VENTURE CAPITAL INVESTMENT DECISIONS IN ALTERNATIVE ENERGY: AN ANALYSIS BASED ON INDUSTRY DIVISIONS AND INVESTMENT TYPES

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Abstract

Alternative energy is a rapidly growing field, and one of the main drivers behind this growth is the investment of venture capital. Because of this recent market expansion, little research has been done analyzing venture capital investment behaviors in specific alternative energy industries. This thesis present an analysis of venture capital investments with regard to industry and type of security invested. A Poisson distribution is used to measure the time in between financing rounds, and a negative binomial distribution is used to measure the change in the sum of equity from round to round.

KEYWORDS: (Venture Capital, Alternative energy , financing rounds, sum of equity, poisson distribution, negative binomial distribution.)

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CHAPTER 1

INTRODUCTION

The alternative energy industry has grown significantly over the last decade. Partly due to the rising price of oil and partly because the industry is in the public spotlight, alternative energy is a very popular investment. This is especially true for venture capitalists (VCs), investors who thrive with early-stage investments in industries with high innovative potential. VCs have greatly increased investments in recent years; Ghosh reports that "in 2002, only 43 clean energy startups received VC funding in the US, raising a combined total of $230 million. In 2008, over 200 startups raised $4.1 billion in venture capital in the US."[1] With a large increase in venture capital investment in alternative energy, or Cleantech, comes a need for modeling the VC activity. This is important in a relatively new market so VCs can find the most efficient investment strategies. An example of how they do this already is seen in analysis of where the money goes right now: "the share of energy efficiency deals done by VCs rose from 24% in 2008 to 32% in 2009 while energy production investments fell from 30% to 18%, and investments in alternative fuels fell from 13% to 8%.[2]" Clearly, VCs are investing where the most innovation is happening and less where large capital intensive projects are required.

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[1] Ghosh, Shikhar and Ramana Nanda. "Venture Capital Investment in the Clean Energy Sector." *Working Paper*, Harvard Business School (2010): 8.

[2] Ghosh and Nanda, 10.

The US is approaching and energy crisis[3]. It is vital that we find not only alternative energy opportunities, but that we turn them into sustainable and economically viable market powers. The issue now is not a lack of technology; it is a lack of financial viability, and therefore a lack of investment. The VCs can help with this investment, and a big help will be needed if they are to compete with fossil fuels and natural gas. This may be the opportune time as well because of less available natural gas and fossil fuel.[4] As oil prices rise, the path is set for alternative energy, and that potential will be realized through venture capital investment. The market now shows a public desire for alternative energy but a lack of availability on a large scale.

In China and Germany, large government subsidies carry the weight of breaking new ventures into the market. The US does not have the same subsidies so other sectors must pick up the slack. Equity financing is one of these areas that can help new ventures, however these are mostly the projects that have high-capital intensity and long-term growth plans. The VCs can take the small projects and make them widespread, which is a practice that is clearly necessary for alternative energies to make a large impact. Analysis of VC financing behavior is vital for future investors and entrepreneurs alike.

The purpose of this paper is to model the time between financing rounds and the quantity increases in equity from round to round. The goal of this research is to make the VC investment process as efficient as possible, providing information to both sides of the negotiation to help funds be invested effectively. The models used are a Poisson model to show

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[3] Barlett, Donald and James B. Steele. "The U.S is Running Out of Energy." http://www.time.com/time/magazine/article/0,9171,1005239,00.html, *Time*, July, 2003.

[4] Barlett and Steele 1.

the timing of the financing rounds and negative binomial model to explain increases in equity from round to round.

Chapter 2 contains an analysis of the literature in general venture capital research, research about alternative energy, and precedents for the use of the Poisson and negative binomial models. Chapter 3 is an explanation of the methodology used in making the models and an outline of the variables or variable that would have been included if the data were available. Chapter 4 contains a full description of the data and how it was manipulated to be useful for the model. Chapter 5 is a detailed description of the results of both regressions and the tests for errors within them. Finally, Chapter 6 contains the conclusion.

CHAPTER 2

LITERATURE REVIEW

There is a long literature about the venture capital industry and its effect on all sorts of industries. In this chapter I first examine the literature that analyzes venture capital as a whole. This is a comprehensive look at how venture capitalists go about making an investment and what the effects are on the new venture. Then, I show how the models I use for my hypothesis have been used before. Finally, I examine the precedents in the literature for using the Poisson and negative binomial probability distributions in this context.

My hypothesis is that there is much disparity in financing among the various Cleantech industries. I expect to find that from industry to industry there will be differences in the occurrence of financing rounds and the quantity increases from round to round. I expect the capital intensive industries such as wind and solar to have larger first round investments and more spread out financing rounds while the research based industries such as biofuel and recycling would have more frequent investment with smaller increases from round to round. I will show this through a Poisson distribution and a negative binomial regression.

For alternative energies to succeed there needs to be a major shift or progression in the innovation of the industry[1]. Because major change is riskier, venture capitalists (VCs) tend to shy away from the more radical innovations and instead invest in less risky spheres such as "energy

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[1] Ghosh, Shikhar and Ramana Nanda. "Venture Capital Investment in the Clean Energy Sector" *Working Paper*, Harvard Business School (2010): 1.

efficiency, software, energy-storage, and transportation[2].” This risk-aversion makes the Cleantech industry a difficult arena for entrepreneurs and limits the scope of new technologies. Ghosh and Nanda describe the environment that venture capitalists deal with using statistics from a leading venture capital firm: 8% of funds invested led to 70% of total returns while another 60% of funds invested led to fewer than 4% of total returns on the portfolio[3]. Because of this trend, venture capitalists must make multiple investments in start-ups that they believe will be winners. If the project is too risky then the VC will not be inclined to invest; however, it can be very difficult to predict which companies will succeed.

One of the primary methods of evaluation of a company used by venture capitalists is the assessment of the management team. The company has a very different look and management style when it is a small start-up compared with when it gets VC funding and eventually debt and equity financing. A CEO and management team with a strong track record of entrepreneurial activity goes a long way in encouraging confidence in venture capital investments.

Ghosh and Nanda go on to show how venture capital funding for clean energy has grown dramatically over the past decade. In 2002, only 43 clean energy start-ups received VC funding in the US, raising a combined total of $230M. In 2008, over 200 start-ups raised $4.1 BN in venture capital in the US. This growth shows how important venture capital funding is to the growth and development of the clean energy sector.

Hall raises a problem with the gap between internal and external financing requirements due to moral hazard. Management pursues two different business goals that do

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[2] Ghosh and Nanda, 2.
[3] Ghosh and Nanda, 3

not necessarily advance the innovative output of the company. Hall explains the two scenarios, "one is the usual tendency of managers to spend on activities that benefit them (growing the firm beyond efficient scale, nicer offices, etc.) and the second is a reluctance of risk-averse managers to invest in uncertain R&D projects[4]." The agency costs reduce the amount of available cash flow and take finances away from R&D. Risk aversion leads managers to put finances in safer places than R&D. Both practices decrease the innovative potential and output of a company. Venture capital addresses these problems because of the hands on approach of the investors.

Hall also explains some of the government programs and shows how they can act like venture capitalists in helping small businesses succeed. The U.S Small Business Investment Company (SBIC) and the Small Business Innovation Research (SBIR) programs disbursed $2.4 billion in 1995, over 60% of the amount disbursed by venture capital in the same year[5]. These funds help grow small business, but the advisory attention from venture capitalists that is given to the companies in which they invest cannot be duplicated by government intervention. The coaching and partnering referenced above is not present with a check from the government, so startup firms likely will distinguish between the two forms of funding. Nevertheless, both forms of financing help to bridge the gap that R&D funding does not cover.

Moore and Wustenhagen examine the role that venture capital plays in sustainable technologies. They report that the energy sector in the United States accounted for approximately 7% of GDP in 2004 but renewable fuels were just a small percentage of that spending. The authors also state how renewable energy will likely not gain more market share in

[4] Hall, Bronwyn H. "The Financing of Research and Development." *Working Paper*, National Bureau of Economic Research (2002): 9.

[5] Hall, 21.

the future because of a low penetration rate in the energy market[6]. Without competitive advantage, renewable energies will always be very small in comparison to fossil fuels as dominant sources of energy. In order to grow at a faster rate than the fossil fuels and gain more market share in the future, renewable energy will have to innovate rapidly.

Moore and Wustenhagen break down the electricity value chain into three sections. The first section is the 'supply side' or generation of energy, including procurement, fuel transportation, and controls. The next link is the 'Grid', consisting of the transmission and distribution of energy. The last step is the 'demand-side' or consumption of energy. This step includes the metering, optimization of software, and conservation of energy. Moore and Wustenhagen state that there are venture capital investment opportunities at every step of the chain[7]. With a good deal of flexibility for venture capital funded projects, it is no wonder there has been a dramatic increase in the amount of venture capital spending in alternative energy over the past decade. This flexibility mean does not necessarily mean that breakthrough technologies are much more attractive. They go on to say that historically, venture capital has been vital in the creation of any new business formation or technological transformation[8].

Moore and Wustenhagen raise three reasons that venture capitalists have become more interested in investing in sustainable energy projects: "deregulation of the power markets, environmental pressures, and security needs[9]." The deregulation of power markets leads to new opportunities for investors that were not available before. Environmental concerns, increasingly in the public eye, make alternative energy investments more attractive from a public relations

[6] Moore, Bill and Rolf Wustenhagen. "Innovative and Sustainable Energy Technologies: The Role of Venture Capital." *Business Strategy and the Environment* 13, (2004): 235.

[7] Moore and Wustenhagen, 236.
[8] Moore and Wustenhagen, 240.
[9] Moore and Wustenhagen, 240.

perspective. Security concerns became more prevalent after 9/11 and this has placed a much higher importance on the "central station configuration" or the desire for energy independence[10].

Kaplan and Stromberg examine how venture capital contracts play out in reality compared to how financial theory suggests they should work. He finds that theory is a relatively strong indicator of reality in venture capital and points out some interesting indices in how venture contracts are formed and benefit both parties involved. The deal is brokered between a venture capital firm and an entrepreneur and it mediates the capital, human, and financial dimensions. Both parties must agree on the allocation of cash flow, board rights, voting rights, liquidation rights, and other control rights. Kaplan and Stromberg state that each of these issues is separately allocated by the venture capital firm in the deal, but some of them interact with each other[11].

Often cash flow and control rights coincide in early stages of entrepreneurial activity, which follows logically because the firm that invests highly in the start-up will want to have enough of a stake to make a strong impact in voting decisions. It shows that venture capitalist investors, like any investor, want to be able to hold sway in the activity of their investment. Kaplan and Stromberg show however that cash flow rights and control rights can be separated to allow the entrepreneurs to act more freely if there are contingencies on financing based on the performance of the new company. These rights consist of how money will be spent, hiring decisions, and other general management and operation rights. This allows the entrepreneurs

[10] Moore and Wustenhagen, 241.
[11] Kaplan, Steven N. and Per Stromberg. "Financial Contracting Theory Meets the Real World: Empirical Analysis of Venture Capital Contracts." *The Review of Economic Studies* 70, no. 2, (2003): 281.

to have less oversight and red tape but also allows the venture capitalists to not commit inordinate amounts of money without first seeing results and returns on their investment.

The same principal holds true for the negotiations of all the rights in the deal. Performance based incentives not only allow cash flow rights to be separated from control rights, they also provide the framework for how the company will grow and develop over time. If we assume that each party wants as much controlling power as possible, i.e. voting rights, board rights etc., then there is a market for controlling power in the deal brokering process. The incentive that the venture capital company creates is for the entrepreneurs to hold more power in their own company if they turn out to be successful. If the company is succeeding then the venture capital company will remove oversight and let the entrepreneurs continue to do what they do best. The intervention of the venture capitalists only needs to come into effect if the company is struggling and their investment is at risk of disappearing.

Kaplan and Stromberg find that venture capitalists with greater control of voting and board rights are “more likely to make the entrepreneur’s equity claim and the release of committed funds contingent on performance milestones[12].” This shows how entrepreneurs have to deal with more oversight when venture capitalists have a tighter hold on the voting parties. Venture capitalists can in this way incentivize growth simply by offering entrepreneurs greater control over their own company.

Ensley et al. study the dynamics of start-ups and the ways the management team must navigate new business territory. It is difficult for new managers to take a company through the early stages to the late stages of a start-up because of the vastly different skills required at each stage of development. Furthermore, start-ups by nature are new and unique, which means any

[12] Kaplan and Stromberg, 282

experience the managers already have will not be used to its full potential. Hence, the management team has to work very well together to survive the early stages of development. Ensley, et al. study the effect of management team conflict on new start-ups and measure how there can be positive conflict and negative conflict. Not surprisingly, there is a strong correlation between positive conflict and organizational performance[13]. Venture capital firms that coach and develop the talent they invest in play a critical role in this dynamic. While it seems that excessive oversight would slow down the entrepreneurs, having an experienced team helping them through the unique new territory of the early stages of development could help greatly with overall growth.

Baum and Silverman examine whether venture capitalists are good at picking winners or building them. The authors acknowledge the extensive research showing the positive effects of venture capital on new businesses, so they look to find the greatest effect of their investment. They find that start-ups' patents, alliances, and top managers are the factors most likely to influence venture capitalists' investment decisions[14]. While venture capitalists do identify the "right technological and relational stuff"[15] they do not necessarily pick the top management team. They put an emphasis on the idea and the business plan in the early stages of investment, and work on building and training the team to help it grow. This is because the best management team is not always identifiable, so it follows logically that venture capitalists would not stake too much of their investment on the management potential.

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[13] Ensley, Michael D., Allison W. Pearson and Allen C. Amason. "Understanding the Dynamics of New Venture Top Management Teams Cohesion, Conflict, and New Venture Performance." *Journal of Business Venturing* 17, (2002): 380.

[14] Baum, Joel A. C. and Brian S. Silverman. "Picking Winners or Building Them? Alliance, Intellectual, and Human Capital as Selection Criteria in Venture Financing and Performance of Biotechnology Startups." *Journal of Business Venturing* 19, (2004): 431.

[15] Baum and Silverman, 431.

The literature clearly shows that venture capital plays a profound role in developing new Cleantech companies and technologies. With this established I will show how the models I have selected can model venture capital in alternative energy. The Poisson distribution has been used extensively in financial and economic models to show how frequently an event will occur. It gives the probability based on prior information on when to expect the same events happening in the future. The negative binomial distribution is used to count quantities over time based on prior information. The distribution can model funding increases over time, which will be helpful for modeling the quantity of equity from round to round.

Murmann uses a compound Poisson process to model the underlying index of catastrophe insurance derivatives. Because of the volatility of catastrophic events such as earthquakes, windstorms, or floods, a standard Poisson distribution would not suffice as an accurate model for projecting derivatives. For this reason Murmann uses a compound Poisson stochastic process as the random variable[16]. One issue with the model is that the stochastic jumps “create an incomplete market… [Therefore] it is not possible to perfectly duplicate the movement and consequent payoffs of insurance derivatives by continuously trading in other securities.[17]” In this model the Poisson distribution is used as the underlying model despite the incomplete nature of the data on which is it based the authors must use another model to measure the losses because fixed loss frequency distributions do not fully express the model. The authors reference the precursor to their model as a model that used a Poisson process with

[16] Murmann, Alexander. “Pricing Catastrophe Insurance Derivatives.” *Financial Markets Group Discussion Paper* 400, (2001): 2.

[17] Murmann, 2.

fixed losses[18]. This shows the diversity that the Poisson process can account for depending on the circumstances.

Ramenzani and Zeng study the effects of good and bad news on stock prices. To find out the nature of the jumps in prices they use an underlying Poisson model to represent the arrival of news. Ramenzani and Zeng use two Poisson models, one for the arrival of bad news and one for good news, and with this established analyze stock prices[19]. The Poisson models have intensity parameters to make sure that there are no outliers and the incoming news has some sort of regularity that can be controlled in the model. This example shows the versatility of the Poisson model and how it can be a basis of other analysis. The Poisson distribution can be used confidently to model the timing of occurrences of events that may not come regularly.

Plassman and Lott use a multivariate Poisson distribution to model crime rates and subscriptions to gun magazines. Because of the large number of zeros and the long right tails in the data, the variance is too large for a normal Poisson distribution[20]. The two variables are also correlated which creates issues for a typical Poisson process. Manipulating the typical univariate model, the authors account for overdispersion from the large number of zeros in the data. They also account for the correlation of the dependent variables using a bivariate Poisson-lognormal model[21]. This does not, however, account for any serial correlation that may occur. Plassman and Lott's example shows that the Poisson model can be manipulated for various types of data and can account for overdispersion and contemporaneous correlation.

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[18] Murmann 2.

[19] Ramezani, Cyrus A. and Yong Zeng. "Maximum Likelihood Estimation of Asymmetric Jump-Diffusion Processes: Application to Security Prices." *Working Paper*, Orfalea College of Business, (1998): 5.

[20] Plassmann, Florenz and John R. Lott, Jr. "More Readers of Gun Magazines, but not More Crimes." *Working Paper*, State University of New York at Binghamton, (2002): 7.

[21] Plassman and Lott, 9

Carr and Wu show that the Poisson distribution can be used in finance to model default arrival rates. Using a stochastic process, the authors study the effects of credit default swaps on stock options. Because credit defaults tend to not occur regularly, the authors use a stochastic model, specifically the Poisson, to account for the dynamic nature of default arrivals. Once the arrival model is specified they analyze the exercise of stock options[22]. Hence, the Poisson can be used in finance to account for variability in arrivals, which may be similar to VC financing rounds that can arrive without regularity.

Chernobai et al. use a compound Poisson process with lognormal loss quantities to determine the effect of truncated or censored data on banks determining their capital charge to account for operational losses[23]. The compound Poisson model is used to measure cumulative losses in order to determine the "required capital charge imposed by regulators."[24] Setting the intensity as non-negative, the authors show that the loss distribution is "sufficiently well behaved so that the parameter can be estimated consistently by maximum likelihood."[25] This example shows that with data that does not have a wide variance or volatile event occurrences, a simple Poisson model will be sufficient to represent the arrival of events, and a non-negative distribution, such as the lognormal, can capture the quantities associated with the events.

In another example from the finance world, Pointon and Hooper use a geometric Brownian motion process to model the movement of the exchange rate to look at the expected call times for callable foreign bonds. Establishing the movement of the exchange, the authors

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[22] Carr, Peter and Liuren Wu. "Stock Options and Credit Default Swaps: A Joint Framework for Valuation and Estimation." *Working Paper*, Bloomberg LP and Courant Institute, New York University, (2006): 4.
[23] Chernobai, A. and C. Menn et al. "A Note on the Estimation of the Frequency and Severity Distribution of Operational Losses." *Applied Probability Trust* 20, (2004): 1.

[24] Chernobai et al., 4.
[25] Chernobai et al. 4.

use a Poisson distribution to model the probability of the arrival of a call within a given time interval. This example shows that there is a "relationship between the call price of the bond and the expected time to the call, at the time of issue."[26] Therefore, a Poisson distribution can provide probabilities of event arrivals robust enough even when there is serial correlation.

Seetharaman and Zhang use a Poisson distribution to model customer inter-purchase times. Looking to create a framework to quantify the expected profitability of a customer, the authors postulate "that a customer's probability of responding to a marketing solicitation follows a discrete hazard process (specifically, the customer's inter-purchase times are distributed Poisson)."[27] This model is bound by parameters measured by observed heterogeneity and unobserved heterogeneity which is assumed to be Gamma distributed. The end model developed through this analysis is called a Gamma-Poisson model. In this case the Poisson distribution is a "uni-modal distribution of inter-purchase times which… is not characterized by a flat ('memoryless') hazard function."[28] The authors cite literature establishing Poisson as acceptable for modeling both inter-purchase times and purchasing rates.[29] For this model the inter-purchase times are assumed to be not flat, so the Poisson model works well in modeling the probability of a customer buying from the firm as a "function of the time elapsed since the customer's previous purchase from the firm."[30] This model has applications for the

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[26] Pointon, John and Vince Hooper. "A Valuation Model for Callable Foreign Bonds." *Working Paper*, Schoold of Banking and Finance University of New South Wales, (2001): 2.

[27] Seetharaman, Seethu and Qin Zhang. "How Much is Your Customer Worth? A Gamma-Poisson Model to Assess Customer Profitability (2006). http://ssrn.com/abstract=903825 or http://dx.doi.org/10.2139/ssrn.903825

[28] Seetharaman and Zhang 9.
[29] Seetharaman and Zhang 10.
[30] Seetharaman and Zhang 11.

model I will use because I expect venture capital financing rounds to be affected by the timing of the previous round.

Anscombe uses the negative binomial distribution to analyze insect counts. The model is explained by two constants, the mean *m* and the exponent *k*[31]. The analysis shows that across different insects there may be a variance in the mean but the exponent *k* remains approximately the same[32]. It is a reasonable assertion to use the negative binomial distribution because the mean depends on external factors but the exponent k is common to the intrinsic reproductive power of each species.[33] This has implications for my research because I expect the mean of investment in each financing round to be similar but the exponent of increase from round to round to only be consistent from industry to industry.

Glaser and Weber use the negative binomial regression to model stock transactions. Analyzing which past returns have the most effect on the volume of trades, the authors find that a Poisson model is not sufficient to model previous stock transactions because the variance greatly exceeds the mean making the data overdispersed.[34] Introducing unobserved heterogeneity to the Poisson model, the authors developed a negative binomial distribution model that shows the probability of the number of event occurrences.[35] In this case the event occurrences are transactions, while in my case they will be dollar amounts per financing round. Analyzed along with a separate Poisson model this should illuminate the nature of venture capital financing rounds over time and in quantity increases.

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[31] Anscombe, F.J. "The Statistical Analysis of Insect Counts Based on the Negative Binomial Distribution." *Biometrics* 5, no. 2, (1949): 165.
[32] Anscombe 165.
[33] Anscombe 165.
[34] Glaser, Markus and Marin Weber. "Which Past Returns Affect Trading Volume." *Journal of Financial Markets* 12, (2009): 14.

[35] Glaser and Weber, 14.

With the literature and precedents established, I will show in the next section specifically which variables should be in the models for my hypothesis. This includes an analysis of variables that cannot be attained in data but would be present in an ideal model. Lastly I describe the formation of the model I run to test my hypothesis.

CHAPTER 3

METHODOLOGY

Building an ideal model for VC investments in alternative energy proved to be simpler than finding data to support it. There are many factors that go into a VC firm's decision to invest and many more that govern how much and how frequently payments are delivered. It is doubly complicated because start-ups decide when they look for each round of financing, so the decisions are not VC firms' alone. In building our model, I found that many factors, such as the evaluation of the management team, are nearly impossible to quantify, and factors, such as the potential upside of the company, cannot be compared with financing rounds data. However, I will develop an ideal model using factors deemed important by the literature, even though they may not be included in our final version. This ideal model will give the most accurate picture of the independent variables that affect the timing and quantity increase in financing rounds. My actual model will be simpler, with fewer dependent variables, but further research and more comprehensive data could test a more accurate and informative model in the future.

A factor that certainly informs VC investment decisions is the size of the market the start-up is entering. The entrepreneur will have an idea of how big the company can potentially grow, and that will necessarily be a consideration of the venture capitalists. Since "venture capitalists commit significant tranches of capital to firms with few assets other than their founders and their business plans,[1]” the potential market size is very important to the VC’s investment decision

Related to market size is market expansion. Typically if a market is large but not growing, a VC firm will be reluctant to invest because it is more difficult to take market share from other firms than to generate new market share. Hargadon and Kenney examine this phenomenon analyzing the most fertile territory for VC investment: “the growth of a market is typically represented as the S-curve of adoption, with a leading edge that can last for decades before a rapid rise in the arrival of new customers that signal the beginning of a radical growth phase.[2]” They go on to show that the most important innovations, and therefore the most desired investments for VC firms, happened in immature industries.[3] The authors also find that VC tends to have very little effect in mature and established industries.[4] Market size and market expansion are not impossible to measure, but there is no way to simply put the data together with data about financing rounds in a way that would effectively show the effect of venture capital on the industry. Especially because Cleantech has grown so much from 2005-2011, the data would likely be correlated but not necessarily significantly. Since the industry as a whole has become more and more popular, the market expansion would likely look like a constant, with VC firms interested in the whole industry even though it does not have immense size.

The next important factor related to market expansion is the scalability of the firm’s production capacity. “The ability of a new venture and its underlying production technologies to

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[1] Hargadon, Andrew and Martin Kenney. “Venture Capital and Clean Technology: Opportunities and Difficulties.” *Working Paper*, University of Berkely, (2011): 7.
[2] Hargadon and Kenney, 10.
[3] Hargadon and Kenney 10.
[4] Hargadon and Kenney 10.

scale as fast as [the growth of the market] is also critical.[5]" When the VC invests in the firm initially, considering the growth of the market, they must also consider how quickly the new venture will be able to respond to that growth to take full advantage and maximize output. Some of this will depend on the first round financing, which could create serial correlation issues in my model, but much will depend on the quality of the management team, the production process, and the nature of the product itself. It may take longer to produce a wind turbine than a solar panel, but both industries may expand at the same rate. This factor is nearly impossible to capture because of the ambiguity of which metric to use. Especially because Cleantech is now becoming an industry with actual market penetration instead of just research projects, it will be possible in the years to come to look at the market retrospectively to see which companies were able to scale in concert with the market expansion. Since VC firms use personal interaction with the management teams and their business plans to determine the scalability of a firm, this variable will be out of the scope of a normal research endeavor.

The upside financial potential of the company is another important factor in a VCs decision to invest. "Because of the risk associated with the new ventures in which VCs invest, 'winning bets' must pay 10-20 times their investments in order to earn an adequate return and cover the fund's losses in other companies.[6]" The data available is for companies with VC funding mostly in the past five years that have not had an IPO. This means that there is no simple way to find and measure the VC firms that have such high returns on their investments. "Considering a venture fund's typical life of 10 years, such winning bets must pay off, or liquidate, within 5-7 years of the initial investment.[7]" This again makes analysis more difficult in

[5] Hargadon and Kenney 14.
[6] Hargadon and Kenney 15.
[7] Hargadon and Kenney 16.

the Cleantech industry because the majority of VC investment in Cleantech has begun in the last 5-6 years. This is another factor, like scalability, that will become more clear and analyzable once the industry matures.

Another important factor in a VC's decision to invest is the innovative significance of the firm. Related to the upside financial potential factor, the innovative significance shows how original a company's product is and the likelihood that it can take or create market share. Technological risk is associated with this factor because it is difficult to know when an innovation will be significant and when it will fail. Ghosh gives a high level overview of why this is an issue specifically for venture capitalists and not for other forms of financing. Comparing the capital intensity of a project to the technological risk of the project, the authors show where debt and equity financing is ideal and where venture capital is the better option. For projects with high capital intensity and low technological risk, debt and equity financing is the best option because it is a low risk investment that simply needs high capital input to succeed. If the project is low in both criteria then it tends to be financed within a company, such as GE with its R&D funding, especially in wind turbines. Venture capital funding goes to the projects that have low capital intensity and high technological risk.[8] These are the projects that are too risky for a company to finance internally, as well as for the debt and equity markets, so venture capital is the better option. Parts of the clean energy sector share these characteristics. However because of the high risk of the investments, venture capital firms must be more diversified than debt and equity financing.

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[8] Ghosh, Shikhar and Ramana Nanda. "Venture Capital Investment in the Clean Energy Sector." *Working Paper*, Harvard Business School (2010): 9.

For these reasons it is vital for a VC firm to determine whether or not a new venture has innovative significance. This is challenging to measure beforehand and each VC investigates this over many hours, looking at the business plan, the underlying technology, and market research. A metric such as patent citations that has been used in the past [9] does not work in this case because if the company has gained patent approval, it will be too young to have been cited in many subsequent patents.

The capital intensity of the project is another factor that VC's consider when investing. As Ghosh stated above, venture capital finds its niche in low capital intensity projects that have high technological risk.[10] If the project is too capital intensive, a VC will back away from it because of the nature of VC investment. As stated above, the upside potential of every company has to be very large because of how many of the investments fail. Therefore if the initial investment is very large, it likely will not be a project that the VCs will want to take on. This factor will certainly depend on the industry, but within every industry in Cleantech there will be large scale development firms and there will be research firms that need less initial capital to implement their business plan. This factor could be measured by an analysis of the first round of financing to new ventures; however this would leave out a large number of zeros in the dataset because VCs decided not to invest due to high capital intensity. Only looking at the successes would give an incomplete picture of the factor, because there would be no way to aggregate all the companies rejected by VCs because of high capital needs.

An important factor in the VC's investment decision is the quality of the management team. Burton et al. find that the experience and prominence of a new venture's top

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[9] Kortum, Samuel and Josh Lerner. "Assessing the Contribution of Venture Capital to Innovation." *RAND Journal of Economics* 31, no. 4, (2000*):* 674–692.
[10] Ghosh and Nanda, 9.

management executives directly correlates with getting more funding from VCs. [11] They also find that management team's prominence is found to be most important in new innovation ventures, rather than in incremental start-ups.[12] Because of the qualitative nature of many of the factors VCs look at in their investment decision, the quality of the management team becomes vitally important. The VCs take a very hands-on approach in growing the company,[13] but they must know whether or not the management team can handle issues of scalability and commitment to innovative significance. Directly related to the team itself are their alliances. If they have solid connections in their field or with companies with which they will interact, their operations and expansion can run much more smoothly. This is also very difficult to capture as social and professional contacts are not publicly recorded.

Related to the quality of the management team is the quality of the business plan. Likely a result of the experience of the management team with new ventures, a solid business plan does a great deal in giving confidence to VCs. I speculate for lack of literature support on the topic that the quality of the business plan directly correlates to an increase in VC funding and a willingness to decrease time between rounds. This factor is nearly impossible to aggregate as it is a qualitative assessment of a document prepared for the new venture. Even if the new venture as a whole could be graded in a quantitative way, it is difficult to know how much investor confidence comes from the quality of the management team, the other factors listed above, and the quality of the business plan. This variable will not be included in my final model because of these difficulties.

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[11] Burton, M.D., J.B. Sorensen, and C.M. Beckman. "Coming from Good Stock: Career Histories and New Venture Formation." *Working Paper*, Sloan School of Management, (2001): 26.
[12] Burton et al., 26.
[13] Baum, Joel A. C. and Brian S. Silverman. "Picking Winners or Building Them? Alliance, Intellectual, and Human Capital as Selection Criteria in Venture Financing and Performance of Biotechnology Startups." *Journal of Business Venturing* 19, (2004): 413.

Also in the mind of a VC investor are the rights of management agreements. This includes agreements such as cash flow rights, board rights, and voting rights. Because of the hands-on and capital intensive approach VCs take in business operations in new ventures,[14] they are very involved in all aspects once the investment is made. Both parties must come to this agreement so their incentives are aligned. For example, "If the firm performs very well, the VCs retain their cash flow rights, but relinquish most of their control and liquidation rights.[15]" For the entrepreneurs, ideally they will succeed and hence gain more operational rights, but they still must consider how much they are willing to give up to convince the VCs to make an initial investment. Kaplan finds that "the allocation of control rights between the VC and the entrepreneur is a central feature of the financial contracts.[16]" Therefore financing is greatly affected by the discussion and execution of control rights. Because these issues are so tied, they are very difficult to measure. Control rights are a negotiation between the start-up and the VC, so they do not have specific measurable metrics to associate with available financing data. Because of these difficulties I do not include control rights in my final model.

The dependent variable, p, is the number of days between the investment rounds. Clearly, data begin at the first inter-round observation, after the first round of financing for a particular company.

Due to constraints on the availability of data, my model can test few factors beyond the specified hypothesis. Included in the model is a dummy variable for the industry of each company in which a venture investment has been made from 2000-2011. The dummy

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[14] Baum and Silverman 413.

[15] Kaplan, Steven N. and Per Stromberg. "Financial Contracting Theory Meets the Real World: Empirical Analysis of Venture Capital Contracts." *The Review of Economic Studies* 70, no. 2, (2003): 282.

[16] Kaplan and Stromberg, 282.

variables are constructed from descriptions of the company and bucketed according to the major areas within Cleantech. These categories include Solar, Wind, Nuclear, Biofuel, Fuel Cell, Hydrogen, Electric, Photovalic, Marine, and Other. The “other” category captures any company that works in renewable energies that does not fall into one of the other buckets. The specific industry within Cleantech will be expressed by δ. There is also data available about how the investment was made, for example whether it was directly a Venture Equity investment or it was made through debt financing or the purchase of preferred stock. These investments are also categorized and turned into dummy variables. The type of investment will be expressed by η.

The expectation is that the timing of the financing rounds will be affected by the size of the previous round, so in the model the sum of equity for each financing round will be expressed by μ. This shows the effect of the amount of previous financing on the time between financing rounds.

The last variable included in the model is the round number itself. This variable shows the effect of how many financing rounds a firm has received on the timing of the next round. More specifically it shows the consistency of timing between rounds given past experience. The round number will be expressed as κ.

I found no theory to support anything but a simple reduced form regression. If data were available for variables like the quality of the management team and the quality of the business plan, it is likely that they would interact in a non-linear fashion. However, given the data available, the reduced form seems most prudent.

Combining these variables with the dependent variable, the model for the Poisson distribution of time between rounds looks like this:

$$\rho = \rho(\delta, \mu, \eta, \kappa)$$

The model for the negative binomial distribution is a similar model but with a different dependent variable. For the negative binomial distribution, the dependent variable, μ , is the sum of equity financing on a given round. The independent variables δ and η are the same as those used in the Poisson model. The variable for days since last investment is similar to the Poisson model. It is an independent variable in the negative binomial model and it has all the first round investments included. This will be expressed by ρ'. This means the dataset is larger by nearly 800 data points than it was in the Poisson model. The negative binomial model looks like this:

$$\mu = \mu(\rho', \eta, \kappa, \delta)$$

The next section shows how the data was manipulated to draw conclusions about the hypothesis.

CHAPTER 4

DATA

The data for this project was difficult to come by for multiple reasons. As explored in the Methodology section, much of the data necessary for modeling VC investment decisions is qualitative and therefore unavailable. Even if VC firms had an effective way of quantifying data, such as the quality of the management team, the business plan, and the control of voting and cash flow rights, there would be no standard by which to measure them across firms. Since each firm investigates investment opportunities in a unique way there is no effective way to aggregate this data. If in further research it becomes clear that this sort of information is vital to the research question, a more directed and restricted approach would be necessary. A case study, for example, could be an effective method for understanding the factors stated above. However, for this research, a case study would not be effective because of how broad the Cleantech industry is. Therefore, we chose to use an aggregated dataset to run regressions that model investment behavior.

All of the data used in the regressions is from the dataset VentureXpert distributed by Thomson Reuters. Bloomberg New Energy Finance reports VC investments as well but does not aggregate them, so the VentureXpert database best served the purposes of this research. The difficulty in retrieving the data is that is only comes from these two sources and it is privately aggregated, so it is not publicly available. After retrieving the data through another university it had to be organized into a file that could be run and interpreted in Stata 11 for the Poisson and Negative Binomial regressions.

The raw data available from VentureXpert consisted of 3574 investments from VC firms in Cleantech companies. The database simply reports all investments that occur. The data goes back to 1/1/2000 and ends 12/31/2011. Included in the information about each investment is the name of the investor firm, the investee company name, the investment date, the amount invested, a description of the company's business operation, the dollar range that the investment fell in for the company, the security type of the investment, the name of the investment firm, and various other variables that were not useful for the model.

From this data I determined what would be most effective in modeling the financing rounds. The company description was the most helpful in determining the industry of the company. Other useful data points were the equity amount, the round number, and the type of security used for the investment. The investment dates were used to determine the timing between rounds. Other than these data points the data was not valuable for our research questions.

To determine the industry I made a formula with the help of Daniel Pyke that registered keywords in the company description and put those companies into specific buckets. The industries used in the final model were Solar, Wind, Nuclear, Biofuel, Fuel Cell, Hydrogen, Marine, and Other. The formula looks at the description of each company;, for example, "Abound Solar, Inc. manufactures thin-film photovoltaic (PV) modules." It registers the word "photovoltaic" and puts it into the bucket for Solar. There are other keywords for the different buckets so by the end of the process there were a few overlaps. This process worked for the model because a company that deals in two or more industries can still be significant in the models. There were 91 company descriptions that did not fall into one of the buckets because they did not contain one of the keywords. So I placed these in buckets manually. The buckets for each industry within Cleantech were then changed to a yes or no, or dummy variable, format where 1 means yes and 0 means no. If the company has a 1 under Solar then it is a solar company and every other 0 means it does not belong in the other industries. This makes the data much simpler to run in regressions in the program Stata. A summary of these variables will follow after an explanation of the compression of the data.

The next data I put into buckets was the security type. I compiled thirty six different types of securities into seven buckets: Acquisition Financing, Debt Financing, Preferred Stock, Venture Capital Equity Investment, Common Stock and Bonds, Notes, and Other. These were split into the same type of 1 or 0 variables as the industries. Once they were in 36 different dummy variables, I compiled them manually into the seven buckets. It was a simple process as each of the 36 variables fit well into one of the seven buckets, for example, Series A Convertible Preferred Stock, Series B Convertible Preferred Stock, Series C Convertible Preferred Stock, etc. are all summed in the general bucket, Preferred Stock. These seven variables all went into the model as dummy variables as along with the industry dummy variables. I will summarize these after an explanation of the data compression for each model.

The first compression of data was to compile all the investments into distinct investment rounds. The raw data has each investment listed in its own row, but for the purposes of the model, each round had to be a distinct investment in each company. That way each company only has as many data points as it has rounds of investment. The raw data is from a high level perspective of the investment firms, whereas the compressed data is from the perspective of the Cleantech companies. After this compilation of data the total number of data points was reduced from 3574 to 1637 distinct investment rounds. As the data was compiled, we took the sum of the equity amount so that the whole round was summed in a distinct data point.

The next variable, "days since last investment," had to be calculated. Using the dates given under the data column "Investment Date," I created a formula measuring the number of days from round to round. This new variable is an integer that shows the number of days in between each round of financing. For the Poisson distribution regression this variable is the dependent variable. All the undefined values had to be removed. This meant sorting by round number and removing all of the first round investments, which led to 751 data points being removed, leaving 886 data points. Some of the reports of investments had undisclosed equity amounts and therefore had zeros. All of these reports were also eliminated, a total of 160 reports, leaving 591 data points. There were 16 more zeros in the "days since last investment" data because there was no report of an earlier investment. This was because in some cases the previous financing round was before 1/1/2000 and in some because of a lack of reported information from the dataset. This left 576 total observations to run the regression.

For the Negative Binomial regression the first rounds did not have to be removed, but the zeros in the equity amount did. After this removal there were 1044 data points remaining. The final data points for both models were the dummy variables for the buckets of industry, the dummy variables for the buckets of security type, the investment round number, and the sum of the equity amount. "Days since last investment" data are included in the Poisson model as the dependent variable.

Following in Table 1 are the summary statistics of the data for the Poisson model.

Table 1 Summary Statistics of Poisson Model Variables					
Variable (all Dummy variables)	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Days since last investment	76	368.75	349.386	2	785
Round Number	76	3.655	2.066	2	3
Sum of equity	76	95.753	242.599	.01	700

The dependent variable in this model is “days since last investment.” It ranges from 2 to 2785 which may show some inconsistency in the data. It means that on the low end of that spectrum companies were getting financing rounds within a week of each other, which would be very rare, and means they likely should have been listed as the same round. Without enough information to analyze the validity of these data, the model will consider it all to be accurate. If it turns out that those distinct rounds should have been listed as the same round, it should not make a significant impact on the model because there are only 17 observations below 30 days, which is a more acceptable number for a young venture. On the other end of the spectrum, there are only 10 observations above 1500 days, showing that the outliers are driving the mean up. This variable ranges evenly in the middle of the range where there are no outliers, so despite the high standard deviation it is still usable in the model.

The investment round number has a range of 2 to 13 with an average of 3.64. AS one would expect there are far more instances of low number of rounds, and the numbers taper off sharply at the high end closer to 13. There are only 20 cases of round 10 and above and only one case of a thirteenth round of financing. It is apparent from the average of 3.64 that the majority of the financing rounds stop after round 4 and 5. Recall that the first rounds are removed because the dependent variable in the model is days since last investment which is undefined for the first round of financing.

The sum of the equity for each round ranges from .01 to 2700 in millions USD. Notice the mean is 95.16 which means that there is an emphasis on the lower end of that scale. This is intuitive as most early round investments are smaller. The standard deviation is very high compared to the mean which shows a good deal of variance in this statistic. Of the 591 observations, only 132 are above the mean, which shows that most of the observations are low and a small amount of high investments drive the mean up. There does not seem to be a direct correlation between a high round number and a sum of equity well above the mean. Of the 40 observations of 300 or above, there are only 8 observations of round numbers above 6. This suggests that the quantity of finances invested depends on more than the previous amount invested or the number of investments previously given.

Below in Table 2 are the summary statistics for the industry dummy variables used in the Poisson model.

Table 2
Summary Statistics of Poisson Model Independent Industry Variables

Variable (all Dummy Variables)	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Solar	76	0.394	0.489	0	1
Wind	576	0.120	0.325	0	1
Nuclear	576	0.010	0.102	0	1
Biofuel	576	0.177	0.382	0	1
Hydrogen	576	0.052	0.222	0	1
Marine	576	0.031	0.174	0	1
Other industry	576	0.226	0.418	0	1

The range of all the variables is the same because they are all yes or no dummy variables. The mean shows how frequently each industry appears. From this it is clear that solar appears most frequently, followed by biofuel and wind. These data show that nuclear, hydrogen, and marine based companies do not receive very much venture capital funding at all. Alternatively, the data could mean that the companies do receive venture capital funding but they are so far behind industries like solar and wind in quantity of financing rounds that it does not show up in the data. A simple count of the data shows this to be true, in that nuclear, hydrogen, and marine amount to 54 investments combined while solar had 227 investments alone. The large standard deviations do not mean very much in this case because of the large number of zeros in the data. All of the “no” counts of zero drive the standard deviations up.

The last variables in the Poisson model are summarized below in Table 3.

Table 3

Summary Statistics for Poisson Model Independent Security Type Variables

Variable (all Dummy Variables)	Observations	Mean	Standard Deviation	Minimum	Maximum
Acquisition financing	576	0.055556	0.229261	0	1
Debt financing	576	0.029514	0.169389	0	1
Preferred stock	576	0.460069	0.498836	0	1
Venture capital	576	0.447917	0.497712	0	1
Common stock and bonds	576	0.065972	0.248449	0	1
Notes	576	0.005208	0.072043	0	1
Other security	576	0.034722	0.183235	0	1

As in the last table the mean shows how frequently each variable was a "yes." Again, as in the last table there are a few variables that were far more common than the others. Venture Capital Equity Investment and Preferred Stock are by far the most common types of securities used. Again in this case the standard deviations are much larger than the means because of the large number of zeros in each case. Even for the most common Preferred Stock variable there are 311 counts of zero or "no" which is 54% of the observations. These summary statistics do not give the same comprehensive analysis with dummy variables that they do with other variables but there is less variance in a dummy variables than a normal dataset.

The Negative Binomial model looks similar to the Poisson model, but the time variable does not have as much of an impact. Table 4 shows the "investment round number" and the "sum of equity per round" variables.

Table 4
Summary Statistics for Negative Binomial Model Variables

Variable (Dummy Variables)	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Round number	1044	2.495	2.027	1	13
Sum of equity	1044	76.602	215.349	0.01	2700

The "Sum of equity" is the dependent variable in this model. "Days since last investment" was left out of this model because of the large number of zeros. Since the dependent variable is "Sum of equity," it made more sense to have more observations than to eliminate almost half of them for the sake of including the time variable. Because of this, “Round number” ranges from 1 to 13 instead of 2 to 13. The same properties apply to this set as in Table 1 where there is a long right hand tail after a short but steep curve down after rounds 9 and 10. There are 454 round 1 observations that were not present in the first model, which drives the mean down to 2.50. The mean of the “Sum of Equity” variable is 76.60, but this is not a very effective figure for analysis because of the large standard deviation. With a standard deviation of 215.35, almost three times the value of the mean, the values are in a very wide range from .01 to 2700. Outliers also cause problems for accurate readings of the mean. There are only 15 observations from 1000 to 2700, which drives the mean up. On the other hand there are 150 observations at 1.00 million USD or below. This shows that the mean is very low given the high number of very small investments recorded as distinct financing rounds. These low VC investments should be considered in analysis of the results.

Table 5 shows the industry dummy variables for the negative binomial model. The characteristics are very similar to those of Table 2 in the Poisson model; however there are almost double the observations in this case.

Table 5
Summary Statistics for Negative Binomial Model Independent Industry Variables

Variable (all Dummy Variables)	Observations	Mean	Standard Deviation	Minimum	Maximum
Solar	1044	0.385	0.487	0	1
Wind	1044	0.133	0.334	0	1
Nuclear	1044	0.008	0.087	0	1
Biofuel	1044	0.170	0.376	0	1
Hydrogen	1044	0.040	0.197	0	1
Marine	1044	0.029	0.167	0	1
Other industry	1044	0.257	0.437	0	1

In this model as well as the last, the solar industry has the most investments by a significant margin. Biofuel and Wind power follow behind as well as the variable for all other projects that do not fall into one of these categories. The means show the frequency of “yes” occurrences for the dummy variables, and the standard deviations show how the data have a high quantity of zeros. In this case, as in Table 2, the data have very high standard deviations, but for dummy variables this does not change how they are analyzed in the regression.

Following are the summary statistics for types of security variables.

Table 6
Summary Statistics for Negative Binomial Model Independent Security Types Variables

Variable (all Dummy Variables)	Observations	Mean	Standard Deviation	Minimum	Maximum
Acquisition financing	1044	0.084	0.278	0	1
Debt financing	1044	0.024	0.153	0	1
Preferred stock	1044	0.377	0.485	0	1
Venture capital equity investment	1044	0.499	0.500	0	1
Common stock and bonds	1044	0.061	0.24	0	1
Notes	1044	0.005	0.069	0	1
Other security	1044	0.023	0.150	0	1

As in Table 3 the mean shows the frequency of “yes” for the type of security. With more observations the most prevalent two variables are “Preferred stock” and “Venture capital equity investment.” These two categories account for nearly all of the investment types. In this case there are very high standard deviations because of the high volume of zeros in the data. This shows that the correlations for “Preferred Stock” and “Venture capital equity investment” will be most reliable of all of the variables in Table 6.

In the next section I will present an analysis of the results of the regressions run with the models explained above.

CHAPTER 5

RESULTS

For both the Poisson model and the Negative Binomial model there were issues of heteroscedasticity, or variance in the standard errors. Therefore, for the initial regressions, the results and all error calculations following from them are robust. Table 7 shows the results of the Poisson model with "days since last investment" as the dependent variable.

Table 7
Robust Poisson Distribution of Days Since Last Investment

Dependent Variable: Days since last investment	**Coefficient**	**Robust Standard Error**	**z-score**	**P>z**	**95% Confidence Interval**	
Sum of equity	0.000471	0.000	2.94	0.003	0.000	0.001
Round number	-0.104	0.024	-4.39	0	-0.15	-0.057
Solar	-0.224	0.104	-2.16	0.031	-0.427	-0.021
Wind	-0.160	0.151	-1.06	0.288	-0.455	0.135
Nuclear	-0.478	0.362	-1.32	0.187	-1.188	0.231
Biofuel	-0.109	0.121	-0.9	0.366	-0.346	0.128
Hydrogen	-0.217	0.150	-1.44	0.149	-0.512	0.0778
Marine	0.2213	0.213	1.04	0.298	-0.195	0.638
Acquisition financing	-0.243	0.195	-1.25	0.212	-0.624	0.138
Debt financing	0.110	0.305	0.36	0.718	-0.488	0.708
Preferred stock	-0.006	0.149	-0.04	0.964	-0.300	0.286
Venture capital equity investment	0.125	0.150	0.84	0.402	-0.168	0.420
Common stock and bonds	0.067	0.194	0.35	0.73	-0.314	0.448
Notes	0.003	0.265	0.01	0.992	-0.517	0.522
Constant	6.301	0.171	36.83	0	5.966	6.636

Number of obs	576
Wald chi^2	40.05
Prob > chi^2	0.0003
Pseudo R^2	0.0822

These results show that industry does not matter a great deal in determining the time between financing rounds. Only the round number, solar industry, and the sum of the equity correlate with statistical confidence ($p<0.05$). Notice the z-scores above the absolute value of 2.0 for "Round number," "Solar," and "Sum of equity." The coefficient is so low for "Sum of equity" that though it is statistically significant, it does not impact the timing of financing rounds. This is intuitive as companies need to finance operations no matter their size. "Round number" negatively correlates with "Days since last investment" with a coefficient of -.10. This means that the impact of increasing one round of financing reduces days between investments by the log count of "Days since last investment." The negative sign shows negative correlation and means that increases in the independent variable decrease the marginal value of the dependent variable. The pseudo R^2 is very low as is the prob>chi^2, which shows that the model does not fit the dependent variable very well. According to the R^2, approximately 92% is unaccounted for by these data. This is to be expected as this model was not meant to be comprehensive but to find correlation within industries and security types. There are many more dimensions to the days since the last investment than what we have captured here.

Table 8 shows a model, called the incident rate ratio, that is simpler to read. With the same z-scores, the model calculates coefficients that show the rate of incident increase or decrease depending of the sign of correlation. The incident rate ratio shows a percentage change based on the coefficient of independent variables.

Table 8 Incident Rate Ratio of Poisson Distribution of Days Since Last Investment						
Dependent Variable: Days since last investment	**Incident Rate Ratio**	**Robust Standard Error**	**z-score**	**P>z**	**95% Confidence Interval**	
Sum of equity	1.000	0.000	2.94	0.003	1.000	1.000
Round number	0.902	0.0212	-4.39	0	0.860	0.944
Solar	0.799	0.082	-2.16	0.031	0.652	0.979
Wind	0.852	0.1282	-1.06	0.288	0.634	1.144
Nuclear	0.619	0.2244	-1.32	0.187	0.304	1.260
Biofuel	0.896	0.1083	-0.9	0.366	0.707	1.136
Hydrogen	0.804	0.1211	-1.44	0.149	0.599	1.080
Marine	1.247	0.2652	1.04	0.298	0.822	1.892
Acquisition financing	0.784	0.1525	-1.25	0.212	0.535	1.148
Debt financing	1.116	0.3406	0.36	0.718	0.614	2.030
Preferred stock	0.993	0.1484	-0.04	0.964	0.741	1.331
Venture capital equity investment	1.133	0.1702	0.84	0.402	0.844	1.521
Common stock and bonds	1.069	0.2079	0.35	0.73	0.730	1.565
Notes	1.002	0.2657	0.01	0.992	0.596	1.685

Number of observations	576
Wald chi^2	40.05
Probability > chi^2	0.0003
Pseudo R^2	0.0822

This model shows that “Round number” has a positive impact on “Days since last investment,” reducing the days by 9.05% with each increase in round number. “Solar” correlates strongly with timing in between financing rounds, and shows a decrease of 20.08% in the number of days since the last investment in the solar company. This number comes from the difference between the coefficient and 1.0. Nuclear is the next closest variable to correlating, showing a 39.01% decrease in days between financing rounds, however this is not significant at the 95% confidence interval.

Security types appear to not have a strong effect on the days in between financing rounds. The highest z-score is 1.25 for “Acquisition financing,” which shows a 21.57% decrease in days between financing rounds, though it is only significant at the 89% level. The other security types do not show strong correlation with days in between financing rounds, so no effective conclusions can be drawn.

Table 9

Cluster Regression of Poisson Distribution of Days Since Last Investment

Dependent Variable: Days since last investment	Coefficient	Robust Standard Error	z-score	P>z	95% Confidence Interval	
Sum of equity	0.000	0.000	2.77	0.006	0.000	0.001
Round number	-0.104	0.021	-4.97	0	-0.144	-0.063
Solar	-0.224	0.107	-2.09	0.037	-0.435	-0.013
Wind	-0.160	0.175	-0.91	0.361	-0.503	0.183
Nuclear	-0.478	0.269	-1.78	0.075	-1.005	0.049
Biofuel	-0.109	0.118	-0.93	0.354	-0.340	0.122
Hydrogen	-0.217	0.14	-1.54	0.124	-0.494	0.059
Marine	0.2213	0.223	0.99	0.321	-0.215	0.658
Acquisition financing	-0.243	0.199	-1.22	0.222	-0.632	0.146
Debt financing	0.1103	0.291	0.38	0.705	-0.460	0.681

Preferred stock	-0.007	0.145	-0.05	0.963	-0.291	0.278
Venture capital equity investment	0.126	0.151	0.83	0.405	-0.170	0.422
Common stock and bonds	0.067	0.198	0.34	0.735	-0.321	0.455
Notes	0.003	10.264	0.01	0.992	-0.514	0.520
Constant	6.301	0.174	36.21	0	5.960	6.642

Number of Observations	576
Wald chi^2(14)	44.27
Probability > chi^2	0.0001
Pseudo R^2	0.0822

Because these data are not exactly panel data, following a single set of observations over a set amount of time, the typical robust regression is not exactly an accurate assessment of the data. To get a tighter fit for these data a cluster regression can be used. Since the data follow a large number of companies over different amounts of time for each, they act in clusters instead of as a normal panel. The cluster regression analyzes the data based on clusters of a specific variable, in this case the company name. The correlations are based on each specific company before the data as a whole. This means that the regression is run bucketed for each company and then analyzed in terms of those buckets. Table 9 shows the cluster regression for the Poisson model.

From this model is it clear that the simple robust Poisson model was very close in assessing the dataset, however the cluster Poisson regression shows some differences in confidence in the variables. The simple robust Poisson model does not analyze this unique data set because it is not exactly panel data or time series data. In the cluster model, the "Solar" z-score went down, however it still correlates at 95% confidence, while "nuclear" went up from 81.3% confidence to 93.5% confidence. "Hydrogen" went up in confidence as well, from 85.1% to 87.5%. Looking at the incident rate ratio for these variables with increased confidence draws new insights into analysis of "Days since last investment."

Table 10

Cluster Incident Rate Ratio for Poisson Distribution of Days Since Last Investment

Dependent Variable: Days since last investment	**Incident Rate Ratio**	**Robust Std. Err.**	**z-score**	**P>z**	**95% Confidence Interval**	
Sum of equity	1.000	0.000	2.77	0.006	1.000	1.001
Round number	0.902	0.019	-4.97	0	0.865	0.939
Solar	0.799	0.086	-2.09	0.037	0.648	0.987
Wind	0.852	0.149	-0.91	0.361	0.604	1.201
Nuclear	0.620	0.167	-1.78	0.075	0.366	1.050
Biofuel	0.896	0.106	-0.93	0.354	0.711	1.130
Hydrogen	0.805	0.114	-1.54	0.124	0.610	1.062
Marine	1.248	0.278	0.99	0.321	0.806	1.932
Acquisition financing	0.784	0.156	-1.22	0.222	0.531	1.158
Debt financing	1.117	0.325	0.38	0.705	0.631	1.976
Preferred stock	0.993	0.144	-0.05	0.963	0.747	1.321
Venture capital equity investment	1.134	0.171	0.83	0.405	0.843	1.52
Common stock and bonds	1.069	0.212	0.34	0.735	0.725	1.577
Notes	1.003	0.265	0.01	0.992	0.598	1.682

Number of observations	576
Wald chi^2	44.27

Prob > chi^2	0.0001
Pseudo R^2	0.0822

Table 10 shows “Nuclear” will decrease days between investments by 38.01%. “Hydrogen” shows a 19.52% decrease in the number of days between investments based on the difference between the coefficients and 1.0.. The R^2 value for the cluster is the same as that of the standard robust Poisson regression. This means that the variables still do not account for a great deal of the model but it does not change the effects of the correlation of variables.

The model had the potential to have issues with endogeneity so the Hausman Test was run to determine any correlation with errors. The error variable was found by taking the predicted residuals from the original robust regression and subtracting them from the actual observed dependent variable. The robust Poisson regression was run again with the error variable included. Table 11 shows the results including the error variable.

Table 11
Hausman Test for Endogeneity in the Poisson Model

Dependent Variable: Days since last investment	**Coefficient**	**Robust Standard Error**	**z-score**	**P>z**	**95% Confidence Interval**	
Sum of equity	0.000	0.000	4.66	0	0.000	0.000
Round number	-0.073	0.010	-7.2	0	-0.093	-0.053
Solar	-0.095	0.055	-1.74	0.082	-0.203	0.012
Wind	-0.250	0.151	-1.66	0.098	-0.546	0.046
Nuclear	-0.273	0.222	-1.23	0.218	-0.709	0.161
Biofuel	0.012	0.058	0.21	0.836	-0.102	0.126
Hydrogen	-0.048	0.084	-0.57	0.57	-0.213	0.117
Marine	0.209	0.096	2.18	0.03	0.021	0.397
Acquisition financing	-0.075	0.086	-0.87	0.384	-0.242	0.093

Debt financing	-0.028	0.088	-0.31	0.753	-0.200	0.144
Preferred stock	0.0327	0.063	0.52	0.604	-0.091	0.157
Venture capital equity investment	0.219	0.062	3.52	0	0.0971	0.341
Common stock and bonds	0.104	0.074	1.41	0.159	-0.041	0.249
Notes	0.177	0.171	1.03	0.301	-0.158	0.512
Error	0.001	9.16E-05	14.73	0	0.001	0.002
Constant	5.917	0.081	73.27	0	5.758	6.075

Notice the error correlates very well within the model with a z-score of 14.73; however, the coefficient is so small with a value of .001 that there is very little effect on the model. This analysis shows that endogeneity is not causing any significant problems in the model.

The next test run was for multicolinearity, which could occur because of relationships across industries or types of securities. To test for multicolinearity, a correlation matrix was run containing all the independent variables.

Table 12
Correlation Matrix to Test for Multicolinearity for the Poisson Model

	Sum of equity	**Round number**	**Solar**	**Wind**	**Nuclear**	**Biofuel**	**Hydrogen**
Sum of equity	1						
Round number	0.116	1					
Solar	0.188	-0.030	1				
Wind	-0.113	0.013	-0.287	1			
Nuclear	-0.017	0.067	-0.083	-0.038	1		
Biofuel	0.023	0.075	-0.356	-0.171	-0.047	1	

Table 12 continued							
Hydrogen	-0.075	0.013	-0.189	-0.087	-0.024	-0.109	1
Marine	-0.058	-0.062	-0.145	-0.066	-0.018	-0.083	0.138
Acquisition financing	0.084	-0.132	-0.103	-0.020	-0.025	0.007	-0.057
Debt financing	-0.023	0.084	0.006	-0.001	0.083	-0.000	0.005
Preferred stock	0.114	0.055	0.104	-0.029	0.077	0.019	-0.028
Venture capital equity investment	-0.123	0.024	-0.062	0.055	-0.024	-0.080	0.072
Common stock and bonds	0.030	0.078	-0.028	-0.055	-0.027	0.152	0.001
Notes	-0.024	0.024	0.040	-0.027	-0.007	0.030	-0.017
	Marine	**Acquisition financing**	**Debt financing**	**Preferred stock**	**Venture capital equity investment**	**Common stock and bonds**	**Notes**
Marine	1						
Acquisition financing	-0.044	1					
Debt financing	0.087	-0.042	1				
Preferred stock	-0.026	-0.178	0.004	1			
Venture capital equity investment	0.019	-0.203	-0.054	-0.740	1		
Common stock and bonds	0.113	-0.034	0.120	-0.091	-0.197	1	
Notes	-0.013	-0.018	0.130	-0.067	-0.065	-0.019	1

The only cause for concern in this matrix is the correlation between “Preferred stock” and “Venture capital equity investment.” With a correlation value of -0.740, it appears that these two variables correlate very strongly; however, because they are not significant in the robust Poisson model, this does not significantly affect the results. The other values in this correlation matrix are all below 0.20 so there is little reason to believe that there are problems with multicolinearity that affect the reading of the original robust Poisson model.

There is also some correlation between "Solar" and "Biofuel." There is little that can be done to correct this or to see how much it affects the model, but it is important to note this correlation of -0.36. Since "Solar" is still significant in the model, it can be assumed that the multicolinearity will not affect that variable greatly. It could be found with more extensive data and further research that "Biofuel" would be significant if not for the multicolinearity. For the purposes of these results it will be assumed that "Biofuel" is not significant in the model.

The next test to run to check for problems with the model was a regression of errors over time to make sure there were no issues with serial correlation. Splitting up the data into distinct round numbers, I tested generated error variables for the data for each round of financing up to round 5. The error variables were taken from running robust Poisson regressions and saving the residuals, then subtracting them from the actual dependent variable. This was the same process as was used in the Hausman test except this time the data was split up by round number. Table 13 shows a regression with the error from round 2 as the dependent variable and the errors from rounds 3, 4, and 5 as the independent variables. Table 14 shows a correlation matrix of the error variables.

Table 13 Regression of Error Variables from Poisson Model Divided by Round to Test for Serial Correlation						
Dependent Variable: errorRound2	**Coefficient**	**Std. Err.**	**t-score**	**P>t**	**95% Confidence Interval**	
errorRound3	0.020	0.164	0.12	0.904	-0.310	0.350
errorRound4	0.121	0.198	0.61	0.543	-0.277	0.520
errorRound5	0.175	0.078	2.23	0.03	0.018	0.331
Constant	-278.005	55.823	-4.98	0	-390.13	-165.88

Table 14 Correlation Matrix of Error Variables from the Poisson Model to Test for Serial Correlation				
	errorRound2	**errorRound3**	**errorRound4**	**errorRound5**
errorRound2	1			
errorRound3	0.058	1		
errorRound4	0.253	0.020	1	
errorRound5	0.381	0.121	0.483	1

In both tables there is correlation between round 2 and round 5, which shows serial correlation. There is also a correlation value of 0.483 between round 4 and round 5, which is cause for some concern about the model. The correlation between the errors from round 2 and round 5 does not make intuitive sense. Practically it demonstrates that the errors from the Poisson distribution from round 2 can predict the errors from a Poisson distribution of round 5 but not the errors for rounds 3 or 4. This could affect how significant my results are, however it seems more likely that this is just coincidence. There is not a simple way to account for this in the model without more comprehensive data so it will be left for further research to determine if this is an actual phenomenon or simply something that appears randomly.

The last test for the Poisson model was a simple test of the normality of the errors. This uses the same variables used in the test for Serial Correlation. It is a simple box graph to analyze the distribution of the errors to make sure they follow a generally normal distribution. Graph 1 shows the error distribution of each of the error variables from rounds 2 through 5. Table 15 shows the summary statistics of the error variables to help interpret the graph.

Figure 1: Box and Whisker Plot of Error Variables from the Poisson Model to Show Normality

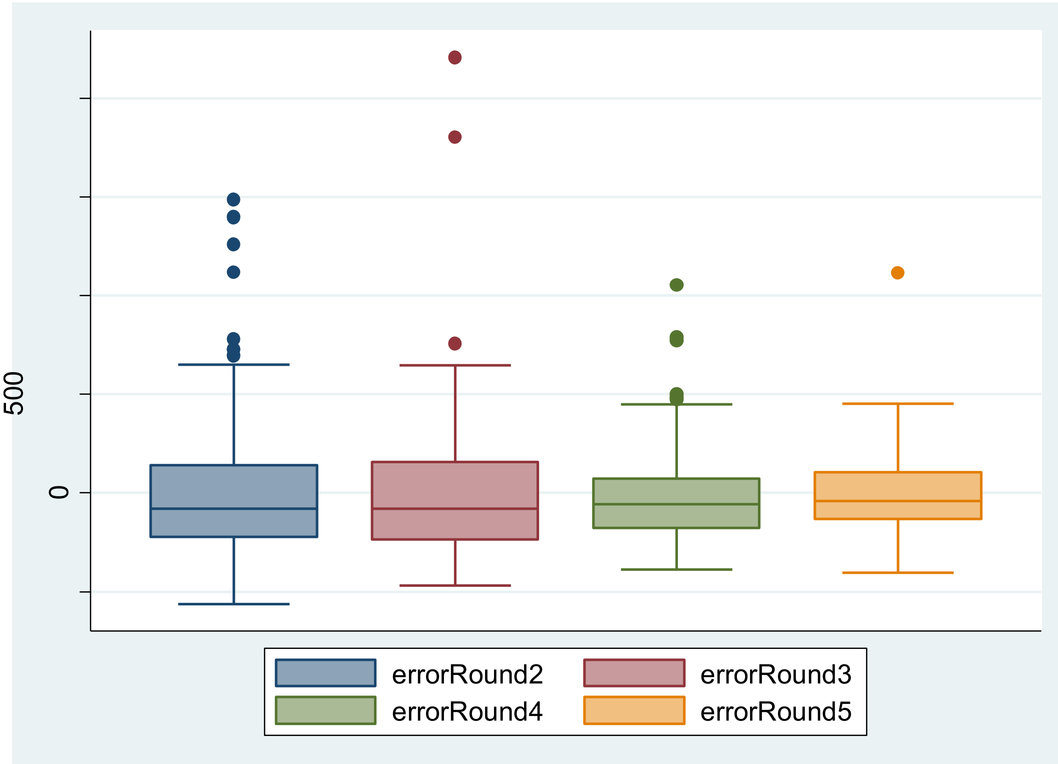


Table 15 Summary Statistics of Error Variables from the Poisson Model to Show Normality					
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
errorRound2	211	1.16E-06	347.483	-562.842	1487.143
errorRound3	138	7.19E-07	355.567	-468.059	2206.876
errorRound4	93	4.92E-07	265.851	-387.027	1051.942
errorRound5	54	-4.24E-06	244.435	-405.671	1115.182

The graph of the errors shows that the distributions of the errors are very normal, with few outliers and means that are very close to zero. Notice that the means shown in Table 15 of the errors are all less than 0.000001. The standard deviations are very large but as seen in the graphs this is because of a few outliers. In general we are confident to say that the errors are normally distributed and therefore do not raise concerns about conclusions for the model.

Next the negative binomial model is presented with the same tests for endogeneity, multicolinearity, and serial correlation.

The negative binomial model has the sum of equity as the dependent variable, with the same independent variables as the Poisson model (excluding the days since last investment.) This model has problems with heteroscedasticity so the original regression will not be shown. The useful regression for this model was run with robust standard errors and is displayed in Table 16.

Table 16
Robust Negative Binomial Model of Sum of Equity

Dependent Variable: Sum of equity	**Correlation**	**Robust Std. Err.**	**z-score**	**P>z**	**95% Confidence Interval**	
Round number	0.202	0.043	4.71	0	0.118	0.286
Solar	0.545	0.191	2.85	0.004	0.170	0.919
Wind	-0.417	0.234	-1.78	0.075	-0.876	0.042
Nuclear	-0.654	0.512	-1.28	0.201	-1.657	0.349
Biofuel	0.262	0.217	1.21	0.226	-0.162	0.687
Hydrogen	-1.28	0.279	-4.6	0	-1.831	-0.737
Marine	-1.463	0.334	-4.38	0	-2.117	-0.808
Acquisition financing	1.953	0.316	6.19	0	1.335	2.572
Debt financing	0.225	0.306	0.73	0.463	-0.375	0.824
Preferred stock	0.557	0.241	2.31	0.021	0.085	1.029
Venture capital equity investment	0.086	0.244	0.35	0.724	-0.391	0.564
Common stock and bonds	0.509	0.305	1.67	0.095	-0.089	1.107
Notes	0.156	0.888	0.18	0.861	-1.585	1.897
Constant	2.933	0.278	10.55	0	2.388	3.478

Number of obs	1044
Wald chi^2	209.07
Prob > chi^2	0

With a p value (“Prob>chi2”) of zero, this model can be confidently described as statistically significant. This means that the independent variables are sufficient to describe a part of this model no matter how they individually explain the entire dependent variable. With this established, it is worthwhile to note that multiple variables correlate in this model. Those that correlate at the 95% confidence level are “Round number,” “Solar,” “Marine,” “Hydrogen,” “Preferred stock,” and “Acquisition financing.” These results show that the size of equity from round to round is affected by the variables stated above. The specific effect on each industry is analyzed more effectively below in the incident rate ratio. In the other cases it may be that they do not have enough observations to determine correlation conclusively, or it could mean that some industries have more regular financing patterns than others.

The incident rate ratio (irr) shows the amount each independent variable affects “Sum of equity.” Table 17 shows the negative binomial irr.

Table 17
Incident Rate Ratio for Negative Binomial Model of Sum of Equity

Dependent Variable: Sum of equity	**Incident Rate Ratio**	**Robust Std. Err.**	**z**	**P>z**	**95% Confidence Interval**	
Round number	1.224	0.052	4.71	0	1.125	1.331
Solar	1.724	0.330	2.85	0.004	1.186	2.508
Wind	0.659	0.154	-1.78	0.075	0.416	1.043
Nuclear	0.520	0.266	-1.28	0.201	0.191	1.417
Biofuel	1.300	0.281	1.21	0.226	0.850	1.987
Hydrogen	0.277	0.078	-4.6	0	0.160	0.478
Marine	0.232	0.077	-4.38	0	0.120	0.446

Acquisition financing	7.053	2.227	6.19	0	3.799	13.095
Debt financing	1.252	0.383	0.73	0.463	0.687	2.281
Preferred stock	1.746	0.420	2.31	0.021	1.089	2.799
Venture capital equity investment	1.090	0.266	0.35	0.724	0.676	1.758
Common stock and bonds	1.663	0.507	1.67	0.095	0.915	3.025
Notes	1.169	1.038	0.18	0.861	0.205	6.665

Number of obs	1044
Wald chi2(13)	209.07
Prob > chi2	0

Looking at the statistically significant variables, confident conclusions can be drawn from this model. First notice that the irr value for “Round number” is 1.224, meaning that there will be an increase of 22.37% in the sum of equity per round for each increase in round. For the “Solar” variable there is a distinct positive correlation, with an irr value of 1.724, showing an increase of 72.44% in the sum of equity if a company is in the solar industry. This is a significant finding, leading to the conclusion that solar is the most desirable industry to invest in for venture capitalists, or that solar projects need more capital than other industries. The “Marine” variable has a strong negative correlation. With an irr value of 0.232, “Marine” reduces “Sum of equity” by 76.84%. This means that marine companies are far less likely to get large financing rounds than companies in other industries, and likely means that marine projects are not as capital intensive as projects in other industries. The last industry that correlates at the 95% confidence interval is “Hydrogen.” This variable shows a strong negative correlation, reducing financing by 72.31%. As in the marine industry, hydrogen firms show some combination of less capital intensive projects and less desirability for VC investment. “Preferred Stock” shows positive correlation, which means that investors who invested in their new ventures using preferred stock ended up investing more than those who did not. With an irr value of 1.760, the increase in financing was 76.0% for preferred stock over other types of investment.

"Acquisition financing" has a strong correlation and a very large irr value. Revisiting the summary statistics we can see that this dummy variable only has 88 counts of yes out of 1044 observations. It is very likely that this is an outlier that shows correlation where there is little to none. If the results were accurate, they would show that investors that used any type of acquisition financing in their investment ended up investing 705.28% more than those who did not. Because of the magnitude of this correlation as well as the small number of observations, we can safely consider this an outlier.

Because the time variable "Days since last investment" has been taken out of this model, it acts more like panel data and does not need to be clustered for further analysis. The simple negative binomial regression with robust standard errors is sufficient to analyze these data. There is still the potential for endogeneity in these data, so the next model displayed in Table 18 is the Hausman Test for endogeneity.

Table 18
Hausman Test for Endogeneity for Negative Binomial Model

Dependent Variable: Sum of equity	**Correlation**	**Robust Std. Err.**	**z-score**	**P>z**	**95% Confidence Interval**	
Round number	0.264	0.027	9.81	0	0.212	0.317
Solar	0.290	0.081	3.56	0	0.130	0.449
Wind	-0.241	0.115	-2.09	0.037	-0.467	-0.015
Nuclear	-0.769	0.312	-2.47	0.014	-1.381	-0.158
Biofuel	0.158	0.099	1.6	0.11	-0.036	0.352
Hydrogen	-1.004	0.201	-5	0	-1.397	-0.610

Marine	-1.108	0.292	-3.8	0	-1.680	-0.536
Acquisition financing	2.131	0.227	9.39	0	1.6860	2.576
Debt financing	0.534	0.196	2.72	0.006	0.149	0.918
Preferred stock	0.762	0.177	4.29	0	0.414	1.110
Venture capital equity investment	0.345	0.180	1.92	0.055	-0.007	0.697
Common stock and bonds	0.730	0.273	2.68	0.007	0.196	1.264
Notes	-0.388	0.402	-0.96	0.335	-1.176	0.400
Error	0.008	0.001	10.76	0	0.006	0.009
Constant	1.937	0.218	8.9	0	1.511	2.363

Using the error variable from the negative binomial regression with robust standard errors included, we can see if the model has problems with endogeneity. The error variable does correlate with dependent variable; however the coefficient is very small. Table 19 shows the irr including the error variable (all other variables not displayed for simplicity).

Table 19
Incident Rate Ratio of Hausman Test for Endogeneity of Negative Binomial Model (all variables expect error not displayed for simplicity)

Dependent Variable: Sum of equity	**IRR**	**Robust Std. Err.**	**z-score**	**P>z**	**95% Confidence Interval**	
error	1.008	0.001	10.76	0	1.006	1.009

Table 19 shows the error variable has a positive effect on the dependent variable in the amount of 0.2%. This does not show much endogeneity but it is significant enough to note. Further research will be necessary to determine if this is affecting the model in a significant way, but given the small irr value we can still be confident in the results.

Next the model was tested for multicolinearity. The same potential for this issue exists as was true in the Poisson model. Table 20 is the correlation matrix that shows correlation among the independent variables.

Table 20
Correlation Matrix of Independent Variables of Negative Binomial Model to Test for Multicolinearity

	Round number	**Solar**	**Wind**	**Nuclear**	**Biofuel**	**Hydrogen**	**Marine**
Round number	1						
Solar	-0.003	1					
Wind	-0.026	-0.275	1				
Nuclear	0.065	-0.070	-0.034	1			
Biofuel	0.055	-0.343	-0.163	-0.040	1		
Hydrogen	0.051	-0.162	-0.080	-0.018	-0.093	1	
Marine	-0.005	-0.136	-0.067	-0.015	-0.063	0.198	1
Acquisition financing	-0.139	-0.162	0.023	0.0130	0.064	-0.062	-0.052
Debt financing	0.101	-0.008	-0.025	0.058	-0.004	-0.000	0.123
Preferred stock	0.153	0.107	-0.049	0.068	0.020	0.012	-0.016
Venture capital equity investment	-0.060	-0.018	0.066	-0.044	-0.086	0.030	0.035
Common stock and bonds	0.076	-0.030	-0.065	-0.023	0.075	0.009	0.123
Notes	0.017	0.059	-0.027	-0.006	0.005	-0.014	-0.012

	Acquisition financing	**Debt financing**	**Preferred stock**	**Venture capital equity investment**	**Common stock and bonds**	**Notes**
Acquisition financing	1					
Debt financing	-0.048	1				

Table 20 continued						
Preferred stock	-0.208	0.020	1			
Venture capital equity investment	-0.296	-0.081	-0.714	1		
Common stock and bonds	-0.063	0.169	-0.059	-0.223	1	
Notes	-0.021	0.080	-0.054	-0.042	0.040	1

The correlation between "Preferred stock" and "Venture capital equity investment" reveals the same correlation issue here as there was in the Poisson model. This is likely not an issue because of how strongly "Preferred stock" correlated in the original robust negative binomial model. Also, "Venture capital equity investment" did come close to correlating, with a z-score of 0.35. Because of these scores, the multicolinearity seen here does not reduce our confidence in the correlation results. For example if one or the other was taken out, it would not change the correlation status of either variable.

The other cell to note is the correlation between "Solar" and "Biofuel." This is not quite large enough to be cause for concern at -0.34, but it is important to note that there is some correlation between the two variables. This likely will result in no change to the results, but further research with more extensive data could find whether these two industries interact with each other in ways that would affect the model.

The next test needed for this model is for serial correlation, which measures the errors across rounds to see if there is any correlation. If the error from one round can predict the error from another then there can be serial correlation issues with the model. Table 21 shows a regression of the errors from negative binomial regressions run with distinct round numbers instead of all at once. For this test, errors were recorded and regressed from regressions of rounds 1-5.

Table 21 Regression of Error Variables from Negative Binomial Model Divided by Round to Test for Serial Correlation						
Dependent Variable: errorRound1	**Coefficient**	**Std. Err.**	**t-score**	**P>t**	**[95% Conf. Interval]**	
errorRound2	0.005	0.081	0.07	0.948	-0.157	0.168
errorRound3	-0.097	0.091	-1.06	0.292	-0.280	0.086
errorRound4	-0.009	0.101	-0.09	0.928	-0.213	0.194
errorRound5	-0.019	0.053	-0.36	0.722	-0.126	0.088
Constant	-9.096	12.993	-0.7	0.487	-35.192	17.001

According to this model, none of the errors correlate with the first round error. This is the most important because it is only an issue if the errors predict futures errors. Table 22 is a correlation matrix of each of the five error variables.

Table 22 Correlation Matrix of Error Variables from Negative Binomial Model to Test for Serial Correlation					
	errorRound1	**errorRound2**	**errorRound3**	**errorRound4**	**errorRound5**
errorRound1	1				
errorRound2	0.029	1			
errorRound3	-0.158	-0.150	1		
errorRound4	-0.018	0.065	0.020	1	
errorRound5	-0.066	0.037	0.099	0.053	1

This table shows no correlation between the errors. This is good news for the model and shows that there are no issues with serial correlation. The lack of correlation in the errors gives one confidence in the original results and shows that no considerations need to be made about the data being observed over time.

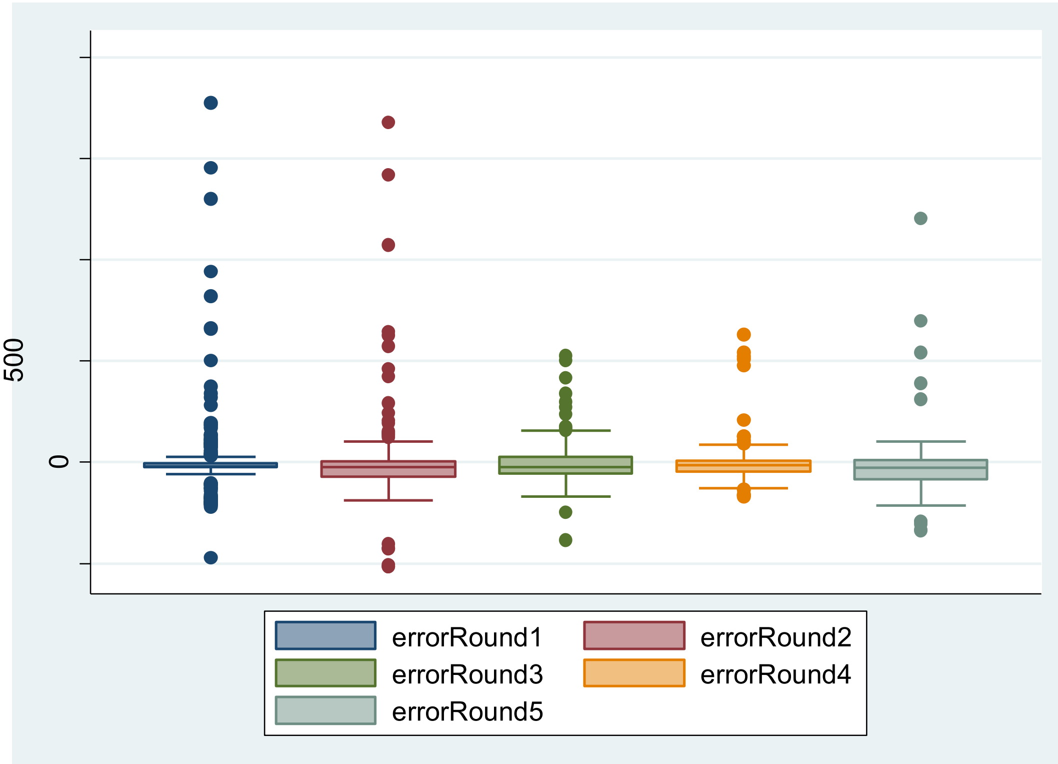
The last test of the validity of the model is that of the normality of the errors. If the errors are not normal then there will be issues with the original model that will likely require further research. Table 23 shows summary statistics of the error variables used in Tables 21 and 22. Graph 2 shows a box chart of the errors to display their normality.

Table 23

Summary Statistics of Error Variables from the Negative Binomial Model

Variable	Observations	Mean	Std. Dev.	Min	Max
errorRound1	453	-0.364	164.066	-474.565	1776.238
errorRound2	220	-4.398	211.371	-516.223	1677.104
errorRound3	140	0.985	118.194	-383.663	527.216
errorRound4	93	6.420	142.802	-168.05	631.760
errorRound5	55	2.735	243.513	-337.325	1201.706

Figure 2: Box and Whisker Plot of Error Variables from the Negative Binomial Model to Show Normality



The table of summary statistics shows that the errors are centered close to zero, with the largest deviation being the error from round 4 with a mean of 6.42. In all cases however the standard deviation is so large that the slight variance in mean does not matter greatly. The graph shows some outliers in each round but generally evenly distributed errors. This means that we can be confident in the results from the original robust negative binomial model as they have been analyzed.

Next, the Conclusion and will summarize these findings and their implications for new ventures, venture capitalists, and policy makers.

CHAPTER 6

CONCLUSION

The results from the previous section show that the timing between financing rounds does not depend greatly on the industry of the new venture or the type of security used in the investment. However if the company was in the solar industry there was a decrease in the amount of time in between financing rounds. Further research can explore why the results correlated for only one industry within Cleantech, but it is likely that the reasons for a VCs investment decision outlined in Chapter 3 explain a good deal of this model. Without quantifiable data explaining the quality of the management team or the scalability of the venture, a good deal of the investment decision goes unexplained. In addition to this issue, the nature of the data makes normal regressions not a perfect fit. Analyzing the cluster data analyzed for each company over time, instead of a simple panel data series, increased statistical significance for some industries. Nuclear and Hydrogen industries correlate well but not quite at the 95% confidence level. So while one cannot say with confidence that these industries affect the dependent variable, more data and further research could show more industries correlating than the one found in this study.

Since the variable for round numbers correlated with statistical significance, one can say confidently that the more rounds of financing receive, the less frequently they arrive. This is all that can be said confidently about the model for the Poisson model, so further research would have to identify additional variables that might correlate with financing rounds.

The negative binomial model shows more variables correlating significantly than the Poisson model, which shows that the quantity of equity invested is better predicted by the industry than is the amount of time in between financing rounds. Not only did the round number and solar industry correlate in the negative binomial model but the hydrogen and marine industries and preferred stock securities as well. The round number, solar industry, and preferred stock variables all showed positive correlation, predicting higher equity amounts in each financing round. The marine and hydrogen industries show a strong negative correlation with the amount received in each financing round.

This information is important to entrepreneurs entering the Cleantech sector. The behavior of venture capitalists is vital to the first few years of a new venture, and unexpected financing activity can be a shock to a young company. These new ventures need all the information available to better predict how to manage operations. According to this research, the amount and timing of financing that a new venture can expect will vary based on the industry they enter.

Venture capitalists will also be interested in these results because there is always room to improve the efficiency of their investments in a relatively new market. Since alternative energy has gotten much more attention in the past decade, there has not been time to explore the most effective investment strategies. These data model some of the practices used in recent history. Further research can build on this to show which of these practices have been effective and which have failed. With this knowledge, investment in alternative energy can become more effective and the industry as a whole can grow more rapidly.

Policy makers will also be interested to see this research because of the way it models private investment activity. Public investment in alternative energy will be necessary to grow the industry while it competes with fossil fuels. There is very little literature that models the activity of venture capitalists in alternative energy because of how recently it has reached the public eye. This information is important because policy makers can legislate more effectively if they know the best practices established by the private sector and what areas need the most investment.

Further research is necessary to quantify the other variables in a VC's investment decision. These qualitative variables capture large aspect of venture capitalists' decisions that is not explained by the securities variables. For the new ventures, there could be more specific variables within the industries studied in these models. More complete data would be needed for further research and that is not available currently. However, as the alternative energy industry becomes more prevalent in comparison to fossil fuels, more research is likely to be done. This means that in coming years there could be new data available that cannot be predicted now.

This research models the activity of venture capitalists in the alternative energy industry. The more this is studied and understood, the closer we become to making this industry a true competitor of fossil fuels.

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