Maastricht University

Post-merger Innovative Performance in the Renewable Energy Sector

Maastricht University

Faculty of Economics and Business Administration

Department Organization and Strategy

Student: Julia Koester

Student ID: i6083623

Supervisor I: Prof. Dr. J. Hagedoorn

Supervisor II: Ass. Prof. Paulo Soares de Pinho

Maastricht, 21st December 2014

Abstract

Due to global warming and shrinking fossil fuel resources, politics as well as society urge for a reduction of green house gas (GHG) emissions. This leads to a re-orientation towards a renewable energy sector. In this context, innovation and new technologies are key success factors. Moreover, the renewable energy sector has entered a consolidation stage, where corporate investors and mergers and acquisitions (M&A) gain in importance. Although both M&A and innovation in the renewable energy sector are important corporate strategies, the link between those two aspects has not been examined before. The present thesis examines the research question how M&A influence the acquirer's post-merger innovative performance in the renewable energy sector. Based on a framework of relevant literature, three hypotheses are defined. First, the relation between non-technology oriented M&A and post-merger innovative performance is discussed. Second, the impact of absolute acquired knowledge on post-merger innovativeness is examined. Third, the target-acquirer relatedness is discussed.

A panel data set of 117 firms collected over a period of six years has been analyzed via a random effects negative binomial regression model and a time lag of one year. The results support a non-significant, negative impact of non-technology M&A on post-merger innovative performance. The applied model did not support a positive and significant impact of absolute acquired knowledge on post-merger innovative performance. Lastly, the results suggest a reverse relation than postulated by Hypothesis 3. Targets from the same industry significantly and negatively influence the acquirers' innovativeness.

Table of Content

List of Tables

1 Introduction

Due to increasing concerns about global warming and shrinking fossil fuel and gas reserves, the renewable energy sector has undergone a rapid growth in the last decade (Yoo et al., 2013). Since global warming and shrinking fossil fuels are topics of worldwide attention, governments all over the world have started to support existing players and motivate new entrants to engage with energy generation from sources that are naturally replenished (Eisenbach et al., 2011). The European Union (EU) for example, committed to a decrease of 20% greenhouse gas (GHG) emission until 2020 (IEA, 2014). Since energy generation and consumption account for the largest part of GHG emission, the energy sector came into focus. However, in order to realize the required reduction of GHG, innovation is acknowledged to be the key for change (Wiesenthal et al., 2012). Consequently, renewable energy business models are maturing and starting to break even, and becoming more attractive for corporate investors.

One way corporate investors can engage with this innovative new field is through mergers and acquisitions (M&A). Defined as the process in which once separated firms combine their resources into one new entity (Hagedoorn and Duysters, 2002), M&A, next to a firm's innovation, are central aspects of competitive strategies in today's business reality (Cassiman et al., 2005).

In this context, the impact of M&A on firms' innovative performance has gained importance in literature (Ahuja and Katila, 2001, de Man and Duysters, 2005, Cassiman et al., 2005, Cloodt et al., 2006). Takeover activity is often driven by market shocks that force the market players to look for growth or change opportunities (Mitchell and Mulherin, 1996). The ongoing change in the energy sector and the increasing importance of renewable energy technologies trigger an increase in the number of M&A (Eisenbach et al., 2011). So far, research about the impact of M&A on firm's innovativeness has mainly focused on the high-technology sector. Low-technology sectors, like the energy sector, have been resistant to change and innovation for many years (Weiss and Bonvillian, 2013). Furthermore, major energy providers that have focused on incremental technology improvements, are now shifting their focus towards renewable energy technology (Eisenbach et al., 2011).

The economic effects of M&A on the firm performance in the renewable energy sector have been discussed and found to be positive (Yoo et al., 2013, Eisenbach et al., 2011). However, to the best knowledge of the author the link between innovation and M&A in this industry has not been examined yet.

Simultaneously, the increasing demand for new technologies will let innovation become a key competitive advantage for the energy sector too (Wiesenthal et al., 2012). Developing the link between the increasing M&A activities in the renewable energy sector and the increasing demand for innovation, the thesis at hand is dedicated to the following research question:

How do M&A influence the acquirer's post-merger innovative performance in the renewable energy sector?

In order to answer the research question, three hypotheses have been developed, focusing on target characteristics, such as background and innovativeness, and on acquisition motivation. The remainder of this study is divided into five further parts: theory development and hypothesis deduction, methodology and data analysis, results, discussion and conclusion, and lastly limitations of the study.

2 Theory Development

This chapter provides a comprehensive overview of the industry as well as a theory background. After highlighting the importance of the renewable energy sector and providing relevant definitions, the industry background paragraph discusses essential challenges, development stages and recent sector trends in M&A. The second paragraph gives an introduction of the underlying theory. The link between innovation and interfirm exchange in general and M&A in particular is discussed and potential challenges are delineated. Thirdly and lastly, three hypotheses are developed based on the industry and the theory background.

2.1 Industry Background – Energy Sector

Since global warming has become a topic of social as well as political interest, the energy market is undergoing major changes (Eisenbach et al., 2011). The focus is shifting towards the generation of energy from renewable and sustainable sources. The International Energy Agency (IEA) defines renewable energy as energy that "is derived from natural processes that are replenished constantly. In its various forms, it derives directly or indirectly from the sun, or from heat generated deep within the earth. Included in the definition is energy generated from solar, wind, biofuels, geothermal, hydropower and ocean resources, and biofuels and hydrogen derived from renewable resources." (IEA, 2014, p.17). These renewables find use in the three main areas of the energy sector: primary energy supply, electricity production, and installed generating capacity (IEA, 2014). In 2013, worldwide renewable power generation rose from 7.8% to 8.5%, which led to a decrease of the energy-generated CO_2 emission by approximately 1.2 billion tones (UNEP-Center/BNEF, 2014).

There are three key parties of stakeholders in the renewable energy sector: society, government, and companies. These three stakeholder groups have partly conflicting goals. In the development process of the renewable energy sector, governmental interventions play an important role, because of the mismatch between social goals and producers and/or consumer incentives. Further challenges of the sector development are market imperfections, like network economies and lumpiness of investments, and public habits. The quasi-free market in energy technology leads to conflicts between innovators, who want to protect their technology through IP, and environmental and security externalities (Weiss and Bonvillian, 2013). Therefore, governmental initiatives, such as research and development subsidies (technology push policies) or deployment subsidies and feed-in tariffs (market pull polices) are supposed to incentivize clean energy innovation and further aimed reduce investment risks (Lee and Zhong, 2014). Albeit stakeholders from both developing and developed countries have expressed their concerns about the negative impact of traditional energy generation on the environment, the different regions still differ a lot in their stage of development (Lee and Zhong, 2014).

Although many studies have found a positive and significant impact of government interventions on inventive activities (Popp et al., 2011), corporate actors play an important role in the market stabilization and expansion process (Corsatea et al., 2014, Klaassen et al., 2005, Popp et al., 2011).

The development stages of the different renewable energy sources and technologies vary noticeably. Hence, the activities of the government and the companies differ too. The renewable energy sector development can be divided into four main stages: (1) technology research, (2) technology development, (3) manufacturing scale-up, and (4) roll-out (UNEP-Center/BNEF, 2014). The financing tools change according to the development stages. While the first two stages are mainly financed through private equity and supported by public research and development (R&D), the third and fourth stage are characterized through increasing M&A initiatives and public markets (Lee and Zhong, 2014 & UNEP-Center/BNEF, 2014). Since in many fields of the renewable energy sector technologies have started to enter stage (3) or (4), it is not surprising that the number of M&A have followed an upward trend in the past 10 years (Yoo et al., 2013, Eisenbach et al., 2011, UNEP-Center/BNEF, 2014). For instance, hydro and thermal energy technologies are already in mature development stages, whereas solar and wind has just started to scale up and role out (Johnstone et al., 2009).

The growth and transformation in the energy market through the emerging renewable energy technologies have led to a strong increase in alliances in general and M&A in particular (Eisenbach et al., 2011). After the M&A activities reached a peak of $73.4 billion total transaction volume in 2011, the activities have slowed down. While asset acquisitions and refinancing declined from a total volume of $48.92 billion in 2012 to $40.28 billion in 2013, the transaction volume of corporate mergers and acquisitions (M&A) increased from $7.91 billion to $11.49 billion in the same time. The decreasing volume is mainly evoked by a decrease in prices along the value chain. The increase in corporate M&A is mainly driven by acquisitions of project developers and power generators (UNEP-Center/BNEF, 2014). In contrast, active acquirers in the renewable energy sector range from renewable energy and traditional energy companies to companies from other industries. The motives behind M&A in the sector include financial and operating synergies, growing market share, risk diversification, green premiums, and policy execution. The green premium is related to the fact that that minimizing CO_2 emission is of growing interest (Yoo et al., 2013).

In summary, the renewable energy sector is not only gaining social but also economic importance. The sector has entered a consolidation stage, in which the number of M&A and alliances increases. Governments and companies have to strive for innovation and learning in order to achieve the ambitions GHG emission reduction goals. By doing so, new technologies can achieve a reduction in CO_2 and newly gained knowledge may reduce costs for technologies and power generation.

2.2 Theory Background – M&A and Innovation

Innovation can be considered as an indirect return of acquisition activities (Ahuja and Katila, 2001). The ability to keep up with the increasing path of technological change has become a fundamental factor to maintain the firm's position in the market. New and disruptive technologies can rob incumbents of their previous dominant position. As such, innovations have the potential to change a mature market (Powell et al., 1996).

Networks are the place where innovation takes place, because breakthroughs often demand skills and knowledge that exceed the capabilities of a single company (Powell et al., 1996). Partnerships, therefore, can be beneficial to the partnering firms through skills and knowledge spillovers, leading to rising numbers of interfirm exchange. Strategies of interfirm exchange, such as M&A, first focus on knowledge distribution, absorption and creation to eventually obtain competitive advantage (Chen et al., 2014). Thereby, the partnering firms get access to a broader scope of information and can better understand and evaluate new technology developments (Ahuja, 2000).

Learning is seen as an improvement in performance and productivity through an accumulation of experience; also known as learning-by-doing (Wiesenthal et al., 2012). Linking the fact of a fast changing environment and the increasing amount of required information and knowledge, companies engage in M&A to keep, gain and improve their flexibility and capabilities. This can take place either if two more or less equal companies merge into one company or if one company acquirers a majority ownership of another company (Hagedoorn and Duysters, 2002). M&A can increase the acquirer's market power and can affect the technology competition, if the acquisition has the potential to create barriers to entry (Cassiman et al., 2005). Through M&A the company takes control over the resources of another company (Yoo et al., 2013). In other words, the firm gains access to the entire innovative abilities of the other firm (de Man and Duysters, 2005). However not all M&A are driven by innovation motives. As aforementioned, they can be also motivated, for example, by market power gains, synergy aims, risk reduction, diversification, or market access (Hagedoorn, 1993, Ahuja and Katila, 2001, Yoo et al., 2013, Cloodt et al., 2006).

Moreover, today's knowledge builds the foundation for future knowledge. It develops the ability to identify and exploit external knowledge. This ability is called absorptive capacity (Cohen and Levinthal, 1989). Absorptive capacity is the ability to learn, incorporate, and apply new external knowledge. The firm's absorptive capacity depends among others on organizational institutions involved (Chen et al., 2014). In other words, the acquisition of an external knowledge stock does not only increase the company's knowledge base, but also improves the ability to identify and exploit trends and changes (Cloodt et al., 2006). Relating it back to the resource-based view, which emphasizes the importance of internal, unique, inimitable and innovative firm capabilities in order to gain or sustain competitive advantage (Barney, 1991), the acquirement of external knowledge and the appropriate use of the knowledge is key to a firm's long-term competitive advantage (Cloodt et al., 2006).

To sum up, a fast changing environment and increasing competition force companies to be innovative. Companies benefit from interfirm exchange through knowledge spillovers. One form of company exchange are M&A. However, M&A are not necessarily driven by innovation motives and are very time and cost consuming. Consequently, not all M&A lead to higher innovative performance.

2.3 Hypotheses Development

M&A of renewable energy companies have emerged as a dominant strategy in the energy sector (UNEP-Center/BNEF, 2014). Moreover, innovation is seen as the key driver to GHG emission reduction. In this context it is crucial to understand the interdependency between both aspects. The following three hypotheses aim to answer the research question with regard to the M&A motive, the absolute acquired knowledge base and the relatedness between target and acquirer. They are based on the study of Ahuja and Katila (2001) and Cloodt et al. (2006), as both studies recognize the fact that M&A do not lead to innovation per se and, hence, provide a comprehensive consideration of the relation between M&A and innovation.

Technology versus non-technology motivated M&A

As mentioned before, the motives of M&A transactions can be various and complex. For example, M&A in the renewable energy sector are often driven by policy execution. In consideration of the corporate control literature, which claims M&A to be a measure of control for internal inefficiencies and agency problems, M&A might not necessarily support research and innovation within the firm (Jensen and Ruback, 1983). They require a large amount of the firm's resources and ask for great attention of the management of the firm (Hitt et al., 1996, Hitt et al., 1991). Therefore, M&A might interfere with existing research activities and decrease available resources for research and development (Cloodt et al., 2006). Hence, if M&A are not driven by innovation oriented motives, they might lead to no or even a negative effect on post-merger innovativeness.

Hypothesis 1: *Non-technological acquisitions will have either a negative or a non-significant impact on the acquirer's post-merger innovative performance.*

Absolute knowledge base

The impact of the target's absolute knowledge base has been examined by Ahuja and Katila (2001) and replicated by Cloodt et al. (2006). The rationale behind the argument can be explained by the absorptive capacity: an increasing knowledge base also increases the ability to recognize, evaluate, and ultimately use new information (Cohen and Levinthal, 1989). Differently spoken, a greater knowledge base increases the opportunities for innovation (Ahuja and Katila, 2001). Furthermore, research has shown that an increasing knowledge leads to a higher innovation output in the renewable energy sector (Klaassen et al., 2005, Popp et al., 2011, Wiesenthal et al., 2012)

Hypothesis 2: *The absolute knowledge base of the target company will have a positive impact on the acquirer's post-merger innovative performance.*

Relatedness of target and acquirer

Positive transfer effects are more likely, if acquirer and target have a similar background (Finkelstein and Haleblian, 2002). It can be distinguished between technological relatedness and market-relatedness. Whereas the further includes technologies that are either complementary or substitutional, the latter includes firms with overlapping product lines and businesses (Cassiman et al., 2005). An acquisition of a related target is more likely to lead to economies of scale and scope, like a shorter innovation lead-time (Hagedoorn and Duysters, 2002). Furthermore, in order to develop a new technology, i.e. to innovate, it supposed to be core of the firm (Chen et al., 2014). The empirical findings of Yoo et al. (2013) further support this argument, as they found a significant and positive effect on post-merger financial performance of M&A of firms that are both from the renewable energy sector.

Based on the idea of absorptive capacity, it is easier for firms to adapt external knowledge that is linked to their already existing knowledge base (Cloodt et al., 2006). Literature about corporate control highlights the potentially negative effect of acquisitions on innovative performance. This negative effect results from agency problems as well as from a shift of management priority from innovation towards organizational integration. In other words, the higher the degree of diversification, the more likely is a non-significant or negative impact on post-merger innovativeness (Hitt et al., 1991). To sum it up, it is expected that the relatedness of target and acquirer has a positive effect on the innovativeness of the acquiring firm.

Hypothesis 3: *The relatedness between target and acquirer has a positive impact on the acquirer's post-merger innovative performance.*

3 Sample and Method

The sample and method chapter explains the data collection as well as the data analysis. First, the used databases, time frames, and existing data are clarified. Next, each variable is defined and examined. The last paragraph explains the applied model and the used statistical tool.

3.1 Data and Sample

The study explores the post-merger innovative performance in the renewable energy sector between 2005 and 2011. The number of M&A has risen immensely within the past 10 years. However, before 2005, renewable energy related companies and technologies were still in early stage of development and hence had a comparably low economic importance and so was the number of M&A (UNEP-Center/BNEF, 2014). Therefore, M&A between 2005 and 2010 have been considered. To be able to consider the time lag between M&A and innovation, post-merger innovative performance one year after the M&A have been analyzed resulting in a period from 2006 to 2011.

The unit of analysis is the acquiring firm. First, the acquirer is considered to be a player in the renewable energy sector and second the acquirer is an active part of the energy value chain, i.e. financial institutions were excluded. The data was extracted from SDC Platinum, a database focusing on M&A and joint venture activities in the US and outside the US. SDC Platinum is operated by Thomson Reuters and considered to be a comprehensive and valid database, which has become even more complete and hence more suitable for research (Barnes et al., 2011). According to the data extracted from SDC Platinum, between 2005 and 2010, 931 acquisitions have taken place in the renewable energy sector in- and outside the US. This sample is limited to acquirers that are already coming from the renewable energy sector in order to ensure that renewable energy is part of their core business. The definition of the renewable energy sector through the primary SIC 499-A includes both the previously defined renewables and traditional players that have a notable share in renewables. The subdivision is based on information provided by SDC Platinum. This left a total number of 10 subsectors. A list of the subsectors including distribution within the sample can be found in Appendix 2.

The data was extracted according to the following criteria: (1) the acquisition/ merger deal took place between the 01.01.2005 and 31.12.2010, (2) the acquirer owns more than 50 % of the target after the acquisition, (3) the deal has been closed and unconditional (4) the acquirer is considered to be part of the renewable energy sector (Primary SIC 499-A). Acquirers that have been acquired or went bankrupt in the time of analysis were excluded. Furthermore, companies without any patent application between 2005 and 2011 have been ignored too. This left a total number of 117 acquirers. Forty six % of the acquirers are from Europe, 40 % from North America, 9 % from Asia, 3 % from others, and 2 % from Latin America.

In order to measure the innovative performance patent application counts are used. Espacenet was used in order to collect the number of patents of both acquiring and acquired company. Espacenet is the patent search platform of the European Patent and is frequently used in studies about innovation in the renewable energy sector (Bointner, 2014, Popp et al., 2011).

3.2 Variables

Dependent variable

Patents can be considered as the innovative output of a firm. In contrast to R&D investment (innovation input), patents are the result of innovation initiatives (Ahuja and Katila, 2001, Hagedoorn and Cloodt, 2002). They are non-negative integer count variables. Patents have positive as well as negative aspects as a measure of a firm's innovativeness. A patent is a strong measure, as it signals economic importance (Scherer and Ross, 1990) and externally accepted novelty (Griliches, 1990). Furthermore, patents have been used as a count for renewable energy innovativeness before (Johnstone et al., 2009, Popp et al., 2011, Bointner, 2014). However, patent counts have certain shortcomings as a measure for innovativeness (Griliches, 1990). For example, not all inventions are patented and hence, patents cover not the entire innovation capability of the firm. Furthermore, the patenting behavior depends on the respective industry (Cohen and Levinthal, 1989). In this paper, patent applications are used as a measure for firms' innovativeness. By doing so, the time difference between the actual invention and the external acceptance is reduced. Patent citation, which might allow evaluating inventions not only on a quantitative level, but also on a qualitative level, are excluded, as it would require in-depth knowledge about the respective technology (Hagedoorn and Cloodt, 2002).

The number of patents has been growing by a factor of 5.6 since 1990. However, patenting was not very common in the energy sector before. This number is not limited to the core technologies of renewables, but extends to complementary technologies like batteries, hydrogen and fuel cells (Bointner, 2014). This leads to a huge variety of patent classifications that are involved in the innovation process of renewable energy. In order to overcome the problem of identifying inventions that are related to clean energy, the European patent office has introduced a new tagging scheme. The tag Y02 was introduced to complement the already existing classifications (Veefkind et al., 2012). In order to count only those patents that are related to renewable energy, the Y02 tag was used for those companies that are active in more than just the renewable energy sector.

For example, electric, gas, and water distribution companies, that do not only distribute renewable energy, but also conventional energy.

Independent variables

Technology versus non-technology M&A

Within a time frame of six years (2005-2010), the number of M&A initiated by renewable energy firms has been collected. These M&A are distinguished in technology and non-technology M&A. An M&A is considered to be technology motivated, if the number of acquired patents is greater than zero. A dummy variable was created to distinguish between technology and non-technology M&A.

Relatedness of target and acquirer

Depending on whether the target and acquirer have the same core business, M&A can be either related or unrelated. Research has shown that M&A in the renewable energy sector yield to a higher premium, if target and acquirer are both coming from the renewable energy sector (Yoo et al., 2013). Finkelstein and Haleblian (2002) found similar results on a more general level. The more the target fits into the strategic orientation of the firm, the higher the acquisition performance will be. The relatedness is measured in terms of industry relatedness. In other words, whether the primary SIC are identical.

Absolute acquired knowledge

In order to measure the absolute acquired knowledge, patents preceding the year of acquisition of the acquired firm have been counted. Since the knowledge depreciation is expected to be between three to five years in the renewable energy sector, patent applications up to five years before the M&A have been included (Klaassen et al., 2005, Wiesenthal et al., 2012).

Control Variables

Acquirer Nationality

On the one hand several studies have found a positive link between technology push policies or market pull polices and the patenting activities of firms in the renewable energy sector (Bointner, 2014, Klaassen et al., 2005, Wiesenthal et al., 2012). On the other hand governmental interventions can also have a negative impact on the innovativeness of the firm (Weiss and Bonvillian, 2013). In order to control for the link between country specific policies and the innovativeness of the firm, a dummy variable representing the different regions has been introduced.

Sub-Sector

The renewable energy sector is characterized by heterogeneity in the level of consolidation as well as technology development. Whereas wind and hydro have the highest level of market concentration, biomass and solar will most likely experience a high M&A activity in the near future (Eisenbach et al., 2011). Three generations of renewable energy exist: (1) mature technologies such as hydropower and thermal, (2) second-generation technologies, which are undergoing rapid changes, such as wind and solar, and (3) third generation technologies in early stages such as bio-energy systems and ocean energy (Johnstone et al., 2009). Therefore, the acquiring firms have been further distinguished according to their core business.

International M&A

The third control variable of the model controls if the M&A has been a national or a cross-border activity. Cloodt et al. (2006), for example, have found a positive impact of cultural distance on post-merger innovative performance.

Patent applications previous year

In order to account for the individual patenting behavior of each firm within the data set, the number of patent applications has been included as a control variable.

Years

A dummy variable has been introduced in order to control for the differences in patenting behavior in each year of the period.

3.3 Method and Model

Since patents are integer, non-negative values, the assumptions of normal distribution and homoscedasticity are violated (Long and Freese, 2006). Therefore, either a Poisson or Negative Binomial regression model has to be applied. A Poisson model, however, follows the restrictive assumption that $V(y) = E(y) = \mu$, i.e. the variance equals the conditional mean. If this assumption does not hold, the data is over dispersed. Since individual counts are usually more variable than the Poisson model requires, over-dispersion is likely to occur (Gardner et al., 1995). The negative binomial regression model addresses these shortcomings by including a random effects component with an error term ε and by adding α to conditional mean $Var(y_i|x) = \mu_i + \alpha\mu_i^2$ (Long and Freese, 2006).

Moreover, the unit of analysis was analyzed in a period of six years. In other words, N observations of n individuals have been observed in T time periods. Therefore, a cross-sectional panel data model is applied.

Panel data models can be divided into pooled, fixed, and random effects models. The fixed effects as well as the random effects model assume an observed heterogeneity across the individuals that might affect the dependent variable. The unobserved heterogeneity is captured by α_i. Whereas the fixed effects model includes α_i as the intercept with the y-axis, the random effects model assumes that α_i is independently distributed of the predicted variables (Wooldridge, 2010). Like Cloodt et al. (2006), this thesis works with random effects and, hence, postulates that the individual effects α_i are independent from the predicted variables.

Therefore, the following negative binomial regression is used:

$$P_{it} = \exp\,(\boldsymbol{X'}_{it-1}\boldsymbol{\gamma'} + \boldsymbol{A'}_{it-1}\boldsymbol{\beta'})$$

$$P_{it} = number\ of\ patent\ application\ of\ acquirer\ i\ in\ year\ t$$

$$\boldsymbol{X'}_{i,t-1} = Vector\ of\ Control\ Variables$$

$$\boldsymbol{\gamma'} = Vector\ of\ regression\ coefficients\ for\ the\ control\ variables$$

$$\boldsymbol{A'}_{it-1} = Vector\ of\ Independent\ Variables$$

$$\boldsymbol{\beta'} = Vector\ of\ regression\ coefficients\ for\ the\ indepedent\ variable$$

In order to compute the model, Stata has been used. First, the following variables have been encoded: company names (acquirer), non-technology M&A, relatedness and international M&A. Second, dummy variables have been created for years, countries, and subsectors. Third, the data set has been set as panel data and the descriptive statistics have been computed. Fourth, the Hausman test has been calculated in order to measure the model fit. Lastly, the random effects negative binomial regression model has been processed. In order to consider the time lag between M&A and innovation (patent application of acquirer), a time lag of one year was introduced. The model included the dependent variable, all encoded variables, the dummy variables, patent applications of the target, and patent applications of the acquirer in the previous year. The results of the Hausman test as well as the results of the random effects negative binomial regression model are presented in the following chapter. The descriptive statistics are presented in Appendix 1.

4 Results

This paragraph shows and discusses the results of the negative binomial regression model of panel data starting with a model fit test. The summaries of the variables and the corresponding descriptive statistics are in Appendix 1.

Appendix 2 provides a generalized negative binomial regression model for each year. In this way, one can see the large differences among the results of the years.

4.1 Model Fit

The Hausman test evaluates the consistency of the fixed effects model versus the random effects model. The test compares the regression coefficients of the random effects model (b) versus the random effects model (B). The H_0 Hypothesis postulates that the random effects model is consistent and efficient. In other words, the difference in coefficients is not systematic (Greene, 2012). Whereas (b) is consistent under H_0 and H_a, (B) is inconsistent under H_a and efficient under H_0. Since Prob>chi2=0.3071, the result is not significant. Hence, the H_0 cannot be rejected and the random effects model has to be applied. Table 1 shows the results of the Hausman test.

Table 1: Hausman test: random vs. fixed effects model

		(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) S.E.
Acquired Patents		.0020902	-.0107398	.01283	.0090553
Non-Tech M&A		-1.870177	.5312175	-2.401395	1.256466
Relatedness		.2764911	-.2402768	.5167679	1.931397
International M&A		-1.827789	.418506	-2.246295	1.522345
Patent App. t-1		1.255417	1.190972	.0644446	.0873779
Year		.616068	.5162268	.0998413	.5459972
chi2(6)	=		(b-B)'[(V_b-V_B)^(-1)](b-B)		
	=		7.15		
Prob>chi2	=		0.3071		

4.2 Results Negative Binomial Regression

Table 2 shows the results of the random effects negative binomial regression. The data set is highly balanced, meaning that no company has entered or left during the time period under investigation.

Hypothesis 1 postulates that non-technology M&A will have either a negative or non-significant impact on post-merger innovative performance. If a target company has not applied for any patents in the 5 years prior the acquisition, the M&A is considered to be a non-technology M&A. The variable “Non-Tech M&A” shows a non-significant and negative value of -.0867943. Therefore, Hypothesis 1 is supported.

Hypothesis 2 argues that the absolute acquired knowledge has a positive impact on post-merger innovative performance. The absolute knowledge base was measured by the number of patent applications of the target in the 5 years prior the acquisition. The number of acquired patents is non-significant and marginally negative (-.0006574). Hence, Hypothesis 2 is rejected.

Hypothesis 3 states that the relatedness between target and acquirer supports the acquirer’s post-merger innovative performance. The relatedness was measured by comparing the primary SIC of target and acquirer. Relatedness is found to have a significant impact on post-merger innovative performance. Interestingly, the impact is negative. In other words the relatedness causes a decrease of post-merger innovative performance by a factor of -.3792313. Evidence for the opposite relation is provided: targets with a diverse industry background positively influence innovative performance.

Several control variables have been included in the hypotheses tests. International M&A have a significant and positive (.6357257) impact on post-merger innovative performance. Moreover, patent applications of the previous year also influence the dependent variable positively and significantly. If a firm has already applied for patents in t-1, it will increase the patent application t by a factor of .0394329.

Dummies for the different countries have been included to account for the country-specific differences like governmental regulations in the energy sector. Australia, Canada, Switzerland, and United Kingdom are significant. Interestingly, all four countries have a negative impact on patent applications in the renewable energy sector (Australia: -1.804159; Canada: -.7261642; Switzerland: -.7682274; United Kingdom: -.7641516).

Subsector dummies control for the differences among the development stages of the different renewable energy areas. Among the ten defined subsectors, only Wind (-.9894818) and Electric, Gas, & Water Distribution (-.6657053) are significant.

Since the results in the different years vary considerably, year dummies have not only been included, but the respective year results are also shown in Appendix 2.

Table 2: Negative Binomial Regression Model

No. Patent App.	Coefficient	Std. Error	z	P>|z|
Acquired Patents	-.0006574	.0009512	-0.69	0.489
Non-Tech M&A	-.0867943	.1452838	-0.60	0.550
Relatedness	-.3792313	.1885202	-2.01	0.044
International M&A	.6357257	.1554215	4.09	0.000
Patent App t-1	.0394329	.0030144	13.08	0.000
Biofuels & Waste	-.2997073	.3344197	-0.90	0.370
Cogeneration Plant	-.4833046	.5338093	-0.91	0.365
Electric, Gas, & Water Distribution	-.6657053	.3168348	-2.10	0.036
Engineering	-.0764403	.3187495	-0.24	0.810
Hydro	1.021791	1.084715	0.94	0.346
Oil & Gas	.1228028	.2955596	0.42	0.678
Solar	-.3680349	.332787	-1.11	0.269
Thermal	.6870043	.4060309	1.69	0.091
Wind	-.9894818	.4339078	-2.28	0.023
Renewable Energy Services	0	(omitted)		
Argentina	0	(omitted)		
Australia	-1.804159	.7786272	-2.32	0.020
Belgium	.9861652	.9975447	0.99	0.323
Brazil	.005195	.6545154	0.01	0.994
Canada	-.7261642	.3227787	-2.25	0.024
China	-.1417924	.5338861	-0.27	0.791
Denmark	.2379778	.4461145	0.53	0.594
Finland	.7154469	.7617737	0.94	0.348
France	-.5572491	.521467	-1.07	0.285
Germany	-.070021	.2801709	-0.25	0.803
Hong Kong	.228898	.5963739	0.38	0.701
India	-.3191331	1.048.739	-0.30	0.761
Ireland	-25.53305	294850.1	-0.00	1.000
Italy	-1.253318	1.076118	-1.16	0.244
Japan	0	(omitted)		
Netherlands	.5537405	.6687451	0.83	0.408
New Zealand	-1.448869	1.033854	-1.40	0.161
Norway	-.2058306	.4226725	-0.49	0.626
Portugal	-.2089444	.4889859	-0.43	0.669
Russia	-.2128278	.9543181	-0.22	0.824
Singapore	.8595906	.8573996	1.00	0.316
Spain	.058946	.2208199	0.27	0.790
Sweden	-1.069845	.9893724	-1.08	0.280
Switzerland	-.7682274	.2745261	-2.80	0.005
United Kingdom	-.7641516	.3175709	-2.41	0.016
United States	0	(omitted)		
Log likelihood	-404.1939			
n	117	(firm id)		
N	702	(M&A)		

Year Dummies are included but not shown

Table 3 provides a summary of the Hypotheses and the respective results of the negative binomial regression analysis. In summary, only hypothesis 1 could be supported. Interestingly, Hypothesis 2 was neither significant nor positive. Moreover, the negative binomial regression shows contrary and significant results for Hypothesis 3.

These findings suggest new and interesting rationales, which are discussed in the next paragraph.

Table 3: Summary of Hypothesis Tests

Hypotheses	Description	Results		
Hypothesis 1	*Non-technological acquisitions will have either a negative or a non-significant impact on the acquirer's post-merger innovative performance.*	insignificant	negative	**supported**
Hypothesis 2	*The absolute knowledge base of the target company will have a positive impact on the acquirer's post-merger innovative performance.*	insignificant	negative	**rejected**
Hypothesis 3	*The relatedness between target and acquirer has positive impact on the acquirer's post-merger innovative performance.*	significant	negative	**rejected**

5 Discussion and Conclusion

This study examined innovation in the renewable energy sector from a new perspective by discussing the influence of M&A on post-merger innovative performance. As M&A as well as innovation have become dominant and important topics in the discussion about sustainable and renewable energy generation, this study filled a research gap by investigating the relation between those two.

Three hypotheses, based on the studies of Ahuja and Katila (2001) and Cloodt et al. (2006) were investigated. First, the impact of technology versus non-technology M&A have been tested via Hypothesis 1. Second, the impact of the absolute acquired knowledge base was examined in Hypothesis 2. Third and last, Hypothesis 3 tested the relation between post-merger innovative performance and target and acquirer relatedness.

Although only Hypothesis 1 could be supported, the present thesis contributes some important insights to research. First, the negative and non-significant effect of non-technology M&A on post-merger innovative performance supports the assumption that M&A do not drive innovation per se. M&A can be driven by several motives and hence do not necessarily aim to increase the acquirer's innovativeness (Hagedoorn, 1993). Moreover, the integration process of newly acquired firms requires a large amount of resources (Hitt et al., 1991). Putting the findings in the context of the sector, the starting consolidation of the renewable energy sector led increase the number of M&A (Eisenbach et al., 2011). Due to price decreases in sectors like wind and solar, corporate investors looked for external growth opportunities (UNEP-Center/BNEF, 2014).

The second contribution of the thesis sheds light on the relation between the acquired absolute knowledge and the acquirer's post-merger innovation performance. Whereas Ahuja and Katila (2001) and Cloodt et al. (2006) found a positive impact of absolute acquired knowledge on the acquirer's innovativeness, this work could not identify any significant relation.

As a third contribution, the thesis disproves the positive impact of relatedness on post-merger innovative performance in the renewable energy sector. Based on findings of Finkelstein and Haleblian (2002) and Yoo et al. (2013), Hypothesis 3 postulated a positive relation. In other words, due to economies of scale and scope, relatedness will eventually lead to a higher post-merger innovative performance than diversity. Conversely, the result recommends that new and diverse acquired knowledge will have a positive impact on the innovative performance of the acquiring firm. In this way the acquirer generates more room for learning (Bartlett, 1993).

The results of Hypotheses 2 and 3 reach the conclusion that not the quantity, but rather the diversity of the acquired knowledge contributes to the acquirer's innovativeness. Disruptive or radical innovation creates new market structures, new market actor, new institutions and new socio-technical configurations (Markard and Truffer, 2008). Moreover, sustainable innovation, like the generation of energy from sustainable sources, is not limited to the development of clean technologies, but includes entire systems of production and consumption. This multi-level perspective asks companies to look for innovation in networks, new learning processes, knowledge infrastructure, and entrepreneurial capabilities (Smith et al., 2010).

Lastly, the integrated control variables give further information about the importance of the firm's individual patenting behavior, the different subsectors, the impact of international M&A, and the role of the acquirer's home country. The results have shown that the different firms vary considerably in their patenting behavior. Whereas some firms have only applied for a handful of patents, others applied for more than 100. The individual past patenting behavior of the firm influences the future patenting behavior.

Interestingly, the different subsectors show mostly insignificant results. Only the subsectors Wind and Electric, Gas & Water Distribution show significant but negative impact on the acquirer's innovativeness. Like Yoo et al. (2013) pointed out, Electric, Gas & Water Distribution companies engage in renewable energy M&A in order to execute policies by external growth strategies than by internal innovative performance. For instance, Richter (2013) found out that Electric Distribution companies do not see the need to innovate yet.

The positive impact on international mergers further support the findings by Cloodt et al. (2006). Although the energy sector is still very national orientated (Klaassen et al., 2005, Lee and Zhong, 2014, Popp et al., 2011, Weiss and Bonvillian, 2013) the results suggest that a more international energy market enhances companies' innovative performance.

Furthermore, the results show a negative impact of some countries on acquirers' innovativeness. These findings are to some extent contradicting to findings of previous research that investigates the relation of governmental interventions and innovation in the renewable energy sector (Johnstone et al., 2009, Klaassen et al., 2005, Popp et al., 2011, Wiesenthal et al., 2012). In contrast, Weiss and Bonvillian (2013), highlight the potential negative impact of governmental interventions on innovation in the energy sector. The negative relation could be partly explained by the worries about a decrease in governmental financial support in countries such as the United Kingdom. The uncertainty of future financial support let decrease the investment in renewable energy in general and in technology and innovation in particular (UNEP-Center/BNEF, 2014). Due to market imperfections and a mismatch between social land corporate goals, governmental support such as R&D subsidies and feed-in tariffs seem to play an important role in the innovation process of companies in the renewable energy market.

By answering the research question, this thesis provides first insights about the rationales behind M&A and post-merger innovativeness in the renewable energy sector. The continuing consolidation lets companies engage in M&A activities. M&A, however, are not innovation drivers per se. This thesis proposes that unrelated and international M&A lead to a higher post-merger innovative performance. It is further suggested that the increasing social need for innovation in renewable energy has to be partly supported by governmental interventions, because uncertainties let decrease the corporate investments.

6 Limitations and Suggestions for Future Research

The study suffers from certain limitations and provides suggestions for future research. The limitation of this work concerns the sample, the collected data, and the employed model.

First, the sample exclusively focused on acquirers that are clearly defined as renewable energy companies by the Primary SIC 499-A. As mentioned before, the change of an entire sector also attracts and creates new players. This restriction biased the sample towards energy generation and distribution companies. Eisenbach et al. (2011), for example, identified 26 different SIC Codes to be linked to renewable energy. Therefore, future research should extend the sample towards a broader definition and sample of renewable energy companies.

Second, limitations regarding collected data are two-folded. On the one hand, innovation was measured in terms of patent counts. They are widely accepted to be an appropriate measure to compare the innovation activity of different companies (Hagedoorn and Cloodt, 2002). However, sustainable and disruptive innovation includes innovation in the business model including a new corporate strategy (Smith et al., 2010). In other words, patent applications are not able to capture the entire dimension of post-merger innovativeness. Future research could build on and extent the innovation measure in form of patenting. On the other hand, the considered time frame and available data on M&A is still fragmented. Energy companies have been focusing on incremental and minor technology improvements and innovation for many years. Only after the discussion about GHG emission reduction has had an economic impact on energy companies, renewable energy became a topic of relevance (Yoo et al., 2013). Hence, patenting in the renewable energy company only became important in the past

20 years (Bointner, 2014). Moreover, the renewable energy sector has just reached a consolidation stage. Only in 2004, M&A started to emerge in the renewable energy sector (UNEP-Center/BNEF, 2014). Thus, the available data is still very limited. In the next years, the data will certainly become more comprehensive, which will improve the data quality.

The applied model was a negative binomial regression model with a panel data set. The model used a time lag of one year in order to account for the time needed to transform the acquired knowledge into an innovation. However, the full extent of the influence of M&A on the post-merger innovative performance might become visible not only in year t+1, but also in the following years. Therefore, a model that applies different time lags could be used for future research purposes.

In summary, the thesis provides first insights about the relation between M&A and post-merger innovative performance. Moreover, it highlights further influential factors like country, subsector, international scope, and individual patenting behavior. The findings call for further research that examines and deepens the question how M&A influence post-merger innovative performance in the renewable energy sector.

7 References

AHUJA, G. 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative science quarterly,* 45**,** 425-455.

AHUJA, G. & KATILA, R. 2001. Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study. *Strategic management journal,* 22**,** 197-220.

BARNES, B., HARP, N. & OLER, D. 2011. Evaluating the SDC mergers and acquisitions database. Working paper, Texas Tech University.

BARNEY, J. 1991. Firm resources and sustained competitive advantage. *Journal of management,* 17**,** 99-120.

BARTLETT, C. A. 1993. Commentary: strategic flexibility, firm organization, and managerial work in dynamic markets. *Advances in Strategic Management,* 9**,** 293-298.

BOINTNER, R. 2014. Innovation in the energy sector: Lessons learnt from R&D expenditures and patents in selected IEA countries. *Energy Policy,* 73**,** 733-747.

CASSIMAN, B., COLOMBO, M. G., GARRONE, P. & VEUGELERS, R. 2005. The impact of M&A on the R&D process. *Research Policy,* 34**,** 195-220.

CHEN, H. H., LEE, A. H. I., XING, X. & CHEN, H. 2014. The relationships of different modes of international alliance with performance of renewable energy enterprises. *Renewable Energy,* 69**,** 464-472.

CLOODT, M., HAGEDOORN, J. & VAN KRANENBURG, H. 2006. Mergers and acquisitions: Their effect on the innovative performance of companies in high-tech industries. *Research Policy,* 35**,** 642-654.

COHEN, W. M. & LEVINTHAL, D. A. 1989. Innovation and learning: the two faces of R & D. *The economic journal*, 569-596.

CORSATEA, T. D., GIACCARIA, S. & ARÁNTEGUI, R. L. 2014. The role of sources of finance on the development of wind technology. *Renewable Energy,* 66, 140-149.

DE MAN, A.-P. & DUYSTERS, G. 2005. Collaboration and innovation: a review of the effects of mergers, acquisitions and alliances on innovation. *Technovation,* 25, 1377-1387.

EISENBACH, S., ETTENHUBER, C., SCHIERECK, D. & VON FLOTOW, P. 2011. Beginning Consolidation in the Renewable Energy Industry and Bidders' M & A-Success. *Technology and Investment,* 2, 81.

FINKELSTEIN, S. & HALEBLIAN, J. 2002. Understanding Acquisition Performance: The Role of Transfer Effects. *Organization Science,* 13, 36-47.

GARDNER, W., MULVEY, E. P. & SHAW, E. C. 1995. Regression analyses of counts and rates: Poisson, overdispersed Poisson, and negative binomial models. *Psychological bulletin,* 118, 392.

GREENE, W. H. 2012. *Econometric analysis,* Boston, MA [etc.], Pearson.

GRILICHES, Z. 1990. Patent statistics as economic indicators: a survey. *Journal of economic literature,* 28, 1661-1707.

HAGEDOORN, J. 1993. Understanding the rationale of strategic technology partnering: Nterorganizational modes of cooperation and sectoral differences. *Strategic management journal,* 14, 371-385.

HAGEDOORN, J. & CLOODT, M. 2002. Measuring innovative performance: is there an advantage in using multiple indicators? *Research policy,* 32, 1365-1379.

HAGEDOORN, J. & DUYSTERS, G. 2002. External sources of innovative capabilities: the preferences for strategic alliances or mergers and acquisitions. *Journal of management studies,* 39**,** 167-188.

HITT, M. A., HOSKISSON, R. E., IRELAND, R. D. & HARRISON, J. S. 1991. Effects of acquisitions on R&D inputs and outputs. *Academy of Management journal,* 34**,** 693-706.

HITT, M. A., HOSKISSON, R. E., JOHNSON, R. A. & MOESEL, D. D. 1996. The market for corporate control and firm innovation. *Academy of management journal,* 39**,** 1084-1119.

IEA 2014. *Renewables Information 2014*, IEA.

JENSEN, M. C. & RUBACK, R. S. 1983. The market for corporate control: The scientific evidence. *Journal of Financial economics,* 11**,** 5-50.

JOHNSTONE, N., HAŠČIČ, I. & POPP, D. 2009. Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts. *Environmental and Resource Economics,* 45**,** 133-155.

KLAASSEN, G., MIKETA, A., LARSEN, K. & SUNDQVIST, T. 2005. The impact of R&D on innovation for wind energy in Denmark, Germany and the United Kingdom. *Ecological Economics,* 54**,** 227-240.

LEE, C. W. & ZHONG, J. 2014. Top down strategy for renewable energy investment: Conceptual framework and implementation. *Renewable Energy,* 68**,** 761-773.

LONG, J. S. & FREESE, J. 2006. *Regression models for categorical dependent variables using Stata*, Stata press.

MARKARD, J. & TRUFFER, B. 2008. Technological innovation systems and the multi-level perspective: Towards an integrated framework. *Research Policy,* 37**,** 596-615.

MITCHELL, M. L. & MULHERIN, J. H. 1996. The impact of industry shocks on takeover and restructuring activity. *Journal of financial economics,* 41**,** 193-229.

POPP, D., HASCIC, I. & MEDHI, N. 2011. Technology and the diffusion of renewable energy. *Energy Economics,* 33**,** 648-662.

POWELL, W. W., KOPUT, K. W. & SMITH-DOERR, L. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative science quarterly***,** 116-145.

RICHTER, M. 2013. German utilities and distributed PV: How to overcome barriers to business model innovation. *Renewable Energy,* 55**,** 456-466.

SCHERER, F. M. & ROSS, D. R. 1990. *Industrial market structure and economic performance,* Boston, Mass., [etc.], Houghton Mifflin.

SMITH, A., VOS, J.-P. & GRIN, J. 2010. Innovation studies and sustainability transitions: the allure of the multi-level perspective and its challenges. *Research policy,* 39**,** 435-448.

UNEP-CENTER/BNEF, F. S. 2014. Global Trends in Renewable Energy Investment 2014. *In:* ANGUS MCCRONE (LEAD AUTHOR, C. E., ERIC USHER (LEAD EDITOR), VIRGINIA SONNTAG-O'BRIEN, ULF MOSLENER (LEAD EDITOR), CHRISTINE GRÜNING (ed.). Frankfurt am Main.

VEEFKIND, V., HURTADO-ALBIR, J., ANGELUCCI, S., KARACHALIOS, K. & THUMM, N. 2012. A new EPO classification scheme for climate change mitigation technologies. *World Patent Information,* 34**,** 106-111.

WEISS, C. & BONVILLIAN, W. B. 2013. Legacy sectors: barriers to global innovation in agriculture and energy. *Technology Analysis & Strategic Management,* 25**,** 1189-1208.

WIESENTHAL, T., MERCIER, A., SCHADE, B., PETRIC, H. & DOWLING, P. 2012. A model-based assessment of the impact of revitalised R&D investments on the European power sector. *Renewable and Sustainable Energy Reviews,* 16**,** 105-112.

WOOLDRIDGE, J. M. 2010. *Econometric analysis of cross section and panel data*, MIT press.

YOO, K., LEE, Y. & HEO, E. 2013. Economic effects by merger and acquisition types in the renewable energy sector: An event study approach. *Renewable and Sustainable Energy Reviews,* 26**,** 694-701.

8 Appendices

8.1 Appendix 1: Descriptive Statistics and Variable Summary

Table 4: Descriptive Statistics

Variable		Mean	Std. Dev.	Min	Max	Variable
Number of Patent Applications (DV)	overall	8.789174	1.825524	0	169	N = 702
	between		1.673889	.1666667	9.033333	n = 117
	within		7.420365	-3.254416	8.745584	T = 6
Non-Technology M&A (IV_1)	overall	.4634146	.4998804	0	1	N = 205
	between		.4424327	0	1	n = 117
	within		.3172595	-.2865854	1.263415	T-bar = 1.75214
Relatedness (IV_2)	overall	.2525253	.4355622	0	1	N = 198
	between		.3970993	0	1	n = 116
	within		.2430071	-.4974747	1.085859	T-bar = 1.7069
International M&A (IV_3)	overall	.3910891	.4892067	0	1	N = 202
	between		.4201026	0	1	n = 117
	within		.2857883	-.4089109	1.141089	T-bar = 1.7265
Acquirer Patent Applications t-1 (CV_1)	overall	8.294017	1.685125	0	119	N = 585
	between		1.586203	0	79.6	n = 117
	within		5.838172	-2.350598	5.869402	T = 5
Biofuels & Waste **22***	overall	.1880342	.3910181	0	1	N = 702
	between		.3924201	0	1	n = 117
	within		0	.1880342	.1880342	T = 6
Cogeneration Plant **6***	overall	.0512821	.2207297	0	1	N = 702
	between		.2215211	0	1	n = 117
	within		0	.0512821	.0512821	T = 6
Electric, Gas, & Water Distribution **23***	overall	.1965812	.3976963	0	1	N = 702
	between		.3991222	0	1	n = 117
	within		0	.1965812	.1965812	T = 6
Engineering **17***	overall	.1452991	.3526535	0	1	N = 702
	between		.3539179	0	1	n = 117
	within		0	.1452991	.1452991	T = 6
Hydro **2***	overall	.017094	.1297142	0	1	N = 702
	between		.1301793	0	1	n = 117
	within		0	.017094	.017094	T = 6
Oil & Gas **3***	overall	.025641	.1581746	0	1	N = 702
	between		.1587417	0	1	n = 117
	within		0	.025641	.025641	T = 6
Solar **12***	overall	.1025641	.303605	0	1	N = 702
	between		.3046936	0	1	n = 117
	within		0	.1025641	.1025641	T = 6
Thermal **4***	overall	.034188	.1818415	0	1	N = 702
	between		.1824935	0	1	n = 117
	within		0	.034188	.034188	T = 6
Wind **13***	overall	.1111111	.3144938	0	1	N = 702
	between		.3156214	0	1	n = 117
	within		0	.1111111	.1111111	T = 6
Renewable Energy Services **15***	overall	.1282051	.3345564	0	1	N = 702
	between		.335756	0	1	n = 117
	within		0	.1282051	.1282051	T = 6
Argentina **1***	overall	.008547	.0921197	0	1	N = 702
	between		.09245	0	1	n = 117

	within		0	.008547	.008547	T =	6
Australia **3***	overall	.025641	.1581746	0	1	N =	702
	between		.1587417	0	1	n =	117
	within		0	.025641	.025641	T =	6
Belgium **1***	overall	.008547	.0921197	0	1	N =	702
	between		.09245	0	1	n =	117
	within		0	.008547	.008547	T =	6
Brazil **1***	overall	.008547	.0921197	0	1	N =	702
	between		.09245	0	1	n =	117
	within		0	.008547	.008547	T =	6
Canada **13***	overall	.1111111	.3144938	0	1	N =	702
	between		.3156214	0	1	n =	117
	within		0	.1111111	.1111111	T =	6
China **4***	overall	.034188	.1818415	0	1	N =	702
	between		.1824935	0	1	n =	117
	within		0	.034188	.034188	T =	6
Denmark **1***	overall	.008547	.0921197	0	1	N =	702
	between		.09245	0	1	n =	117
	within		0	.008547	.008547	T =	6
Finland **2***	overall	.017094	.1297142	0	1	N =	702
	between		.1301793	0	1	n =	117
	within		0	.017094	.017094	T =	6
France **3***	overall	.025641	.1581746	0	1	N =	702
	between		.1587417	0	1	n =	117
	within		0	.025641	.025641	T =	6
Germany **8***	overall	.0683761	.2525701	0	1	N =	702
	between		.2534757	0	1	n =	117
	within		0	.0683761	.0683761	T =	6
Hong Kong **2***	overall	.017094	.1297142	0	1	N =	702
	between		.1301793	0	1	n =	117
	within		0	.017094	.017094	T =	6
India **3***	overall	.025641	.1581746	0	1	N =	702
	between		.1587417	0	1	n =	117
	within		0	.025641	.025641	T =	6
Ireland **2***	overall	.017094	.1297142	0	1	N =	702
	between		.1301793	0	1	n =	117
	within		0	.017094	.017094	T =	6
Italy **3***	overall	.025641	.1581746	0	1	N =	702
	between		.1587417	0	1	n =	117
	within		0	.025641	.025641	T =	6
Japan **1***	overall	.008547	.0921197	0	1	N =	702
	between		.09245	0	1	n =	117
	within		0	.008547	.008547	T =	6
Netherlands **1***	overall	.008547	.0921197	0	1	N =	702
	between		.09245	0	1	n =	117
	within		0	.008547	.008547	T =	6
New Zealand **1***	overall	.008547	.0921197	0	1	N =	702
	between		.09245	0	1	n =	117
	within		0	.008547	.008547	T =	6
Norway **3***	overall	.025641	.1581746	0	1	N =	702
	between		.1587417	0	1	n =	117
	within		0	.025641	.025641	T =	6
Portugal **2***	overall	.017094	.1297142	0	1	N =	702
	between		.1301793	0	1	n =	117
	within		0	.017094	.017094	T =	6
Russian Federation **1***	overall	.008547	.0921197	0	1	N =	702
	between		.09245	0	1	n =	117

	within		0	.008547	.008547	T =	6
Singapore **1***	overall	.008547	.0921197	0	1	N =	702
	between		.09245	0	1	n =	117
	within		0	.008547	.008547	T =	6
Spain **14***	overall	.1196581	.3247927	0	1	N =	702
	between		.3259573	0	1	n =	117
	within		0	.1196581	.1196581	T =	6
Sweden **2***	overall	.017094	.1297142	0	1	N =	702
	between		.1301793	0	1	n =	117
	within		0	.017094	.017094	T =	6
Switzerland **4***	overall	.034188	.1818415	0	1	N =	702
	between		.1824935	0	1	n =	117
	within		0	.034188	.034188	T =	6
United Kingdom 7*	overall	.0598291	.237339	0	1	N =	702
	between		.23819	0	1	n =	117
	within		0	.0598291	.0598291	T =	6
United States **33***	overall	.2820513	.450319	0	1	N =	702
	between		.4519337	0	1	n =	117
	within		0	.2820513	.2820513	T =	6
Year Dummies (2006-2011)	overall	.1666667	.3729437	0	1	N =	702
	between		0	.1666667	.1666667	n =	117
	within		.3729437	0	1	T =	6

* Number of M&A

8.2 Appendix 2: Negative Binomial Regression for 2007-2011

Table 5: Negative Binomial Regression 2007

Generalized Negative Binomial regression			
Log pseudolikelihood =	-79.185.088	Number of obs. =	34
		Wald chi2(11) =	.
		Prob > chi2	.
		Pseudo R2 =	0.1790

No. of Patent Appl.	**Coefficient**	**Std. Err.**	**z**	**P>|z|**
No. of Patent Appl. 2006	.0815309	.0348355	2.34	0.019
Acquired Patents 2006	.0066708	.0217424	0.31	0.759
Tech M&A	.1589918	.4081712	0.39	0.697
Relatedness	-2.670808	.	.	.
Intern. M&A	.1810632	.5215958	0.35	0.728
North America	-.3882104	.4824694	-0.80	0.421
Europe	-.1424418	.6038029	-0.24	0.814
Asia	-1.051866	.9232505	-1.14	0.255
Biofuels & Waste	1.156746	.8018064	1.44	0.149
Cogeneration Plant	0	(omitted)		
Electric, Gas & Water Distribution	-.1351701	.5913847	-0.23	0.819
Engineering	.8000677	.4922825	1.63	0.104
Hydro	0	(omitted)		
Oil & Coal	0	(omitted)		
Solar	-2.280.848	.	.	.
Thermal	1.366.852	.6878258	1.99	0.047
Wind	1.170.245	.7472857	1.57	0.117
Renewable Energy Services	0	(omitted)		
_cons	.4403209	.6701296	0.66	0.511
lnalpha _cons	-.5434565	.4271392	-1.27	0.203

Table 6: Negative Binomial Regression 2008

Generalized Negative Binomial regression			
Log pseudolikelihood =	-71.379268	Number of obs. =	30
		Wald chi2(11) =	.
		Prob > chi2	.
		Pseudo R2 =	0.2923

No. of Patent Appl.	**Coefficient**	**Std. Err.**	**z**	**P>|z|**
No. of Patent Appl. 2007	.0638811	.0055975	11.41	0.000
Acquired Patents 2007	.032604	.0136548	2.39	0.017
Tech M&A	-.2548574	.1912431	-1.33	0.183
Relatedness	-1.462.789	.8488755	-1.72	0.085
Intern. M&A	-.5654504	.3870667	-1.46	0.144
North America	.2364361	.9101398	0.26	0.795
Europe	.991812	.8011669	1.24	0.216
Asia	-4.285.162	.	.	.
Biofuels & Waste	.5304985	.4738508	1.12	0.263
Cogeneration Plant	0	(omitted)		
Electric, Gas & Water Distribution	-.1034808	.1184759	-0.87	0.382
Engineering	-.0375346	.3260765	-0.12	0.908
Hydro	0	(omitted)		
Oil & Coal	1.296446	.711569	1.82	0.068
Solar	.9559996	.4216629	2.27	0.023
Thermal	1.775.728	.461794	3.85	0.000
Wind	0	(omitted)		
Renewable Energy Services	0	(omitted)		
_cons	.2556071	.8300581	0.31	0.758
lnalpha _cons	-1.741.291	3.655336	-0.48	0.634

Table 7: Negative Binomial Regression 2009

Generalized Negative Binomial regression			
Log pseudolikelihood =	-91.91055	Number of obs. =	37
		Wald chi2(11) =	.
		Prob > chi2	.
		Pseudo R2 =	0.1893

No. of Patent Appl.	**Coefficient**	**Std. Err.**	**z**	**P>|z|**
No. of Patent Appl. 2008	.0484138	.007493	6.46	0.000
Acquired Patents 2008	-.0028679	.0010863	-2.64	0.008
Tech M&A	.2404512	.3684114	0.65	0.514
Relatedness	-.1528277	.3715658	-0.41	0.681
Intern. M&A	.7279959	.4494765	1.62	0.105
North America	1.441591	1.079993	1.33	0.182
Europe	1.107821	1.031346	1.07	0.283
Asia	0	(omitted)		
other	0	(omitted)		
Biofuels & Waste	-.5573162	.7748386	-0.72	0.472
Cogeneration Plant	.2980471	.4398426	0.68	0.498
Electric Gas, & Water Distribution	.1503559	.325968	0.46	0.645
Engineering	1.606961	.5000349	3.21	0.001
Hydro	0	(omitted)		
Oil & Coal	1.296446	.711569	1.82	0.068
Solar	.9559996	.4216629	2.27	0.023
Thermal	0	(omitted)		
Wind	.2669517	.4960319	0.54	0.590
Renewable Energy Services	0	(omitted)		
_cons	-.9336382	1.055469	-0.88	0.376
lnalpha _cons	-.7214152	.404376	-1.78	0.074

Table 8: Negative Binomial Regression 2010

Generalized Negative Binomial regression			
Log pseudolikelihood =	-83.183848	Number of obs. =	35
		Wald chi2(11) =	.
		Prob > chi2	.
		Pseudo R2 =	0.2100

No. of Patent Appl.	**Coefficient**	**Std. Err.**	**z**	**P>|z|**
No. of Patent Appl. 2009	.0488559	.0187639	2.60	0.009
Acquired Patents 2009	.0997533	.0549122	1.82	0.069
Tech M&A	-.513572	.5540855	-0.93	0.354
Relatedness	.1081754	.6505688	0.17	0.868
Intern. M&A	-.066989	.4663699	-0.14	0.886
North America	-.1472935	.9531854	-0.15	0.877
Europe	.0991898	.9671824	0.10	0.918
Asia	1.422.443	1.171051	1.21	0.224
other	0	(omitted)		
Biofuels & Waste	-.994169	.7612457	-1.31	0.192
Cogeneration Plant	-.7641738	.9625814	-0.79	0.427
Electric, Gas, & Water Distribution	-.1591844	.6506808	-0.24	0.807
Engineering	.9171959	.6012442	1.53	0.127
Hydro	0	(omitted)		
Oil & Coal	.3797795	1.029253	0.37	0.712
Solar	-.4669292	.9956333	-0.47	0.639
Thermal	1.329505	.8193412	1.62	0.105
Wind	-.089622	.923395	-0.10	0.923
Renewable Energy Services	0	(omitted)		
_cons	.8666201	.8955787	0.97	0.333
lnalpha _cons	-.7684714	.5718196	-1.34	0.179

Table 9: Negative Binomial Regression 2011

Generalized Negative Binomial regression			
Log pseudolikelihood =	-108.46501	Number of obs. =	45
		Wald chi2(11) =	.
		Prob > chi2	.
		Pseudo R2 =	0.2248

No. of Patent Appl.	Coefficient	Std. Err.	z	P>|z|
No. of Patent Appl. 2010	.0448611	.007957	5.64	0.000
Acquired Patents 2010	.0058348	.0032227	1.81	0.070
Tech M&A	.5730087	.3521026	1.63	0.104
Relatedness	1.333.138	.437296	3.05	0.002
Intern. M&A	.8815738	.5131015	1.72	0.086
North America	-1.061.678	.7072124	-1.50	0.133
Europe	-1.881.362	.8845018	-2.13	0.033
Asia	-.9392362	.5541332	-1.69	0.090
other	0	(omitted)		
Biofuels & Waste	1.533.671	.9228676	1.66	0.097
Cogeneration Plant	1.263.516	.9911179	1.27	0.202
Electric, Gas, & Water Distribution	.6511862	.5537209	1.18	0.240
Engineering	2.486.163	.7760621	3.20	0.001
Hydro	1.325.375	.804272	1.65	0.099
Oil & Coal	3.538.392	.9246241	3.83	0.000
Solar	1.120.303	.6885398	1.63	0.104
Thermal	.2123665	.8257618	0.26	0.797
Wind	.9893356	.6477819	1.53	0.127
Renewable Energy Services	0	(omitted)		
_cons	-.2936826	.5110377	-0.57	0.566
lnalpha _cons	-.5516359	.3346329	-1.65	0.099