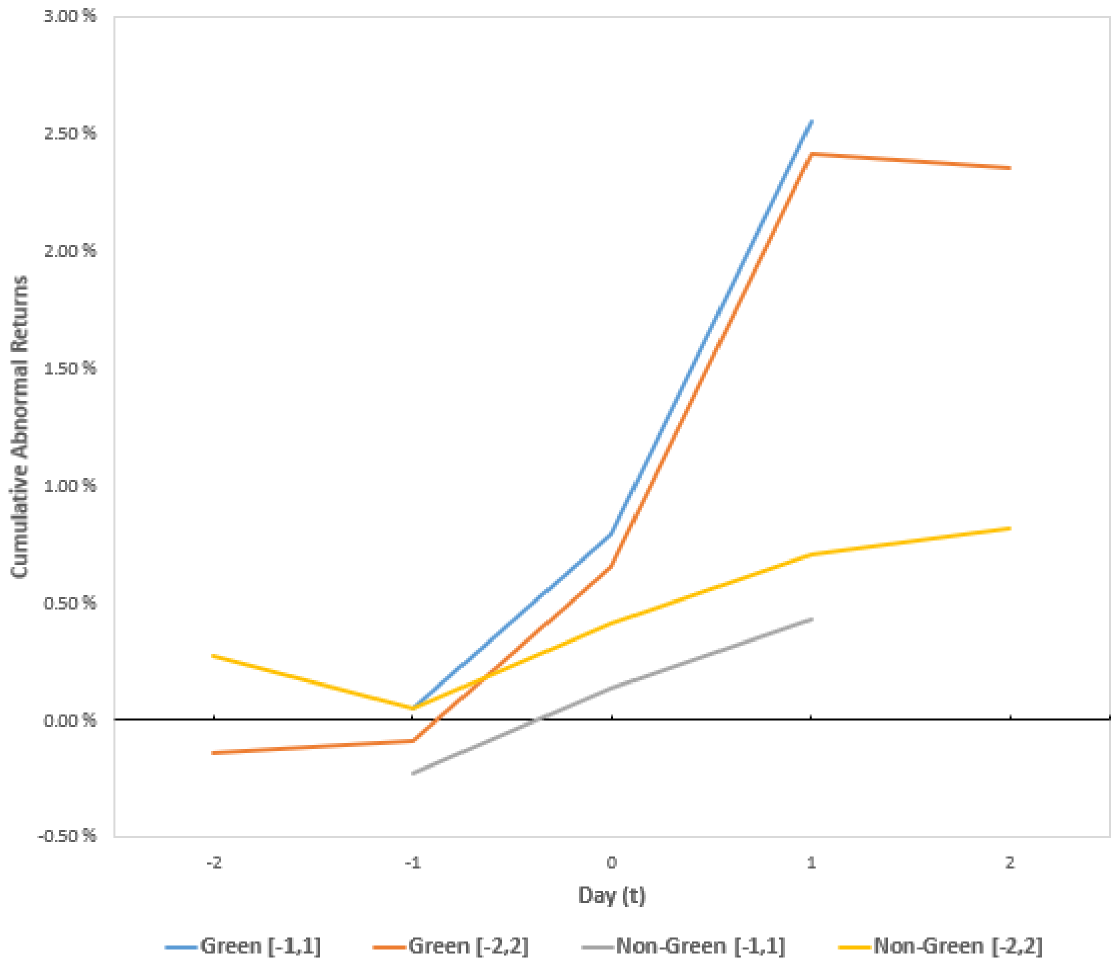



Figure 6.1 shows the $\overline{CAR}$s for both Green and non-Green observations during both the event windows. The table displays a higher $\overline{CAR}$ for Green acquisitions than non-Green acquisitions during both event windows.

**Table 6.1:** Market Model results

This table shows the results of the estimated abnormal and cumulative abnormal returns over five days, with two windows: [-1,1] and [-2,2]. The market model is applied to calculate the abnormal returns with estimation window of 250 trading days, ending ten days prior to the event of interest (announcement date). The abnormal returns are estimated using OLS with the S&P 500 and FTSE All Share indices for US and UK companies, respectively. The abnormal returns are aggregated through time and across events in order to compute the AAR's and CAAR's for each event window. The sample as a whole contains 80 firms, seperated into two subgroups: "Green" and "Non-Green", with 40 events in each group. The Green sample is our main sample, whilst the Non-Green sample is a sample of matched events. A t-test is applied to AAR's. The Patell Z test is applied to test if the CAARs and AARs are statistically significant from zero. In addition, the Standardized Cross-sectional test (BMP) is applied to the CAARS along with a sign-test to check if the returns are statistically different from zero.

**A: Abnormal Returns**

| Day | Green | | | Non-Green | | |
|---|---|---|---|---|---|---|
| | AAR | t-test | Patell Z | AAR | t-test | Patell Z |
| -2 | -0.142 % | -0.364 | -0.840 | 0.276 % | 1.102 | 0.963 |
| -1 | 0.054 % | 0.171 | -0.002 | -0.224 % | -1.154 | -0.898 |
| 0 | 0.742 % | 1.604 | 0.310 | 0.359 % | 0.654 | 0.111 |
| 1 | 1.760 % | 2.036** | 3.497*** | 0.295 % | 0.458 | 2.205** |
| 2 | -0.053 % | -0.145 | 0.123 | 0.112 % | 0.473 | 0.625 |
| N | 40 | | | 40 | | |

**B: Cumulative Abnormal Returns**

| Event window | Green | | | | | Non- Green | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | CAAR | Patell Z | BMP | Sign | Pos:Neg | CAAR | Patell Z | BMP | Sign | Pos:Neg |
| [-1,1] | 2.56 % | 2.192** | 0.927 | 2.322** | 24/40 | 0.430 % | 0.818 | 0.503 | 0.211 | 20/40 |
| [-2,2] | 2.36 % | 1.381 | 0.655 | 1.137 | 24/40 | 0.818 % | 1.342 | 0.915 | 0.680 | 17/40 |
| N | 40 | | | | | 40 | | | | |

*Note: *p < 0.10, **p < 0.05, ***p < 0.01*

Table 6.1B shows the CAARs for both event windows, with Green and Non-Green deals separated.

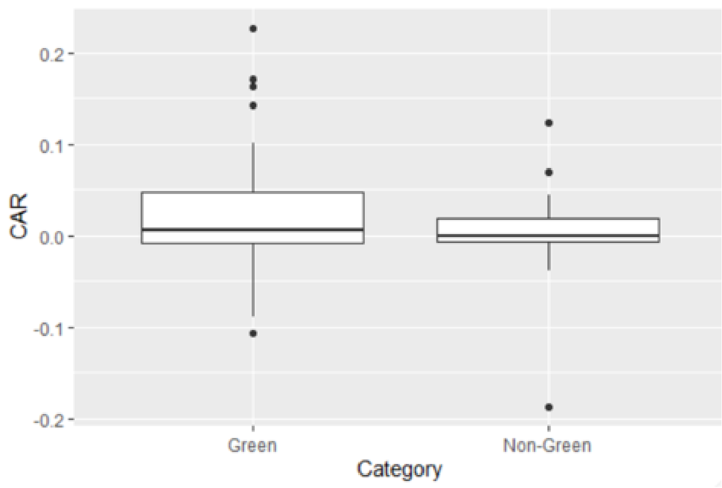
We observe a positive AARs on the announcement day for our Green sample. We applied the Patell Z test with standardized forecast errors to ensure robustness, and we observe that the AAR during day 0 in our event window is not significant on this parameter. For day 1, we still observe positive AARs for the green sample, statistically significant with a p-value $<$ 5 % and 1 % through the traditional t-test and the Patell test, respectively. The matched, non-green results also yield positive AARs during day 1 in the event window, however the results from the Non-Green sample only shows significance through the Patell test, with a p-value $<$ 5 %. Also note that the AARs for the green sample is higher than the AARs from the matched sample. During day 2 of the event, we find no evidence that the AARs are different from zero on any statistical level for both green and Non-Green deals. Similarly, we observe statistical significance for the AAR with a positive mean on day one through the constant mean return model and market adjusted model (please see appendix 3).

The statistical significance during day 1 in the event window suggests that the announcements tend to happen after the market's opening hours on the day of announcement. The lack of significance prior to the announcement date suggests that our sample does not suffer from leaked news, thus the announcement comes a surprise, as one of the assumptions of an event study (McWilliams and Siegel, 1997).

In table 6.1B, we observe that for green acquisitions, the CAAR is positive during both event windows. We find statistical significance for the Patell Z test for our main event window, with 24/40 positive outcomes. However, the BMP test (standardized cross-sectional test) provides no statistical significance on any level. We applied the BMP test to ensure robustness from our results, and its inclusion should lower the probability of wrongly rejecting a null hypothesis (for further reasoning, please see chapter 4.2.3). The sign test only shows significance in the shortest window. The statistical parameters are all stronger during the shortest window, suggesting that our initial event window is of appropriate length. This is also expected in accordance with the efficient market hypothesis, one of the assumptions for the event study to hold (McWilliams and Siegel, 1997). As our results are insignificant through the BMP-test, and thus not robust to the event-induced variance, we deem it hard to draw any conclusion without further discussing the results. The results from the constant mean return model and market adjusted model again provides us with similar results, suggesting that the model also is robust in the estimation of CARs (please see appendix 3).

The varying signals from our statistical parameters can possibly be explained by the standard deviation of our observations. We illustrate the effect our outliers have on our mean through the boxplot in figure (6.2):

**Figure 6.2:** Boxplot




The boxplot illustrates the three day-event window [-1,1] grouped by green and non-green acquisitions. We observe the outliers effect on the the $\overline{CARs}$.[9]

With no statistical backing through the BMP-test, along with the analysis of our sample outcomes, we deem it hard to reject the null hypothesis. In other words, we cannot say that green acquisitions are statistically significant from zero, nor creates shareholder value. This supports the result of previous M&A research, where gains by the acquiring company often are negative or not statistically significant from zero.

[9] We also tried to winsorize the CARs for both samples to illustrate the effect of outliers, resulting in a mean of 1.52 % and 0.572 % for the Green and Non-Green sample respectively. The winsorization was done with a 95 percentile.

## 6.2 Cross-sectional analysis

The table below displays the results of number regressions with $CAR_i$ as the dependent variable during our [-1,1] event window. We report heteroscedasticity-robust standard errors, as discussed in chapter 4. We included several variables to identify any relationship between the cumulative abnormal returns and firm characteristics/deal characteristics. In the regression, we also added dummy-variables for each year of observations in order to control for year-fixed effects (Please see appendix 3 for regression results without controlling for year fixed effects and the inclusion of the cross-border dummy). We consider the dummy-variable Green to be the main variable, as we are analyzing whether there are differences between Green and Non-Green acquisitions.

**Table 6.2:** Regression results, Cross-sectional study

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | CAR | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Green | 0.022* | 0.022* | 0.019 | 0.021 | 0.014 | 0.021* | 0.013 | 0.011 |
| | (0.013) | (0.013) | (0.012) | (0.013) | (0.012) | (0.012) | (0.012) | (0.011) |
| DVTA | | −0.033 | | | | | −0.030 | |
| | | (0.053) | | | | | (0.056) | |
| DVMCAP | | | −0.101*** | | | | | −0.102*** |
| | | | (0.032) | | | | | (0.035) |
| CrossIndustry | | | | −0.021 | | | −0.032** | −0.039*** |
| | | | | (0.017) | | | (0.015) | (0.015) |
| M2B | | | | | 0.007** | | 0.007*** | 0.006** |
| | | | | | (0.003) | | (0.003) | (0.003) |
| lnMCAP | | | | | | 0.004 | | |
| | | | | | | (0.006) | | |
| Observations | 80 | 80 | 80 | 80 | 80 | 80 | 80 | 80 |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.133 | 0.149 | 0.238 | 0.154 | 0.230 | 0.149 | 0.283 | 0.367 |
| Adjusted $R^2$ | −0.019 | −0.016 | 0.091 | −0.010 | 0.081 | −0.016 | 0.117 | 0.221 |
| Residual Std. Error | 0.063 | 0.063 | 0.060 | 0.063 | 0.060 | 0.063 | 0.059 | 0.055 |
| F Statistic | 0.873 | 0.901 | 1.613 | 0.939 | 1.543 | 0.902 | 1.708* | 2.514*** |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 | | |

In regression (1), we only included the dummy-variable Green in order to compare the differences in mean between Green and Non-Green acquisitions. The coefficient of the variable Green displays significance with a p-value lower than 10 %. This indicates that, all else equal, an acquisition where the target identifies as a Green company yields a statistically significant higher cumulative abnormal return than otherwise. The model, however, displays a negative adjusted R-squared. This indicates that the model is performing poorly in explaining cumulative abnormal returns. In addition, the F-statistic is insignificant.

In regression (2), we added the DV/TA variable as an explanatory variable. We observe that the sign and standard deviation of the Green dummy remains equal to regression (1), thus keeping its statistical significance. Similarly to regression (1), the model displays a low explanatory power with an R-squared lower than zero. The F-statistic is hardly affected, signalizing that adding the variable DV/TA does not add much explanatory variables to the model.

Regression (3) displays the addition of the DV/MCAP variable. We observe that the Green variable becomes insignificant, in contrast to regression (1) and (2). The DV/MCAP variable, on the other hand, provides statistical significance with a p-value lower than 1 %. The sign indicates that, all else equal, a one unit increase in DV/MCAP destroys shareholder value. In other words, there seems to be a negative relationship between the relative size of the deal (measured in market value) and the cumulative abnormal returns. The relative size of the deal measured in market capitalization thus seem to be better at explaining cumulative returns than the relative size measured by book-values. We observe a similar sign for DV/MCAP as for DV/TA in regression (2). The explanatory power of the model increases substantially to an adjusted R-squared of 0.091. The F-statistic also increases, suggesting that regression (3) is better at explaining the cumulative abnormal returns than the previous regressions discussed.

In regression (4), we provide a dummy-variable (CrossIndustry) equal to one where the acquiring company operates in another sector than the target company, denoted by their SIC (NAICS) code. The coefficient displays a negative sign, but is not statistically significant. However, the inclusion of the CrossIndustry variable reduces the sign of the Green dummy-variable. Thus, the Green dummy is not statistically significant when we controll for CrossIndustry acquisitions. The model, similarly to regression (1) and (2), displays an adjusted R-squared below 0, suggesting that the model is bad at explaining cumulative abnormal returns.

In regression (5), we included the market-to-book variable. The market-to-book variable is statistically significant with a p-value below 5 %, indicating that there is a positive relationship between an increase in the market-to-book parameter and cumulative abnormal returns, all else equal. This suggests that companies in a growth-phase is more likely to create shareholder value when performing an acquisition. The inclusion of the variable, however, lowers the sign of the Green variable, which becomes insignificant through all our statistical thresholds. The model provides an adjusted R-squared of 0.081, whilst the F-statistic is 1.543, approaching the threshold of statistical significance.

Regression (6) provides the inclusion of the natural logarithm of the firms market capitalization as an explanatory variable. We observe no significant relationship between the size of the acquirer and the cumulative abnormal returns. Thus, it seems to be the relationship between the deal value and the size of the company that seems to be of relevance when explaining cumulative abnormal returns (as in regression (3)). Though the model displays statistical significance for the Green variable, we observe an adjusted R-squared below zero, again suggesting that the model performs poorly in explaining cumulative abnormal returns.

In regression (7), we provide the inclusion of DV/TA, CrossIndustry and M2B as explanatory variables in addition to the Green variable. Similarly to regression (3), (4) and (5), the Green variable loses its statistical significance. The DV/TA variable remains insignificant as in regression (2). Oppositely, the CrossIndustry variable becomes statistically significant with a p-value below 5 % in contrast to regression (4). This suggests that, when adding other deal and firm-specific characteristics, the CrossIndustry variable is able to explain some of the differences in cumulative abnormal returns. The M2B variable remains significant, but now with a p-value lower than 1 %, in contrast to 5 % as in regression (5). The model also provides the highest adjusted R-squared so far. The F-statistic of the model is also statistically significant, with a p-value lower than 10 %. The results suggests that regression (7) is able to explain the differences in cumulative abnormal returns across our sample.

In our final regression (8), we included similar explanatory variables to regression (7), except for the measure of relative deal-size. In regression (8) we applied DV/MCAP as a measure of relative deal size, displaying a negative coefficient within the same statistsical threshold as in regression (3). The CrossIndustry coefficient displays remains its negative sign, now with a p-value below 1 %. A possible explanation might be that firms over-invest when diversifying into other sectors (Berger and Ofek, 1995). The market-to-book coefficient remains statistically significant with a p-value lower than 5 %. Through this regression, we observe the lowest value for the Green variable of all our regressions. The model also reports the highest adjusted R-squared of all the regressions we ran, with an F-statistic significant with a p-value lower than 1 %. This suggests that, when adding firm and deal-specific characteristics such as relative size, market-to-book and CrossIndustry, the value of the Green variable diminishes, along with its statistical parameters value.

The results from our regressions provides an interesting discussion. Whilst including only the Green variable, we obtain a statistically significant coefficient. This suggests that, holding all other variables equal, shareholders observing a Green acquisition is more likely to experience value-creation through M&As. However, our results suggests otherwise when we add more explanatory variables. We show that, by adding firm and deal-specific characteristics, our model increases its explanatory power along with the loss of significance for our Green variable. Our findings thus suggest that the cumulative abnormal returns does not depend on the target being Green, but rather deal and firm-specific characteristics. In addition, the results from the regression analysis without year-fixed effects as well as the inclusion of cross-boarder effects (see appendix 3) suggests the same conclusion, observing no statistical significance for the Green dummy-variable. The trend of our analysis shows that the model is prone to model specifications. As a result, we cannot reject the null-hypothesis that Green acquisitions provide different cumulative abnormal returns than Non-Green acquisitions.

# 7 Discussion

In this chapter, we provide a discussion on our study by assessing the sample size, event study and the cross-sectional study.

## 7.1 Sample size

One potential limit to the result our study may be the size of our sample. In order to draw conclusions on statistical inferences through an event study, as well as a cross-sectional analysis, the power of the model is largely dependent on the size of the sample. When performing statistical tests, one often assumes that the assumption of normality holds, which is rarely the case in a very small sample. Our sample consists of a total of 80 events, divided into two sub-samples containing 40 events each. Thus, both our samples are well above the requirement of 30 observations for the central limit theorem. Furthermore, other authors (Brown & Warner, 1985) have applied the event methodology to studies with as little as five observations. We would also argue that the sample consisting of 40 green observations were all the observations we were left with after our filtering. In order to increase the size of our sample, we would thus have to reduce the criteria for an event to be included in our sample. We argue in chapter 5 that there is a trade-off between reducing the criteria we applied and the number of samples in our study, and thus we feel that our final sample contains the properties we find most suitable to conduct our study. Expanding our time frame could potentially increase the number of events in our sample. However, as we argued in chapter 5, the cleantech industry, and focus towards ESG and CSR, is relatively new and have not been focused upon during the last twenty years, as within the last decade.

## 7.2 Assessment of the event-study

To analyze the robustness of our event study, we conducted a market-adjusted and constant-mean return model in order to identify if our results were robust to the methodology applied. The results (please see appendix 3) indicate that our results are robust to the choice of model, as the supplementary analysis yields somewhat similar results. The results from the supplementary methods shows somewhat lower means in cumulative abnormal returns. We also notice that the models provide similar signs for cumulative abnormal returns across both the Green and Non-Green sample, along with somewhat similar values of statistical significance. Thus, we consider the analysis we conducted to be robust to the choice of method.

## 7.3 Assessment of the cross-sectional study

### 7.3.1 Multicollinearity

In order to conduct a correct analysis, one relies on the model specifications. We applied the explanatory variables by applying our financial knowledge and by reading previous literature. Several issues might arise under the introduction of variables in the model, such as multicollinearity. The problem of multicollinearity arises when there is a high correlation between two or more independent variables Wooldridge (2016). By applying a VIF-test (Variance Inflation Factor), we were able to assess the potential issue of multicollinearity. As can be seen from the results of the VIF-tests, the inclusion of lnMCAP displays a VIF-factor close to five. According to Alauddin and Nghiem (2010), the common rule of thumb is that when the VIF-test displays a value lower than 10, multicollinearity usually is not an issue. They also argue that more conservative authors would conclude that multicollinearity is not an issue when the VIF-test displays values below 5.

Table 7.1 displays the VIF-values for the independent independent variables we applied in our regressions. None of these displays a value above 5, thus we conclude that multicollinearity is not a serious issue in our analysis. Consequently, we kept variables such as DV/TA and DV/MCAP seperated, as it is intuitive to think that these variables will by highly correlated, unless the deviation between Total Assets and Market Capitalization is large.

**Table 7.1:** VIF-test

| | Regression | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Green | 1.425 | | 1.429 | 1.426 | 1.450 | 1.427 | 1.454 | 1.455 |
| DVTA | | 1.292 | | | | | 1.325 | |
| DVMCAP | | | 1.168 | | | | | 1.23 |
| CrossIndustry | | | | 1.936 | | | 1.991 | 2.015 |
| M2B | | | | | 1.474 | | 1.509 | 1.527 |
| lnMCAP | | | | | | 4.817 | | |
| Year(dummy) | 1.033 | 1.051 | 1.045 | 1.076 | 1.05 | 1.156 | 1.105 | 1.102 |
| Mean VIF | 1.229 | 1.1715 | 1.214 | 1.479 | 1.325 | 2.467 | 1.477 | 1.466 |

As shown in the table, we only observe a large VIF-parameter for the lnMCAP variable. The other VIF-parameters are rather low, whilst our final regression (8) displays a mean VIF of 1.466.

In table 7.2, we report the correlation-matrix for our variables of interest.

**Table 7.2:** Correlation matrix

| | CAR | Green | DVTA | DVMCAP | CrossIndustry | M2B | lnMCAP |
|---|---|---|---|---|---|---|---|
| CAR | 1 | 0.175 | -0.066 | -0.279 | -0.056 | 0.334 | 0.092 |
| Green | 0.175 | 1 | 0.008 | -0.065 | 0.028 | 0.177 | 0.046 |
| DVTA | -0.066 | 0.008 | 1 | 0.852 | -0.083 | -0.060 | -0.380 |
| DVMCAP | -0.279 | -0.065 | 0.852 | 1 | -0.013 | -0.157 | -0.459 |
| CrossIndustry | -0.056 | 0.028 | -0.083 | -0.013 | 1 | 0.223 | 0.045 |
| M2B | 0.334 | 0.177 | -0.060 | -0.157 | 0.223 | 1 | 0.368 |
| lnMCAP | 0.092 | 0.046 | -0.380 | -0.459 | 0.045 | 0.368 | 1 |

We notice that our main variable (Green) displays little correlation with the other explanatory variables we applied. In addition, we show that none of the variables included in the same regression display high correlation. This supports the results of our VIF-analysis, and we do not deem multicollinearity as a serious issue in our analysis.

### 7.3.2 Omitted Variables

Another potential source of misspecification is omitted variables (Wooldridge, 2016). In our study, we perform an analysis on the acquiring companies. Whilst focusing on the acquirer, we allowed for non-public targets. This provides a trade-off, as the non-public targets are not listed, the effect M&As have on the target is unobserved in our study. This reduces the potential of explaining synergies created through M&As. Furthermore, it might be hard to perceive the potential premiums paid when acquiring a non-public target, as only public targets have an observable market value. Under the acquisition of a publicly traded target, the premium is observed as the residual between the acquiring company's bid and the observed market price of the target company prior to the bid. Thus, our results might deviate from other studies analyzing the acquisitions of publicly traded targets.

# 8 Conclusion

Throughout our study, we have examined the effects M&A announcements have on security prices, particularly when the acquiring company acquires a green target in the US and UK. The event study method, as described by MacKinlay (1997), was conducted to test whether the announcements of both Green and non-Green acquisitions had a significant impact on the valuation of the tested companies' equity value. The data from M&A announcements and deal characteristics was collected from the SDC Platinum database, with a sample of green acquisitions consisting of 40 unique deals, with a matching non-green sample consisting of 40 corresponding deals, resulting in a total of 80 events analyzed between January 1st 2009 to July 1st 2019.

Through our analysis, we find cumulative average abnormal returns of 2.556 % during a three-day event window for acquiring shareholders during the announcement of acquisitions for our Green sample. In our corresponding group of non-green deals, we find cumulative average abnormal returns of 0.430 % during a three-day event window. We applied numerous statistical tests in order to ensure robustness of our results, and eventually we found that the acquisition of Green company does not affect shareholder value. The standardized cross-sectional test provides no statistical evidence that the cumulative abnormal returns differs across our two samples. We thus concluded that the announcement of green acquisitions does not seem to create shareholder value during our three-day event window. Nor does the announcement of a Green acquisition provide higher returns than the announcement of Non-Green acquisitions.

Our analysis of average abnormal returns on a daily basis shows statistical significance through both the traditional t-test and the test of Patell. We find little evidence of any statistical abnormalities prior to the event, suggesting that our sample does not suffer from leakage of information prior to the event. Day one of our event window shows the strongest statistical parameter for the average abnormal returns, which gives us reason to believe that the announcement, in most cases, happen after the markets close on the announcement date. This also suggests that the event windows applied through our study is of appropriate length, as we seek to estimate the short-term effect of M&A announcements, limiting the potential issue of confounding events when expanding the event window. Our findings also suggest that the efficient market hypothesis holds, on a semi-strong form.

Through our cross-sectional analysis, we found that the difference between green acquisitions and non-green acquisitions becomes smaller on an average basis when adding other explanatory variables. The dummy-regression initially tested showed signs of statistical significance between cumulative abnormal returns and the Green dummy-variable, with a coefficient of 2.3 % if the target company of the deal was Green, all else equal. After controlling for other variables, and adding other traditional explanatory variables, we obtain a higher F-statistic and explanatory power of our model. The inclusion of other explanatory variables results in the loss of statistical significance for our Green dummy-variable, suggesting that deal and firm-specific characteristics are better at explaining the differences in cumulative abnormal returns. We find that there is a positive relationship between the market-to-book multiple and cumulative abnormal returns. Lastly, we find that there is a negative relationship between the relative deal size (Deal value divided by market capitalization) and cumulative abnormal returns.

The loss of statistical power for our Green dummy-variable when adding other independent variables suggests that the differences in cumulative abnormal returns seem to stem from other deal and firm-specific characters, rather than the expansion or diversification into clean technology. We thus find no evidence that investors perceive the acquisitions of Green companies any better than the acquisition of a Non-Green acquisition.

This supports the evidence of previous M&A literature, which usually finds negative, or at best, no changes in the equity value for the acquiring company.

Summarized, we find that investors, on average, does not perceive the acquisition of a Green company differently than the acquisition of a Non-Green company. In line with previous research, we find that the acquiring company on average does not create value during a short-term window through M&As within the cleantech industry. Put differently, one might postulate that value-creation through M&As depends on deal and other firm-specific factors, limiting the potential of greenwashing by the acquiring management.

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# Appendix

## A 1 Appendix 1

### A 1.1 Constant-mean return model

The constant mean return model assumes that the normal performance of a stock during the event window can be computed as the average return obtained during the estimation window. This can be illustrated as in equation A.1:

$$R_i t = \mu_i + \varepsilon_{i,t} \tag{.1}$$

Where $\mu_i$ is obtained by:

$$\mu = \frac{1}{L_1} \sum_{t=T0}^{T1} R_{it} \tag{.2}$$

Where $\mu_i$ is the average return for security $i$ during the estimation window. Furthermore, $L_1$ denotes the number of days during the event window. $\varepsilon_i, t$ denotes the error term, which has an expectancy of zero, and a variance of $\sigma^2_{\varepsilon_i}$.

### A 1.2 Market-adjusted return model

The market-adjusted model assumes that the returns within the event window can be explained by the general movements of the market. This is quite similar to the market model, less the fact that one assumes that the market movements during the event period is similar to the market ($\beta$=1). Thus, the abnormal returns are computed as the difference between the real-observed returns from the security, less the return of the market. This can be illustrated as in equation A.2:

$$AR_{i,t} = R_{i,t} - R_{m,t} \tag{.3}$$

### A 1.3 BMP

When performing a standardized cross-sectional test (BMP), we divided the cumulative abnormal returns by the adjusted forecast error. The method proposed by Boehmer et al.

(1991) considers $S_{CAR_i}$ to be computed as from Mikkelson and Partch (1988), illustrated in equation A.4.

$$S^2_{CAR_i} = S^2_{AR_i}(L_i + \frac{L_i^2}{M_i} + \frac{(\sum_{t=T_1+1}^{T_2}(R_{m,t} - \bar{R}_m))^2}{\sum_{t=T_0}^{T_1}(R_{m,t} - \bar{R}_m)^2}) \tag{.4}$$

Thus, we obtained the standardized cumulative abnormal return $SCAR_i$ for each security $i$:

$$SCARi = \frac{CAR_i}{S_{CAR_i}} \tag{.5}$$

Where $S_{CAR_i}$ is the standardized standard deviation for each securit $i$. In order to perform our analysis, we aggregated the standardized CARs across the sample. By doing this, we obtained the average standardized CAR ($S\bar{C}AR$):

$$S\bar{C}AR = \frac{1}{N}\sum_{i=1}^{N} SCAR_i \tag{.6}$$

Lastly, we obtained the test statistics for the cumulative abnormal returns as:

$$Z_{BMP} = \sqrt{N}\frac{S\bar{C}AR}{\sqrt{var(S\bar{C}AR}}) \tag{.7}$$

# A 2 Appendix 2

**Table A 2.1:** Industry keywords

This table displays the keywords we applied to our text search. The keywords are, as discussed, motivated by Zephyr (2013).

| | | |
|---|---|---|
| ALTERNATIVE ENERGY | HYDROPOWER | GREEN CONSTRUCTION |
| ALTERNATIVE POWER | HYDRO-POWER | GREEN BUILDINGS |
| BIOMASS | BIO-DIESEL | SMART METER |
| BIOENERGY | BIODIESEL | SMART GRID |
| BIO ENERGY | ENERGY RESOURCE MANAGEMENT | ENERGY MONITORING |
| BIO-ENERGY | ELECTRIC VEHICLE | MARINE ENERGY |
| BIOFUEL | WATER PURIFICATION | SOLAR THERMAL |
| FUEL CELL | INTELLIGENT POWER | ALGAE |
| HYDROGEN | AIR QUALITY | GREEN ENERGY |
| PHOTOVOLTAIC | ENERGY EFFICIENCY SOFTWARE | CLEANTECH |
| RENEWABLE ENERGY | ENERGY EFFICIENCY | CLEAN TECH |
| REUSABLE ENERGY | THIN FILM ENERGY | ENVIRONMENTAL TECHNOLOGY |
| RE-USABLE ENERGY | THIN-FILM ENERGY | GREENTECH |
| SOLAR | ENERGY STORAGE | CHARGING STATIONS |
| WASTE TO ENERGY | BATTERY POWER | GREEN INFRASTRUCTURES |
| WIND POWER | WATER TREATMENT | CLEAN ENERGY |
| WIND FARM | WASTE MANAGEMENT | TIDAL ENERGY |
| WAVE POWER | BIOGAS | TIDAL POWER |
| GEOTHERMAL | ANAEROBIC DIGESTION | BIODEGRADABLE |
| GEO-THERMAL | WASTEWATER | ALTERNATIVE FUEL |

**Table A 2.2:** Green acquisitions

| Date announced | Acquirer name | Target Name |
|---|---|---|
| 02:03:2009 | First Solar Inc | OptiSolar Inc |
| 18:09:2009 | Babcock International Group | UKAEA Ltd |
| 22:10:2009 | MEMC Electronic Materials Inc | SunEdison LLC |
| 25:11:2009 | Quantum Fuel Systems Tech Inc | Schneider Power Inc |
| 10:02:2010 | IHS Inc | Emerging Energy Research |
| 28:04:2010 | First Solar Inc | NextLight Renewable Power LLC |
| 24:05:2010 | MEMC Electronic Materials Inc | Solaicx Inc |
| 16:09:2010 | NRG Energy Inc | Green Mountain Energy Co |
| 01:04:2011 | Waste Connections Inc | Hudson Valley Waste Hldg Inc |
| 01:06:2011 | Tutor Perini Corp | Frontier-Kemper Constructors |
| 06:06:2011 | TRC Cos Inc | RMT Inc-Environmental Bus Unit |
| 28:07:2011 | Waste Management Inc | Oakleaf Global Holdings Inc |
| 24:08:2011 | Gtat Corp | Confluence Solar Inc |
| 03:10:2011 | Targa Resources Partners LP | Targa Sound Terminal |
| 23:12:2011 | SunPower Corp | Tenesol SA |
| 24:09:2012 | Curtiss-Wright Corp | PG Drives Technology Ltd |
| 15:11:2012 | Seagate Technology Plc | Solyndra LLC-Assets |
| 16:11:2012 | Atlantic Power Corp | Ridgeline Energy Holdings Inc |
| 10:01:2013 | Google Inc | EDF-Spinning Spur Project |
| 09:04:2013 | Advanced Energy Industries Inc | REFUsol GmbH |
| 05:11:2013 | Green Plains Renewable Energy | BioFuel Energy-Ethanol Plants |
| 06:01:2014 | Worthington Industries Inc | Aritas Basincli Kaplar Sanayii |
| 07:04:2014 | Us Ecology Inc | EQ Parent Co Inc |
| 28:04:2014 | Bel Fuse Inc | Power-One Inc-Power Solutions |
| 20:05:2014 | Rps Group PLC | GaiaTech Inc |
| 26:06:2014 | Pattern Energy Group Inc | El Arrayan Wind Farm Project |
| 13:07:2014 | AECOM Technology Corp | URS Corp |
| 17:11:2014 | SunEdison Inc | First Wind Holdings LLC |
| 24:12:2014 | Atlantic Tele-Network Inc | Green Lake Capital LLC |
| 02:01:2015 | Cantel Medical Corp | Pure Water Solutions Inc |
| 12:05:2015 | James Fisher & Sons PLC | X-subsea UK Hldg Ltd-Asts & |
| 02:11:2015 | Green Plains Inc | Hereford Renewable Energy LLC |
| 13:06:2016 | Green Plains Inc | Abengoa Bioenergy-Ethanol Plan |
| 05:07:2016 | NextEra Energy Partners LP | Bayhawk Wind Holdings LLC |
| 03:07:2017 | Aggreko PLC | Younicos AG |
| 18:09:2017 | Itron Inc | Silver Spring Networks Inc |
| 05:09:2018 | NextEra Energy Partners LP | NEP Renewables LLC |
| 11:01:2019 | Cantel Medical Corp | Vista Research Grp Llc |
| 31:01:2019 | Marlowe PLC | Atana Ltd |
| 08:04:2019 | AO Smith Corp | Water Right Inc |

**Table A 2.3:** Non-green acquisitions

| Date announced | Acquirer name | Target name |
|---|---|---|
| 22.07.2009 | Hubbell Inc | FCI Americas Inc |
| 02.11.2009 | Virage Logic Corp | NXP Semiconductors-Assets |
| 19.11.2009 | Spartan Motors Inc | Utilimaster Corp |
| 16.03.2010 | Emdeon Inc | Healthcare Tech Mgmt Svcs |
| 12.04.2010 | Maxim Integrated Products Inc | Teridian Semiconductor Corp |
| 10.05.2010 | PMC-Sierra Inc | Adaptec Inc-Cert Asts & Bus Op |
| 16.04.2010 | Constellation Energy Group Inc | Navasota Energy Partners LP- |
| 09.05.2011 | Nvidia Corp | Icera Inc |
| 26.01.2011 | Silicon Laboratories Inc | SpectraLinear Inc |
| 13.02.2012 | Juniper Networks Inc | Mykonos Software Inc |
| 04.10.2012 | Calpine Corp | Bosque Power Co LLC-Plant,TX |
| 24.09.2013 | Google Inc | Building Portfolio(6) |
| 07.06.2013 | Silicon Laboratories Inc | Energy Micro AS |
| 17.12.2013 | Renewable Energy Group Inc | Syntroleum Corp |
| 18.11.2014 | MACOM Technology Solutions Hol | BinOptics Corp |
| 09.12.2014 | Entergy Corp | Union Power Partners-Union |
| 11.11.2014 | RF Industries Ltd | Comnet Telecom Supply Inc |
| 30.06.2014 | Consolidated Commun Hldg Inc | Enventis Corp |
| 03.03.2015 | James Fisher & Sons PLC | Subtech Group Holdings (Pty) |
| 01.06.2015 | Platform Specialty Products | OM Grp Inc-Electn Chem |
| 01.02.2016 | Balchem Corp | Albion Laboratories Inc |
| 01.02.2016 | Dominion Resources Inc | Questar Corp |
| 24.11.2017 | Speedy Hire PLC | Prolift Access Ltd |
| 03.01.2018 | Dominion Energy Inc | SCANA Corp |
| 10.06.2009 | AMEC PLC | GRD Ltd |
| 06.04.2011 | Clean Harbors Inc | Peak Energy Services Ltd |
| 03.01.2011 | Tutor Perini Corp | Fisk Electric Co |
| 31.03.2011 | The KEYW Holding Corp | JKA Technologies Inc |
| 04.07.2011 | Clean Harbors Inc | Destiny Resources Svcs Corp |
| 05.05.2011 | Kinder Morgan Energy Partners | KinderHawk Field Services LLC |
| 31.12.2012 | Curtiss-Wright Corp | Exlar Corp |
| 01.08.2014 | Worthington Industries Inc | Midstream Equip Fabrication |
| 05.06.2014 | TexCom Inc | Peak Water Sys,Bennett SWD #1 |
| 29.04.2014 | Utilitywise Plc | ICON Communication Centres sro |
| 31.12.2014 | VSE Corp | Killick Aerospace-Businesses |
| 12.06.2015 | STERIS Corp | Black Diamond Video Inc |
| 14.03.2019 | Stryker Corp | OrthoSpace Ltd |
| 25.04.2019 | Photo-Me International PLC | Sempa Sarl |
| 27.11.2018 | AMETEK Inc | Spectro Scientific Inc |
| 15.02.2017 | Integra LifeSciences Hldg Corp | DePuy Synthes Cos-Codman |

# A 3 Appendix 3

**Table A 3.1:** Results from market-adjusted model

This table shows the results of estimated abnormal returns (Panel: A) and cumulative abnormal returns (Panel: B) over five days, with two windows [-1,1] and [-2,2]. The market-adjusted model is applied with the same specifications as the market model applied in our analysis. This implies a beta-coefficient equal to one, assuming that the price changes of the security can be explained by the movements of the benchmark. We apply similar test-statistics to the market-model analysis.

A: Abnormal returns

| Day | Green | | | Non-Green | | |
|---|---|---|---|---|---|---|
| | AAR | t-test | Patell Z | AAR | t-test | Patell Z |
| -2 | -0.270 % | -0.740 | -1.065 | 0.16 % | 0.735 | -0.613 |
| -1 | -0.083 % | 0.235 | 0.229 | -0.29 % | 1.240 | -1.320 |
| 0 | 0.678 % | 1.419 | 0.148 | 0.43 % | 0.835 | 0.394 |
| 1 | 1.660 % | 1.856* | 3.200*** | 0.32 % | 0.537 | 2.441** |
| 2 | -0.090 % | -0.241 | 0.050 | 0.10 % | 0.544 | 0.401 |
| N | 40 | | | 40 | | |

B: Cumulative Abnormal Returns

| Event window | Green | | | Non-Green | | |
|---|---|---|---|---|---|---|
| | CAR | BMP | Sign | CAR | BMP | Sign |
| [-1,1] | 2.254 % | 0.907 | 1.924* | 0.465 % | 0.521 | 0.5792 |
| [-2,2] | 1.894 % | 0.631 | 0.709 | 0.722 % | 0.745 | 0.458 |
| N | 40 | | | 40 | | |

Note: *p < 0.10, **p<0.05, ***p<0,01

**Table A 3.2:** Results from constant-mean model

This table shows the results of estimated abnormal returns ( Panel: A) and cumulative abnormal returns (Panel: B) over five days, with two windows: [-1,1] and [-2,2]. The constant-mean return model is applied with the same estimation and event windows as the results from the market model. Furthermore, we apply a traditional t-test in order to test the abnormal returns, and apply the Generalized sign test to test the cumulative abnormal returns.

A: Abnormal returns

| Day | Green | | Non-Green | |
|---|---|---|---|---|
| | AAR | t-test | AAR | t-test |
| -2 | -0.506 % | -1.262 | 0.055 % | 0.202 |
| -1 | 0.057 % | 0.131 | -0.004 % | -1.322 |
| 0 | 0.582 % | 1.181 | 0.007 % | 1.340 |
| 1 | 1.599 % | 1.705* | 0.004 % | 0.634 |
| 2 | -0.031 % | -0.073 | 0.403 % | 1.402 |
| N | 40 | | 40 | |

B: Cumulative Abnormal Returns

| Event window | Green | | Non-Green | |
|---|---|---|---|---|
| | CAR | Sign | CAR | Sign |
| [-1,1] | 2.238 % | 1.672* | 0.008 % | 1.117 |
| [-2,2] | 1.702 % | -0.088 | 0.466 % | 1.351 |
| N | 40 | | 40 | |

Note: *p < 0.10, **p<0.05, ***p<0,01

**Table A 3.3:** Regression results without controlling for year-fixed effects

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | CAR | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Green | 0.021 | 0.021 | 0.019 | 0.021 | 0.015 | 0.021 | 0.014 | 0.013 |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.012) | (0.013) | (0.012) | (0.012) |
| DVTA | | −0.015 | | | | | −0.013 | |
| | | (0.050) | | | | | (0.046) | |
| DVMCAP | | | −0.074** | | | | | −0.083** |
| | | | (0.037) | | | | | (0.042) |
| CrossIndustry | | | | −0.008 | | | −0.019 | −0.018 |
| | | | | (0.013) | | | (0.014) | (0.014) |
| M2B | | | | | 0.007** | | 0.007** | 0.008** |
| | | | | | (0.003) | | (0.003) | (0.004) |
| lnMCAP | | | | | | 0.003 | | −0.006 |
| | | | | | | (0.005) | | (0.004) |
| Constant | 0.004 | 0.006 | 0.012 | 0.010 | −0.011 | −0.018 | 0.003 | 0.054 |
| | (0.009) | (0.008) | (0.008) | (0.011) | (0.012) | (0.048) | (0.013) | (0.035) |
| Observations | 80 | 80 | 80 | 80 | 80 | 80 | 80 | 80 |
| Year Fixed Effects | No | No | No | No | No | No | No | No |
| $R^2$ | 0.031 | 0.035 | 0.102 | 0.034 | 0.125 | 0.038 | 0.146 | 0.214 |
| Adjusted $R^2$ | 0.018 | 0.010 | 0.079 | 0.009 | 0.103 | 0.013 | 0.101 | 0.161 |
| Residual Std. Error | 0.061 | 0.061 | 0.059 | 0.061 | 0.058 | 0.061 | 0.058 | 0.056 |
| F Statistic | 2.454 | 1.400 | 4.385** | 1.364 | 5.524*** | 1.501 | 3.215** | 4.036*** |
| *Note:* | | | | | | *p<0.1; **p<0.05; ***p<0.01 | | |

**Table A 3.4:** Regression results with Cross-boarder dummy

| | *Dependent variable:* | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | CAR | | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Green | 0.022* | 0.022* | 0.020 | 0.022* | 0.015 | 0.021* | 0.015 | 0.014 |
| | (0.013) | (0.013) | (0.012) | (0.013) | (0.012) | (0.012) | (0.012) | (0.011) |
| Crosscountry | −0.007 | −0.011 | −0.015 | | −0.003 | −0.004 | −0.005 | −0.010 |
| | (0.014) | (0.015) | (0.015) | | (0.014) | (0.015) | (0.014) | (0.014) |
| DVTA | | −0.037 | | | | | −0.024 | |
| | | (0.054) | | | | | (0.049) | |
| DVMCAP | | | −0.106*** | | | | | −0.084** |
| | | | (0.031) | | | | | (0.035) |
| Crossindustry | | | | −0.010 | | | −0.022 | −0.019 |
| | | | | (0.013) | | | (0.014) | (0.013) |
| M2B | | | | | 0.007** | | 0.007*** | 0.006** |
| | | | | | (0.003) | | (0.003) | (0.003) |
| lnMCAP | | | | | | 0.004 | | |
| | | | | | | (0.006) | | |
| Observations | 80 | 80 | 80 | 80 | 80 | 80 | 80 | 80 |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $R^2$ | 0.135 | 0.153 | 0.247 | 0.138 | 0.231 | 0.150 | 0.258 | 0.317 |
| Adjusted $R^2$ | −0.033 | −0.027 | 0.087 | −0.030 | 0.068 | −0.031 | 0.073 | 0.146 |
| Residual Std. Error | 0.064 | 0.063 | 0.060 | 0.064 | 0.060 | 0.064 | 0.060 | 0.058 |
| F Statistic | 0.806 | 0.852 | 1.547 | 0.823 | 1.414 | 0.829 | 1.394 | 1.855** |

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