The Evolution of Wind Energy in Colorado and Iowa

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# Abstract

This study attempts to answer two overarching questions: How has the wind industry evolved in Colorado and Iowa, and is this evolution typical of a large industry? These questions are answered by examining the market concentration of each state, as well as the innovation, past turbine sale, and adoption rates of each manufacturer therein. With conclusive results for all parts except past turbine sales, this study finds that the wind turbine manufacturing industry, at least within these two states, is typical in the metrics used to evaluate its markets, though the dynamics contained have some unique characteristics, such as high innovation by small manufacturers. The process also demonstrates that Colorado is a unique space within the United States due to its market concentration.

# Preface

Wind energy is a relatively new industry that has taken hold within the last thirty or so years, and is competing with oil, gas, and coal industries that have been entrenched in western society since the 1800s. It is evidently of interest to many parties what the future of this new industry will be, as well as how it has been functioning, and how it will in the future. Will wind become the next globally dominant energy source? Will it be solar? Will fossil fuels triumph against renewables?

Growing up in Colorado, I have always cared deeply about the environment. As I moved to college I realized that there is nothing I am more passionate about, and also that the environment is in trouble at the hands of thus far unbridled anthropocentric climate change. I often felt discouraged by all of the bad news about the climate, and the lack of hope in many environmentally minded spaces. Then I took a class in wind energy meteorology and it sparked my interest and gave me hope, as I learned how wind energy works as a solution. Since then I have dedicated much of my educational and professional time to learning about the wind industry and how to make myself part of the solution.

This thesis is a culmination of my progress in academic research methods, interest in wind, and new knowledge in business. I have learned much about all of these areas through this year long process, as well as met many brilliant professors that are truly inspirational, and hope that I can use what I have learned here to further a future career in wind energy.

I would like to acknowledge Daniel Kaffine first and foremost, as the first professor I met that was interested in my modelling of wind turbine adoptions. Professor Kaffine then outlined how I would go about doing that modelling using Mathematica, a program I had never heard of, much less knew how to use. The guidance and help he provided in re-writing the modelling equations was also instrumental in completing the thesis. I would also like to acknowledge everyone that helped me secure a University of Colorado membership to the American Wind Energy Association, including Dale Miller and Jean Lindhal. Their assistance made a complicated process much easier. Finally, I want to thank all of the advisers on my current committee, who all worked hard to fill a gap when professor Kaffine was no longer able to assist me, and without whose help I would not have succeeded in writing this thesis.

#### **Chapter 1: Introduction and Research Questions**

This paper examines wind energy adoption and innovation, investigating the industry dynamics shown in the past decades of wind power development. There is a long history of research on the topic of product and technology adoption, but relatively little with respect to wind energy specifically and many of the questions that this project asks. The motivation for this thesis is to discover what the prospects are for wind energy, and if it will indeed be the energy of the future. Because it is impossible to predict the future without analyzing the past, this study takes an economist's historical approach to understand a fundamental question: How has the wind energy industry evolved? And can this evolution illuminate some unknown dynamics of the wind industry, ways that the industry is unique, or show that this business will continue to grow in the future?

This project is relevant because wind energy has only recently become a "mature" technology, and is gaining traction from a cost-competitive standpoint, though it is still unclear whether wind, solar, or fossil fuels will be the primary energy source in the future. Businesses and engaged citizens that care where their energy will be coming from in the future can benefit from knowing more about the industry that produces that energy. Finally, there has recently been a shift in the climate change narrative from one of despair, to one of hope. The outcome of this research certainly has an impact on such a narrative, whether by strengthening or weakening it.

The overarching research question – How has the wind energy industry evolved? – is broad and could be interpreted many ways. Therefore, several subsets of more substantive research questions, that are each relevant in describing the industry's evolution, are formulated: 1. What has been the rate of new turbine product development?

Answers to this question can reveal more than a simple adoption curve that shows only cumulative sales. Analyzing this question shows whether the rate of innovation for the technology has overall slowed, or speeded up. Furthermore, the rate of innovation is intimately related to adoption rates and the product life cycle as a whole.

2. What has been the extent of adoption of past turbine models?

This question is supplementary to the previous in that it attempts to capture how quickly changes are being made within the industry, but adds the component of whether or not those changes are successful. Analyzing this question leads to a greater understanding of how manufacturers are marketing their turbines, and whether a brand is preferred more than a new technology.

3. Can normal adoption curve models fit real wind turbine data accurately?

Answering this question is potentially the most impactful. Theoretical rates of adoption, if they describe real world data well, can be used to forecast future adoptions. This is the primary goal of this research and can provide an outlook for the industry as a whole. Furthermore, this analysis shows which market variables have the most effect on the wind energy industry by comparing adoption curves that focus on different parameters. Additionally, results of adoption modelling inform whether government incentives have been able to "choose winners" and make the market unpredictable. Such insights can lend suggestions for future policies. 4. How will policy affect future wind markets?

Answering this question is difficult because there are innumerable factors that can influence development, from the cost of materials, to political movements. However, using the highest performing model curve, third party projections, and qualitative discussion of the market variables from the first two questions, it is possible to estimate future growth of the wind industry.

## **Chapter 2: Background and Popular Industry Theories**

# Product Life Cycle

In order to understand industry and product dynamics, it is first necessary to understand the product life cycle. This is a theory that is well known because it has shown real world application. Many attribute its definition to a work from Joel Dean in 1950 (Osland 1991); the theory states that there are four stages to any product's "life". The stages are introduction, growth, maturity, and decline (Kerin 2009). The stages are self-describing and typically result in an "S" shaped curve that declines in the last stage. However, there are many shapes that the life cycle may take depending on marketing strategies (Kerin 2009) and may refer to sales, profits, marketing actions, or other aspects of selling. However, the product life cycle stages primarily attempt to describe that all marketing actions and reactions are dynamic over time. They also provide the temporal context on which theories of innovation and adoption overlay.

# **Product Innovation**

Innovation is a concept that is intimately related to adoption as well as the product life cycle. Innovation by a firm is the act of changing the characteristics of either a product or a process to fulfill a strategy. That strategy can change with the stages of the product life cycle, and typically does, such as the use of harvesting towards the end of the life cycle (Kerin 2009). In a seminal paper on the subject, Utterback and Abernathy define stages of both process and product innovation. They determined that process innovation typically moves from uncoordinated towards a systemic process, resulting in a rate of process innovation curve closely resembling that of the product life cycle (Utterback 1975). The rate of product innovation, the primary focus in this study, is quite different. They describe how product innovation is constantly slowing, as the brand and product become more defined, and as the process becomes

the focus of maintaining profit (Utterback 1975). Aiding this decline is the diffusion of information about an innovative product or technology, and the logical theory that an increasing number of firms "with greater diffusion...[will] reduce the rate of product change and innovation" (Utterback 1975), because it reduces the profitability of acting to innovate. This theory has held up for many years and continues to be the typical case for innovation over time (Stockton 2016). Figure one visualizes Utterback's theories.



Figure 1 Innovation and Stage of Development (Utterback 1975)

Another theory less dependent on the passage of time is that of Joseph Schumpeter, and is based primarily on the size of firms, and how different sized actors innovate in relation to each other. A common interpretation of this theory is that "large firms should have the relative innovative advantage in concentrated markets imposing significant barriers, while the small firms should have the innovative advantage in markets more closely resembling the competitive model" (Acs 1987). The methodology used to test this is a simple comparison of the number of innovations in any chosen time period with either the number of employees or the number of sales. Audretsch and Acs investigated the claim empirically and found that it generally holds true. Though these two methods for describing innovation are very different, they can both be

useful in understanding a market; the Utterback hypothesis describes how the market relates to adoption and consumers, while the Schumpeter describes how a market is related to all of its individual pieces.

# Market Concentration

It is crucial in analyzing markets in terms of the hypotheses above, to study the competition of firms within those spaces. As stated by Acs and Audretsch, in detailing their method, "the most obvious index measure for the extent of imperfect competition in a market is the degree of concentration" (Acs 1987). To discern this concentration, a common metric is the concentration ratio, "which consists of the market share of the four largest firms in an industry, expressed as a percentage" (Investopedia 2005). While this ratio might be calculated for any number of firms, it appears that the four-firm concentration ratio is the most common, and has been used in numerous academic papers such as Willard Mueller's Trends in Industrial Market Concentration 1947 to 1970 which attempts to prove the validity of the metric (Mueller 1974). The meaning of the resulting percentage is a placement on the spectrum of a perfectly competitive market as 0%, and a purely monopolistic market as 100%. Though widely used, there are some objections to its use, claiming that the ratio is "a weak measure of market power at best, and in practice contain substantial error" (Acs 1987). Other studies found that the Herfindahl index – which is calculated as the sum of the market concentrations squared – "and the [concentration] ratio cannot easily be substituted for each other...with the H-index as the superior measure" (Sleuwaegen 1986). In reality there are many concentration measures, and there is little consensus as to which is the best. In any case, there is some indication that regardless of metric, "the dramatic increase in market concentration...speaks ill for the future performance of these industries" (Mueller 1974).

# **Product Adoption**

The founding paper in this field was written by Frank Bass in 1969. This paper describes the most basic shape of an adoption curve. The model yields the quintessential "S" shape previously described, and has been the basis for describing product adoption from the fields of economics to marketing ever since. This curve is useful because it demonstrates reliably -for most products- how they move through the product life cycle. This curve is also useful because it describes how players in a market affect this life cycle and the number of product sales. There are different groups of consumers that adopt a given product or technology at different times, such as early adopters, the majority, and laggards, and all groups that are not innovators are considered imitators (Bass 1969). These groups also correspond to the stages of the life cycle, though the shape is different; the distribution of groups follows a typical bell curve (Kerin 2009). Considering this shape, it is understandable that as the percentage of the community that adopts a technology peaks and then declines, so will cumulative adoptions or sales. This is a theory that is widely accepted, and furthermore, has "been successfully demonstrated in...industrial technology" (Mahajan 1985). Figure two is displayed in Bass' seminal paper and demonstrates the application of his theory.



Figure 2 Frank Bass Adoption Curve (Bass 1969)

Despite the generally robust nature of the basic adoption model created by Bass, the literature in this field since shows that "in some cases the simple diffusion models work well and in other cases the results are not so good" (Mahajan 1985). Some proposed reasons include that the Bass model "does not include marketing-mix variables, and that restricts the model's suitability" (Radas 2005). The amount of literature on this topic has grown and splintered, with many researchers creating new or tweaked curves. Some include variables such as advertising expense and others, variables of imitation. Sonja Radas collected many of these models in a literature review and considered the differences between them, and how they are used. This examination finds that there are two approaches to creating these curves: one where the parameters are considered constant, and the other where the parameters are time-varying. Radas finds that the time varying models "exhibit a better fit than Bass" (Radas 2005) and therefore, this project will primarily consider models from Radas' collection of those with time varying parameters. Specifically, the models chosen are the Easingwood model that emphasizes the

traditional imitation versus innovation variables, and the Horsky and Simon curve as one that considers marketing mix variables such as advertising (Radas 2005). Together these curves are represented extensively in the literature and yield a diverse examination of what parameters are relevant for wind energy, while remaining within the reasonable scope of this project.

The goal of the curve analysis part of this project is to investigate what curves, if any match data from the wind energy industry. As most of the literature on this topic was written many years before the wind energy industry developed, it does not consider wind energy, or what parameters of adoption curves are most relevant to this particular industry. However, as these curves are shown to generally work with most technologies and industries, this examination is worthwhile. Furthermore, to accommodate the special interest of analyzing the future of the wind energy industry, it is pertinent to note that "sales forecasting is…one of the objectives of diffusion models" (Mahajan 1985).

# Renewable Energy Policy

A critical consideration and caveat to the relevance of innovation and adoption theory in reference to wind energy, is policy. As with many new technologies, especially those that have the potential to better the economics and health of the United States, there are government incentives in place to encourage wind power creation. These include, but are not limited to R&D efforts on the part of the government, monetary incentives such as the Production Tax Credit (PTC), political goals at the state level, such as Renewable Portfolio Standards (RPS), and even some proposed federal regulations such as the Clean Power Plan (CPP).

Before considering the effects of policies on wind turbine production, it is necessary to understand the complicated nature of business in the electricity generation and transmission. There are two electric power market structures relevant to this study, the traditional wholesale,

and the Independent System Operator (ISO). In the southwestern states, including Colorado, the system is that of a traditional wholesaler market. This means that "utilities are responsible for system operations and management, and, typically, for providing power to retail consumers. Utilities in these markets are frequently vertically integrated" (FERC 2016). The dominating utility in Colorado is Xcel Energy, and it fits into this designation. In contrast, the Midwest region employs the ISO system where the "ISOs operate the transmission system independently of, and foster competition for electricity generation among, wholesale market participants" (FERC 2016) like the non-utility wind farm owners. For example, in Iowa, only 31 of 100 physical wind project sites are owned by the same group as the power purchaser (AWEA 2016), while most projects in Colorado are owned by the utility. Further complicating the web is that many wind farms include turbines from multiple manufacturers. Altogether, these complications make the process of dividing incentives between these players a difficult ordeal.

In general, the policies that have affected utility and transmission conglomerates in the past were those federal and state initiatives like the RPS and PTC. The RPS's are state regulations, each different, that act on the owners of power transmission in that region to regulate the percentage of electricity output that is renewable. Therefore, this does not directly affect turbine manufacturers. In the way that the RPS is the stick for utilities, the PTC is the carrot. In an effort to make renewable electricity economically comparable with other sources, the PTC was introduced in 1992 and currently provides a \$0.023/kWh tax incentive for wind powered electricity producers (DSIRE 2016). This incentive only applies directly to the companies which own the electricity itself. However, demand for development from manufacturers is sometimes driven by those electricity owners, like utilities. For example, in 2013 there was a much lower installed capacity than previous years "as a result of a late extension of the production tax credit"

(Wiser 2014). More than just effecting the overall capacity, the market changed as "a result of the market uncertainty caused by the expiration of the PTC at the end of 2012, many smaller OEMs were forced to reconsider their position in the U.S. market... Consequently, 98% of wind capacity installed in 2013 and 2014 came in the form of GE Renewable Energy, Vestas, and Siemens wind turbines" (Hunt 2016). The PTC is a short term incentive, applying only to the first 10 years of operation (DSIRE 2016) and has expired and been extended six times. Most recently, a phase-out of the PTC was approved beginning December 31, 2016 (DSIRE 2016) and so the frequent volatility that the PTC created in the past, may no longer be present over the next decades. Therefore, the majority of effects from this policy have already been realized. At the state level, Iowa and Colorado have both had completed RPS's for several years (Holshouser 2015), and so that policy is particularly negligible for those states, unless the RPS amount is changed. As of 2015, these states have no plans to increase their RPS (Gallagher 2015). In short, because there are many market factors driving adoption besides policy, it is extremely difficult if not foolhardy to attempt quantification of these factors, especially at a state level, without a powerful all-encompassing energy economics model.

The policy that is more likely to affect future turbine development – and one that has been studied using extensive models – is the Clean Power Plan (CPP). As perhaps the largest facet of President Obama's 2013 Climate Action Plan, this EPA regulatory action was designed to cut carbon emissions by pushing states to implement plans of their own to reduce emissions. Though states can meet the standards in many ways, this evidently points to an increase in renewables development as one of the major solutions. While the PTC is fading away and the RPS is largely a policy lingering from the first wave of development, the Clean Power Plan will likely be the driving force, if implemented. Currently the plan is locked in a stay from the Supreme Court, as many states argue the legality of the attempt to "regulate CO2 emissions from existing power plants under section 111(d) of the Clean Air Act" (EIA 2015). The uncertainty of whether or not the rule will be enacted presents several different possibilities for the amount of development in the future. For example, if the CPP is overturned, it would result in fewer renewables than if it is accepted. Other effects would be felt if tax incentives like the PTC were again extended, and the price of natural gas and oil will likely also reduce renewable development. There are many more scenarios that might affect growth, and just as many entities that are studying the possibilities, such as NREL, the Rhodium Group, the U.S Energy Information Administration (EIA), and professors like Danny Cullenward of Berkley. The common thread among these studies, however, is that aside from the obvious consideration of whether or not the CPP will be implemented, they are all concerned about the effects of low oil and natural gas prices. If those prices continue to be as low as they are currently, the competitive price for energy will also be lower as a whole. As it is currently, renewables are very near competitive pricing; however, an ever lower competition price point will present significant barriers to additional renewable developments in the future.

### **Chapter 3: Methods**

The methods used to answer the above questions are based on statistical analysis of secondary data sources. Most of the analysis is done using the publicly available WindFarm dataset from the USGS, an example of which is shown in Appendix A. This is supplemented with wind turbine model data from the American Wind Energy Association (AWEA) market reports, which offer much of the same data necessary, such as manufacturer, model and installed capacity per year, and include the years 2014 and 2015, unlike the WindFarm set.

Because the primary interest of this research is the industry within Colorado in particular, and in order to make the first stages of analysis manageable, only two states are initially considered. Data from Colorado is considered first, followed by Iowa. While Colorado is interesting in terms of wind resources, Iowa is much more homogeneous and has more wind installations than Colorado. These two states are used for proof of concept for the analysis methods, which could be used in future, wider research.

Here quantitative methodology is described in order of which it is carried out. The four research questions are each investigated individually. However, before analysis begins, it is necessary to build a comprehensive and organizationally effective data set. This is done using data extracted from the WindFarm dataset as well as AWEA market reports and manipulation in Microsoft Excel. This process involves first extracting all data marked as coming from either of the target states, Colorado and Iowa, and separating those into two separate sheets. Next, for each state, the data is filtered for manufacturer, pulling all turbine information for each unique manufacturer into its own sheet. The datasets contain much information that is not needed for analysis and therefore is excluded. Furthermore, the Market Report data is in a form very different from that of the WindFarm set, which is already in an Excel spreadsheet format.

Therefore, the AWEA data is assimilated into the WindFarm set. The basic desirable data are the year (ranging from 1998 to 2015), state, manufacturer, total number of turbines installed per each installation, model, site name, and decommissioned status. These data types are not all necessary to answer all of the research questions and will need to be supplemented as well, but further discussion of the chosen factors for each is detailed later. Once these factors are isolated and the sources assimilated, it is the manufacturer sheets that are then manipulated. It must be noted as well that not all manufacturers are considered; for the purpose of statistical workability and significance, only those manufacturers which sold more than 10 turbines in the desired states are considered.

# Market Concentration:

Before considering innovation, adoption, or policy, it is necessary to categorize the two target markets, Iowa and Colorado. The most relevant categorization is a comparison of the concentration and competition within them. This is done using the four-firm concentration ratio method. Not only is this a very common metric, but it is the one considered by Acs and Audretsch, and therefore relevant to the Schumpeterian hypothesis that is to be tested. To determine these ratios, first market share is calculated for each manufacturer, in each state, by dividing that manufacturer's sales by the number of total turbines across all firms. As the second and final step, those four percentages are summed, resulting in the concentration ratio for that market.

## Question 1 Methods - Innovations:

In order to determine the rate of innovation or new turbine product development, three data types are needed: manufacturer, year, and model. The rate of innovation is derived by first aligning the data for each manufacturer chronologically. A mark is placed each time the manufacturer introduced a new turbine model. Rates are then determined by dividing the number of innovations in a given year by the number of years since the previous innovation. It is expected that this method yields a slope resembling that outlined by Utterback. Finally, the slopes for each product line are averaged to create a generalized innovation rate for all manufacturers combined. A shallower slope equates to a more innovative company because it shows that the rate of innovation declined less. As outlined by Acs and Audretsch, there is also a standardized consideration of innovation rate. Rather than dividing by the number of years since the last innovation, these standardized rates are calculated by considering the total number of innovation instances and dividing that number, first by number of employees and then by the number of manufacturer sales per company. As the companies considered tend to be very large, the number used to represent employees in this case is the actual number of employees divided by one thousand, as Acs suggests (Acs 1987). However, some companies that still have working turbines and data within the dataset, have been acquired by others. Zond was acquired by GE in 2002 and NEG Micon merged with Vestas in 2004. Therefore, with no current number of employees, those two companies are necessarily skipped in this standardized method.

# Question 2 Methods – Past Turbine Adoptions:

Similar to question one, a mark is placed on the first year where a particular model is sold. Then, the number of occurrences of that model's purchase after a newer model has been innovated, is counted. These are the number of instances of past turbine adoption for a given product. These data may be analyzed on their own, but in the event that there are not enough instances to be elucidative, the methods of standardization are again employed.

# *Question 3 Methods – Adoption Curves:*

To answer this question, the data is again organized by state and then by manufacturer. Within these designations, the analysis of all the curves requires only the total number of turbine adoptions per year, and for the Horsky and Simon model, information on the advertising spending of each manufacturer. The analysis follows both the chronological and complexity progression of these curves, beginning with the Bass model, and ending with Horsky and Simon. Fitting of the theoretical curves to actual data is done using the NMinimize function in the program Mathematica to perform a sum of least squares analysis. This tool "always attempts to find a global minimum of f subject to the constraints given" (Wolfram 2014) meaning that given constraints provided by the data, the program finds the optimal values for unknown parameters that create a line with the minimum error from that of the data.

# The Bass Curve

This curve is considered first, as the seminal work in this field and basis for the following models. As written by Radas, the Bass curve is:

$$\frac{dF(t)}{dt} = p + (q-p)F(t) - qF(t)^2$$

F(t) = cumulative distribution function p = coefficient of innovation q = coefficient of imitation (Radas 2005)

In practice, using Mathematica, the discrete Bass curve is written as:

$$\min_{\alpha,\beta,\overline{N}} \sum_{t} \left( \left[ \frac{N_t - (N_{t-1})}{\overline{N}} \right] - \left[ \left( \alpha + \beta \left( \frac{N_t}{\overline{N}} \right) \right) \left( 1 - \frac{N_t}{\overline{N}} \right) \right] \right)^2$$

where  $N_t$  = total number of adoptions at time t,  $\overline{N}$  = the total potential number of adoptions, and  $Ft = \frac{N_t}{\overline{N}}$  (Easingwood 1983). The factors alpha and beta are unknown and defined by the data. An optimal value is obtained for these variables – resulting in the minimal amount of error.

#### The Easingwood Curve

As a close relative of the Bass curve, the Easingwood curve is considered next. The curve as written by Radas is this:

$$\frac{dF(t)}{dt} = \left[p + qF^{\delta}(t)\right]\left[1 - F(t)\right]$$

 $\delta$  = constant F(t) = cumulative distribution function p = coefficient of innovation q = coefficient of imitation (Radas 2005)

This model is simply the Bass model but "includes a nonuniform influence term" (Easingwood 1983) the unknown delta. This is the changing term that allows for varying times of peaking adoption, and asymmetrical curve shape, a characteristic which is essential according to Easingwood. This follows his logical assumption that word-of-mouth (and therefore rate of adoption) does not remain constant over time (Easingwood 1983). This is an assumption that has been confirmed in much of the literature, but Easingwood provides consideration of five other curves, (notably the Jeuland model) and how this method captures real data better than similar curves with a time varying component. Furthermore, this curve is one of five time varying models suggested by Radas.

In practice, as outlined by Kaffine, the discrete Easingwood model takes the form of:

$$\min_{\alpha,\beta,\overline{N},\delta} \sum_{t} \left( \left[ N_t - (N_{t-1}) \right] - \left[ \overline{N} \left( \alpha + \beta \left( \frac{N_t}{\overline{N}} \right)^{\delta} \right) \left( 1 - \frac{N_t}{\overline{N}} \right) \right] \right)^2$$

where again,  $N_t$  = total number of adoptions at time *t*, and  $\overline{N}$  = the total potential number of adoptions. However, in this case the factors alpha, and beta are unknown and defined by the data, as well as delta.

### The Horsky and Simon Curve

This model is chosen as one that exemplifies unique qualities from other time varying curves. The curve as written by Radas is:

 $S(t) = [\alpha + \beta \ln(A(t)) + qY(t-1)][m - Y(t)]$  A(t) = constant  $\beta = \text{effectiveness of advertising}$  S(t) = sales at time t Y(t) = cumulative sales up to time t m = market potential(Radas 2005)

This model employs an additional term, At, which describes advertising spending on the part of the chosen firm. This term is based on real data, and therefore more is collected and included in the dataset for this particular curve analysis. Because advertising spending over time is not a statistic readily broadcast by the manufacturers, this is satisfied with a proxy for advertising spending. The method chosen for quantifying this advertising proxy is that of counting articles found in the archives of the prominent wind energy trade magazine, Wind Power Monthly. This source provides the number of articles included in its publishings about each of the major wind turbine producing companies, in chronological order. The articles are first filtered to accommodate only those labelled as "technology" focused, as this most closely resembles advertising for a manufacturer's particular turbine. These values given for each year are directly input into the model equation. Though this method serves as a relevant proxy in that the values are based on both the individual manufacturer and their technologies specifically, certainly introduces some uncertainty into this analysis, because these articles are not necessarily a result of money spent advertising. Additionally, as an alternative to this proxy source, simple Google searches are also used. By using the advanced search tool on the engine and refining to show results dated from each year 1998-2015, the total number of hits given when searching the

company name plus "wind energy" at each year serves as the proxy value. All hits are considered, though not all are related. The hits are not checked for relevancy due to the time requirement, but assuming that the search method is kept constant, there is equal chance for unrelated hits for any given company, and therefore those bad hits are both proportionate and negligible. This method is relevant as a proxy because Google is the most used search engine and therefore, articles or mentions of any company, though not a form of advertising for which they payed, can be thought of as word of mouth. Word of mouth leads to greater knowledge of the company and its products, which is the goal of advertising, and therefore is closely associated.

In practice, the Horsky and Simon curve takes the form:

$$\min_{\alpha,\beta,\bar{N},\delta} \sum_{t} ([N_t - (N_{t-1})] - [\alpha + \beta \ln(A_t) + \delta(N_{t-1})][\bar{N} - (N_{t-1}])^2$$

where again,  $N_t$  = total number of adoptions at time *t*, and  $\overline{N}$  = the total potential number of adoptions and the factors alpha, beta, and delta are again unknown and defined by the data.  $A_t$  is directly input from the collected dataset.

These curves can all be solved and fitted for either the differential solution  $(\frac{N_t - (N_{t-1})}{N})$  or simply for the cumulative adoptions  $(N_t)$ . Both solutions are considered for all companies and then for the combined companies in each state as a whole. Finally, statistical comparison using mean absolute error, root mean squared error, and R-squared methods yield the closeness and correlation of fit for each curve in relation with the real world data.

#### Question 4 Methods - Policy Implications:

The EIA seems to have the most extensive analysis of the CPP's potential effects, coming both from its Annual Energy Outlook (AEO) studies, as well as considerations independently geared towards CPP analysis. While some papers such as those from Cullenward and the Rhodium Group critique the EIA's analysis in how the its model is constructed and on the fact

that "natural gas price assumptions in AEO2015 are also higher than what we are currently seeing" (Larsen 2016) most of the analyses done by other entities reference the EIA's model. In fact, the NREL analysis states that "fuel price assumptions are used from the AEO2015 (NREL 2016). The AEO studies seem to have the most readily available and abundant data concerning the factors relevant to renewable developments, and that is why they are referenced by nearly all the other studies. Due to its availability and already structured relevance, the EIA data is used for analysis of the CPP's potential effects. As per calculations done on the EIA dataset (appendix A), the EIA has several predictions concerning wind energy capacity specifically, stating that with the CPP, U.S wind capacity will grow by 249% by 2040, 210% without the CPP, and 239% with the CPP and low oil prices.

Using these numerical predictions, the aggregate adoption curves for Colorado and Iowa are extended. Because data for  $N_t$  is needed for all of the curve equations to perform, the last data point from each state (i.e. the total cumulative adoptions through 2015) is multiplied by 2.49, 2.10, and 2.39 as per the EIA predictions. Then a slope is calculated between the 2015 number and the 2040 number, that is used to generate future data for  $N_t$  based on each policy case. Then, the Mathematica process is re-run to create curves that predict future adoptions. This is done using only the equation that performs best statistically in predicting the past trends.

If either Horsky curve proves the best statistically, it is necessary to create future data predictions for the advertising variable  $A_t$  as well. These are generated simply by finding the linear trend of the past advertising data and extending it on to the year 2040.

# **Chapter 4: Hypotheses Generation**

# Market Concentration:

The market in Iowa contains more wind turbine installing companies. In addition, that market is older, and has many more turbines in total as compared with Colorado. For these reasons, it is expected that the market concentration in Iowa is less than in Colorado. This would mean that Iowa is a more competitive market.

An alternative hypothesis is that despite having fewer companies operating in the space, the manufacturers in Colorado have more even market share, and therefore have a lower concentration ratio than is found in Iowa.

# Question 1 - Innovations:

Based on background research, it is clear that Utterback and Abernathy's conclusions about innovation rates are robust and currently relevant. Therefore, it is expected that the innovation rates follow this shape closely. It can also be expected however, that in years when the PTC was not extended, there are lapses in innovation unexplained by the typical curve. In consideration of the standardized innovation methods, the hypothesis is that of the Schumpeterian theory as previously outlined, and that large firms will show more innovation in a market with high concentration ratios.

An alternative hypothesis is that the wind industry, due to policy incentives and because it is a novel technology, has distinctions from typical industries. In such a way, it would have declining innovation rates overall, which results in a Schumpeterian consideration that does not uphold that theory.

# *Question 2 – Past Turbine Adoptions:*

It is unlikely that there are many instances of past turbines being resold. Efficiency is paramount in electricity generation and economic competition, and therefore it is unlikely that many inferior turbines are produced, and even fewer purchased. However, through simple reasoning, a hypothesis is evident which is essentially the reciprocal of the Schumpeterian theory. If a firm has a business model focusing on innovation and is spending resources doing so, it is less likely to be advertising and selling past models. Therefore, small firms should have the relatively greater past turbine sale in concentrated markets imposing significant barriers, while the large firms should have the relatively greater past turbine sales in markets more closely resembling the competitive model. This serves as a null hypothesis.

In contrast it is understandable that if innovation rates slow overall, as is predicted by Utterback, due to technical and market parity, purchase of past turbines increases. This is because in later years, prices for older models may decline, though they may be essentially equal in efficiency to newer models. This serves as the alternative hypothesis.

## *Question 3 – Adoption Curves:*

Because the literature has largely already proven the usefulness of the Bass curve, it is expected that this method yields good results for real data, but does not perform as well as the Easingwood or Horsky and Simon models. In a null hypothesis, it is expected that the Easingwood model outperforms the others. While the Horsky and Simon model includes the manufacturer-specific advertising variable, unlike any other models, the validity of this term is compromised by data availability. Because a proxy is needed to substitute advertising spending, this model likely correlates with real data less closely than expected, and as compared to the Easingwood curve.

The alternative hypothesis is that the increased complexity of the Horsky model indeed outperforms the other models.

# *Question 4 – Policy Implications:*

Colorado and Iowa are both exemplary cases for wind energy development, and have already surpassed their RPS requirements, long before the due date. Therefore, it is reasonable to believe that their future growth rates are either the same or greater than predicted for the entire U.S. Because the other equations depend solely on  $N_t$ , if it is statistically useful based on analysis of the past, the Horsky curve should be the most interesting for predicting the future. It is important to note whether the  $A_t$  variable has a significant effect on the outcomes.

An alternative hypothesis is that the values predicted using the modelled curve are less than the purely linear EIA predictions, whether as a result of the past data in Iowa and Colorado, or due to the complexity of curves like the Horsky model.

# **Chapter 5: Results**

# Market Concentrations:

Company	Market share (%)	
GE	69.6	
Mitsubishi	11.6	
Vestas	9.0	
Siemens	3.5	
NEG	3.2	
Nordex	3.1	

The market share calculations for Colorado are as such:

Adding the four largest market shares, from GE, Mitsubishi, Vestas, and Siemens, the resulting concentration ratio is 94%. This is extremely high, as an oligopolistic market, nearing monopoly.

The market share calculations for Iowa are as such:

Company	Market share (%)	
GE	32.5	
Siemens	26.6	
Vestas	16.4	
Zond	7.1	
Gamesa	6.0	
NEG	4.1	
Nordex	1.5	
Mitsubishi	1.4	
Suzlon	0.5	
Clipper	0.39	

Adding the four largest firms' market share, from GE, Siemens, Vestas, and Zond, the resulting concentration ratio is 83%. This is high on the spectrum of concentration and is considered a slightly more competitive oligopoly.

# *Question 1 – Innovations:*

All individual graphs for time rate innovation are included in Appendix B. Using the time dependent rate method, nearly all companies operating within Colorado showed declining innovation over time and an average slope of -0.105. However, GE was an outlier in being the only company with net increasing innovation over time. This company shows decreasing innovation rate for most of the years, yet sold a new model of turbine each year from 2013 through 2015. Another interesting aspect of GE's innovation is the constant rate for many years. From the beginning of its operation through 2013, an innovative turbine was released every three years. Other trends of note are the recent uptick in Vestas' rate over time, as well as the fact that NEG was the only smaller company to have more than one instance of innovation in Colorado.

In Iowa, all manufacturers show negative relationships between innovation and time with an average slope of -0.093. The shallower slope demonstrates that the companies created and sold more innovative models in Iowa as compared with Colorado.

Despite some valid results using the time rate method, these time rates should not be compared between individual companies because there is no standardization. In considering the states' aggregated innovations over time, it is evident that innovation in Iowa is declining as well. Strangely, innovation in Colorado actually increases overall.

Number of Employees	Manufacturer	Number of Employees
13,000 (Siemens 2016)	Gamesa	6,431 (Gamesa 2014)
13,000 (GE 2016)	Nordex	3,148 (Nordex 2015)
20,461 (MHI 2015)	Clipper	500 (Clipper 2016)
20,507 (Vestas 2015)	NEG	N/A
7,500 (Suzlon 2016)	Zond	N/A
	Number of Employees   13,000 (Siemens 2016)   13,000 (GE 2016)   20,461 (MHI 2015)   20,507 (Vestas 2015)   7,500 (Suzlon 2016)	Number of Employees Manufacturer   13,000 (Siemens 2016) Gamesa   13,000 (GE 2016) Nordex   20,461 (MHI 2015) Clipper   20,507 (Vestas 2015) NEG   7,500 (Suzlon 2016) Zond

The employee size data used for standardization are shown here:



# The results for employee standardized innovation are as such:





The results for sales standardized innovation rate are as such:

The trend lines generated for each graph are those that gave the highest R-squared value, from the trend options linear, exponential, logarithmic, second order polynomial, and power. Standardization by total sales seems the most accurate measure to compare firms' overall innovation rate, as the R-squared values for both states are significantly higher for the sales standardized rates than those standardized by number of employees.

# Question 2 – Past Turbine Adoptions:

There are very few results for question two from the state of Colorado; though there are seven instances of resale from GE, there is only one instance of resale from Vestas, and none from any of the other manufacturers. Comparison between firms with so few data points is neither interesting nor telling, and therefore discussion in the context of question two focuses on Iowa.

The results for question two in Iowa are as such:





There are few if any patterns in the ranking of the manufacturers from one method to another. Only two real consistencies are present, if one segments the graphs into two sections, one holding the larger firms Vestas, Siemens, and GE, and one holding the rest of the smaller companies. First, Nordex tends to have values that are consistently higher than the other smaller companies. Second, Siemens consistently has the lowest value of the large manufacturers in both methods. Between the two manufacturers with the highest U.S. market share currently – GE and Vestas – neither is consistently higher than the other. However, Vestas does consistently demonstrate a moderate amount of past turbine sale in both methods, when considering the entire spread.

# *Question 3 – Adoption Curves:*

All individual graphs for adoption modelling are included in Appendix C.

#### Differential Solutions

In considering the modelling of the differential solution for adoption curves, it is evident that producing a good fit is difficult for all three equations. The Bass model is clearly the worst. For all nineteen manufacturers across the two states, the Bass model outputs near-zero values for every differential solution, regardless of how many installation instances or actual installations there are. For manufacturers where the data was sufficient to calculate all curves, the other three methods are all equally accurate. Each of those appears to be qualitatively the best for four out of twelve trials, though none is able to match the shape of the actual adoptions in each year.

# Cumulative solutions

In terms of modelling the cumulative adoptions solution, all curves have their strengths. The Bass curve, for its simplicity does well in predicting the shape and magnitude of the actual adoption curve when there is only one instance of installation, at best with an error of less than five turbines difference for Suzlon in Iowa (Appendix C). However, this method shows a large margin of error overall, especially when predicting actual data that has multiple instances of installation, the worst error as high as twelve hundred turbines difference for Gamesa in Iowa (Appendix C). Typically, the Bass model under-predicts the number of actual adoptions, though some of the largest errors occurred when the model makes an over-prediction.

The Easingwood model is, as expected, very similar to the Bass model, with slight improvements. Again, the shapes predicted are exactly like those of the actual data, but the magnitude of the curves are never quite right. There are more instances over-prediction with the Easingwood model than for the Bass, but there are also several moments of under-prediction as well, with no consistent pattern for when the model would over or under-predict. The margin of error is between as low as five turbines difference for Nordex in Colorado, and as high as two hundred turbines difference for GE in Iowa (Appendix C).

The Horsky and Simon model using the Windpower advertising proxy is subjectively the best in the majority of cases. Though the shape is never quite the same as the actual data, the magnitude of curve prediction is not only close to actual, but consistently less than five turbines difference in error. The second proxy method, reliant on Google searches, is also better than either the Easingwood or Bass model. The only caveat that made this method less accurate than the first proxy method is the volatility of the lines due to the Google proxy. The Google search values are often increasing and decreasing with no pattern, and more so than the Windpower article count. This is most evident in the examination of NEG in Iowa (Appendix C). However, the Google method actually outperformed the Windpower method, as for Gamesa in Iowa, GE in Colorado, and Nordex in Iowa (Appendix C), where the movements of the predicted line follow the actual quite well in some instances. It is also important to note that the Horsky models

somehow predict the number of adoptions perfectly when there was only one instance of installation for that manufacturer.

There is a reason that the models had difficulty in predicting the differential solution, and why the Horsky model was able to predict single installations perfectly, while the other models did not. These unforeseen anomalies can be explained by the nature of wind turbine installation. After turbine installation, it functions for many years, and hence there is no need for installations every year, resulting in the volatile shape of the actual differential curves. However, the models are meant to characterize single products sold to individual consumers, like televisions and dryers (Easingwood 1983, Bass 1969) or services that are bought and resold in subsequent years (Horsky 1983). Wind turbines are a different kind of product in that a developer purchases them in large quantities in order to construct a farm, rather than one at a time. That is why the actual differential values are not continuously increasing, and why a two or three order equation simply cannot create such a trend. This is why the fourth order Horsky model does better than the others at predicting differential changes, but still is not accurate. Therefore, in the context of wind turbines it is more apt to consider cumulative adoptions, which show continuously increasing data and are more similar to many consumers buying one product each.

#### Aggregated statistics

A possible solution for the problem of solving the differential equations is to simply aggregate data. One of the reasons that the differential data is so volatile is that there are not always adoptions in each year, and the value often drops to zero. However, if aggregating all manufacturers within a state to consider total turbine adoptions per year, this is less likely. Aggregating data and running statistical analyses such as root mean squared error (RMSE), mean absolute error (MAE) and R-squared, can also make it more clear which model equation is actually the best.



	Mean Absolute Error	Root Mean Square Error	R- Squared
Bass	186.6	259.5	1.030E-05
Easingwood	90.5	135.2	0.240
Horsky 1	94.5	152.8	0.077
Horsky 2	97.4	153.2	0.075

In Colorado, the Easingwood model proves to be the best in predicting the shape and magnitude of the differential curve. Though all curves have a very low R-squared value as expected, considering the nature of turbine purchase as discussed earlier, the Easingwood curve with a value of 0.24 is much better than either Horsky method with values of about 0.08 and the
Bass model, again with a value approaching zero. In addition, the MAE and RMSE are smallest for the Easingwood model in this situation.



	Mean Absolute Error	<b>Root Mean Square Error</b>	<b>R-</b> Squared
Bass	264.4	360.9	1
Easingwood	146.0	191.0	.99
Horsky 1	94.5	152.8	0.94
Horsky 2	97.4	153.2	0.94

In Colorado, the Horsky model, with a Windpower proxy, performs the best in estimating cumulative adoptions. Though it has a lower R-squared value at 0.94 than the Bass model at a perfect 1, this statistic is less useful than it is in considering the differential values, as discussed earlier. However, the first Horsky method clearly resulted in the best values for both MAE and RMSE.



	Mean Absolute Error	<b>Root Mean Square Error</b>	<b>R-</b> Squared
Bass	202.4	294.7	0.11
Easingwood	139.5	192.1	0.21
Horsky 1	138.3	176.6	0.33
Horsky 2	146.6	194.6	0.19

In Iowa, the Horsky model, with a Windpower proxy, demonstrates the best fit for the differential data. With the lowest values for MAE and RMSE, this method also has the highest R-squared value. Though still very low at only 0.33, this r-squared value was also higher than any shown for Colorado, and the line itself even shows some visual similarities to the real data.



	Mean Absolute Error	<b>Root Mean Square Error</b>	R- Squared
Bass	5724.1	7214.9	1
Easingwood	139.5	192.1	.99
Horsky 1	138.8	176.7	0.98
Horsky 2	146.6	194.6	0.97

In Iowa, the Horsky model, with a Windpower proxy again results in the best fit with the cumulative data. With a better MAE and RMSE than all other methods, and a higher R-squared value than its Google search counterpart, this model proves superior.

With three out of the four statistical trials, as well as many of the individual manufacturer tests pointing towards the Horsky with Windpower model, it is decidedly the most accurate for predicting wind turbine adoptions.

### *Question 4 – Policy Implications:*

Based on the results of the aggregated statistics, the Horsky model with a Windpower proxy is chosen for the analysis of future turbine adoptions.

## <u>Colorado</u>

Strictly based on the EIA increase predictions, if the CPP were to go into effect, there would be an increase to 4753 turbines in Colorado, 4009 without the CPP, and 4563 with low oil prices (Appendix A). When including the predicted values for advertising, the resulting turbine capacities are 4719, 3966, and 4526 respectively. Therefore, the calculated capacities are smaller than the EIA capacities in all cases.



Iowa

The EIA predictions state that with the CPP, capacity would increase to 9071, 7650 without it, and 8707 with low oil prices. Using the advertising variable, the values are 9109, 7673, and 8475 respectively. The analysis considering with and without the CPP are higher than the EIA predictions, while the calculated oil price case is lower.



In both states, the worst scenario of the three for wind turbine development, is the absence of the Clean Power Plan, whereas its presence shows the greatest growth. In both states, it is also evident that even with the CPP, if oil prices are low; there are significant decreases in the total capacity in the year 2040. Therefore, it is easy to imagine that a case without the CPP and low oil prices would be much worse than any presented above.

### **Chapter 6: Discussion**

#### Market Concentration

The results of the market concentration methodology support the simple null hypothesis that Iowa has a lower concentration than Colorado, and therefore is a more competitive space. It is surprising that both markets have very high ratios, and can be considered oligopolistic. However, when considering national statistics, as reported by AWEA in figure three, it is evident that the concentration ratio for the United States as a whole is 83%, just the same as that in Iowa. Thus, the more interesting finding is that the wind turbine industry in Colorado is more concentrated than the rest of the country.



Figure 3 United States Market Share (Hunt 2016)

#### Question 1 – Innovations

Almost all of the individual time rates for innovation, and certainly the averaged slopes support the hypothesis that firms within the wind industry have declining innovation levels over time as is consistent with Utterback's theory. However, one possibly distinguishing feature

within these markets is the presence of an uptick in innovation during recent years for some of the larger companies (GE and Vestas in Colorado, Vestas and Siemens in Iowa) and even increasing innovation for GE in Colorado. This is not a shape predicted by Utterback, and wind energy policy may be the answer. Three of the four firms that showed an uptick (excluding Vestas in Iowa) had innovations during the year 2012, one of the years in which the PTC was scheduled to expire. Perhaps the impending expiration pushed these companies to try to get their newest turbines out to the market and installed before the deadline. However, there were also innovations during 2013 and 2014 for those companies, years for which there was no PTC and a renewal of the PTC respectively. Therefore, based on only a loose connection, it cannot be concluded that the PTC policy is the answer for these atypical innovation shapes. Nevertheless, there is some indication that the normal rules do not always apply for large companies in the wind industry.

In terms of the standardized innovation methods, it appears that the sales standardized rate is the most effective. This is because the R-squared analysis of the relationship between sales and innovation instances is more significant that the relationship between employee size and innovations. It seems that the results do not support the Schumpeterian hypothesis. In both states and especially in Iowa, the smaller and more specialized firms are more innovative than the large ones. Recall the original interpretation of the theory: "Large firms should have the relative innovative advantage in concentrated markets imposing significant barriers, while the small firms should have the innovative advantage in markets more closely resembling the competitive model" (Acs 1987). According to the prior analysis of market concentration in the two states, both are found to be highly concentrated, and therefore ought to favor innovation by the larger companies. This is not the case, and both states show innovation favoring the smaller

manufacturers. There are some academic papers, though older than Acs and Audretsch, that claim this is normative as "Philips (1965) argued that concentration should promote the innovative activity of small firms more than that of large firms" (Acs 1987).

Considering the small differences between the two states themselves, Iowa is the more competitive space, and therefore should show less innovation by larger firms than does Colorado. This is true for all of the largest companies excluding Mitsubishi, and is the one piece of evidence that still supports the Schumpeterian hypothesis. Next, if one disregards the general scale of concentration ratios, and recognizes that the entire United States shares the same market concentration ratio as Iowa, it can still be argued that the null hypothesis as outlined by Schumpeter is valid. In the wind turbine manufacturing industry, smaller firms are more innovative than larger ones overall, but larger firms innovate comparatively more as market concentration increases. In any case, an important note is that as of 2015, GE has the highest market share in the U.S., followed by Vestas and then Siemens (Hunt 2016). These are the three largest companies aside from Mitsubishi, that seems generally undedicated to wind based on its consistently low innovation, and no past turbine sales. This shows that innovation does not dictate market share, but may be a necessary way for smaller, specialized companies to compete with larger companies.

#### *Question 2 – Past Turbine Adoptions:*

There are almost no instances of past sales in Colorado. For that reason, it is difficult to draw conclusions in relation to the hypotheses. However, when considering what results do exist in terms of that hypothesis, it appears that the null cannot be accepted. The Iowa market is a more competitive space, and thus the large companies should have the greatest sales. In contrast, both methods and R-squared values showed that there were very weak correlations at best

between company size and past turbine sales, and that large firms did not consistently sell more past models.

While the results shown are ambiguous in themselves, AWEA provides some stability, finding that "the most popular turbine model installed in 2015 was GE Renewable Energy's 1.7-100 platform with 950 installations. Vestas' V100-2.0 turbine model was the second most popular with 829 units, while Siemens' SWT-2.3-108 turbine model rounded out the top three with 526 installs" (Hunt 2016). If this is true, then the null hypothesis would hold. Though the correlation is extremely low, the employee standardized method does reflect this ranking. Still, this cannot be considered an end-all answer to the question, as the AWEA analysis is only of one year rather than the entire period as was the goal. However, this result seems to support the original hypothesis that larger firms are better at reselling past turbines in a competitive space such as the entire U.S market. It also serves as another confirmation that the results attained from the dataset used are insufficient to accept or reject either hypothesis.

#### Question 3 – Adoption Curves

The results of the curve modelling methodology are unsurprising, though they support the alternative hypothesis, that the Horsky model is the most accurate for predicting turbine adoptions. The results follow the chronology of adoption curve development as well as complexity. The results presented also support the logical assumption that the models improved over time, and that a higher order model can create a line more fitting with complex real world data, than can a simpler model. The more novel suggestion from the results is that the method for selecting a proxy is effective in both cases. This is unexpected and surprising, as the publication of articles in a third party, online trade catalog gives no indication of a manufacturer's actual advertising expenditure. It is more a reflection of how effective those advertising efforts were,

regardless of their cost. Even the Google proxy demonstrates good predictive ability, as that model also garners better results than the Easingwood curve when generating a cumulative adoption prediction. This is even more astounding as Google searches are hardly considered advertisements, and many of the hits are likely unrelated to the manufacturer entirely. Rather, this method captures a diverse word-of mouth-phenomenon. Judging from these somewhat rudimentary proxies, it can be assumed that if real advertising expenses were obtainable, they would enhance these results. In all cases, the implication is that the advertising variable is predictive of cumulative adoptions, and that perhaps an even higher order model with more parameters would show more improvement.

The results found are also interesting from a policy perspective. The results suggest that the wind industry is typical in terms of methods for modelling adoptions. As stated before, the model equations were derived for very mundane products, in markets with little to no monetary government incentive. The relevance of these models to the very different product of wind turbines suggests that past monetary policies like the PTC, were not choosing winners, a common argument against federal incentives. As discussed before, there are instances of support in the literature that the PTC was making competition difficult for some firms, but the found results demonstrate that these effects were not enough to disrupt a typical growth of the industry's capacity. The implication from such a conclusion is that tax credits would not be detrimental to typical growth, if extended.

#### Question 4 – Policy Implications

The results of the policy methodology reveal some generalities about wind energy markets in the future, as well as some deeper implications for the Horsky model. The results themselves are split between the two hypotheses proposed. The Iowa results for both CPP outcomes support the null hypothesis, that the predicted values are slightly higher than the EIA forecasts. In contrast, the Colorado predictions all support the alternative hypothesis, as the values are lower than the EIA forecasts. There are two ways to reconcile these conflictions.

First, the differences may be attributed to the advertising variable. It is conceivable that a lack of advertising or waning of it in recent years, as is observed in the Windpower proxy data (Appendix A), may be changing the rate of adoptions. It has already been shown that the advertising variable is significant in accurately predicting past data. Therefore, if those advertising values continue to slow in their growth, or decline, the result would be less than predicted for the entire United States, as shown by the Colorado results. The stipulation of this analysis is that two of the results in Iowa are larger than the EIA predictions, while the advertising data from Windpower is not state specific. Perhaps this points to the presence of an unconsidered parameter, or simply lessens the significance of the advertising variable.

The second possible conclusion from these results is that they demonstrate some characteristics of these markets at the state level as compared with the U.S as a whole. In this framework, it would seem that Iowa is relatively ahead of the rest of the country in its wind capacity, and is likely to continue as such in the future. In comparison, Colorado is and will be falling behind in the growth of its turbine market. After the prompting of this result, more research was done, finding that there is evidence to believe this is the more believable analysis as well. One prediction claims that "by 2020…wind growth [in Colorado] will slow to a trickle" (Nedell 2016) as is demonstrated by figure four. The analysis by The Department of Energy in its recent release of the interactive "Wind Vision" tool is commensurate. Qualitatively, Colorado's growth in that animation is visually much slower than that of Iowa, and truly many of the other states as shown in figure five.



As illustrated above, the rate of wind growth is expected to slow significantly post-2020.14





Figure 5 Energy.gov Wind Vision Tool (Energy.gov 2015)

While there are certainly many other factors which contribute to growth – or lack thereof – in a large industry, one implication of these results is that wind manufacturers will need to increase advertising efforts as the former policies phase out, and as the initial growth stages of wind's life cycle fade. Though this will not be a deciding factor, advertising will certainly come into play as the existing firms, and those attempting to enter within each space, vie for the remaining market capacity.

Another form of analyzing Colorado's dying growth is in terms of the concentration of its market. As compared with the rest of the nation, Colorado has less competition in its wind turbine industry. Furthermore, as states by Mueller, an overly concentrated market is unhealthy and will lead to a bleak future. Considering Colorado's electricity purchasing structure, where a single utility purchases most developments and owns most of the grid, perhaps the onus is upon Xcel Energy to continue diversifying its energy sources. Though its political obligations have been met thus far, if the utility does not continue purchasing wind power, the state will fall behind in this industry. An alternative to urging the utility to purchase is increasing municipal electric power. This would create a system more like that shown in Iowa, where more customers foster more competition between manufacturers, and thereby more growth in capacity in the future.

### **Chapter 7: Future Research**

Due to the time and resource restrictions of this thesis, there are several weaknesses in its analysis. If remedied, there would be improved certainty in the conclusions drawn here. There are several opportunities for further research on this topic ranging from a larger and more transparent dataset, to the possibility of optimization of a new curve.

The most apparent improvement would be an expansion to consider the entire United States wind turbine dataset, or even every manufacturer within every state. This would improve the results for question one by confirming that the employee standardization method is relevant to analyzing innovation within this industry. It might also illuminate any patterns within sales standardization that were not evident when considering just two states. This would also solve the confusion associated with the analysis of question two, where with data only from one state, it was unclear whether past turbine sales are more common for large or small companies. The results achieved here appeared contradictory to the countrywide data, as well as the logical hypothesis, and consideration of more state markets is necessary to determine whether those results are valid or not. Increasing the dataset to include all U.S turbines would also benefit the analysis of adoption curves. By aggregating the single manufacturer data into state-level datasets, the ability of the models to produce valid differential solutions was increased, because there were fewer instances of zero adoptions in a given year. It can be assumed that if all the data is aggregated at a national level, these improvements would be even more evident, and the models might possibly be able to solve for the differential shape, as they are supposed to do.

Another improvement to the dataset would be that of transparency and relevance, specifically in considering the advertising variable. With more resources in terms of partnerships with any of the turbine manufacturers, it might be possible to use real advertising expenditures,

as was the original intention for Horsky's model. There is much uncertainty introduced by the use of a proxy, and utilizing real data would not only minimize this uncertainty, but create greater certainty in the conclusions drawn about other variables, such as market size, competition, and performance.

Improvements on the outcomes of question two can be made by a more rigorous definition of innovation. It was considered at the onset of this study that information about the purpose of each new turbine model is necessary to discern its status as innovative or not. If a turbine is built for a unique purpose, for example, to withstand high winds, it cannot logically be designated as an innovation when compared with a turbine meant for a different purpose such as functioning in low winds and high turbulence. There are simple methods for deriving this distinction from the wind class standards set forth by the International Electrotechnical Commission. These standards categorize winds into six classes, characterized by the general speed of winds, and their percentage of turbulence (Turbine Wind Class 2016). Following this method, the online database "TheWindPower" has compiled information on past and present turbines for all manufacturers, including the proposed wind class of each turbine model (Market Intelligence 2016). Turbines would follow in an innovative succession of each other, if they are built for the same wind class. This methodology was not used because of the shortage of data, where of the past turbine sales in Iowa, few were found to be in the same turbine class, and therefore would result in no rate over time.

If it were of great interest to determine the validity of the claim that the adoption curve results support federal incentives, more research would need to be conducted. While there is a convincing argument proposed by the results, the analysis of question one may argue the opposite. If the adoption curves' typicality support incentives, then the equally robust and

atypical results for standardized innovation refute them. The results for sales standardized innovation showed that despite the wind industry being very concentrated, small companies innovated the most. Perhaps this is due to those policy incentives, making it easier for small firms to compete with large ones in the wind industry, where that would not be the case in an industry without those incentives. It would be very difficult to test these possibilities because there has essentially never been a case where the wind industry did not include policy incentives. It may be useful to consider other markets internationally that may have had different policy landscapes during the same years, but would evidently require a much larger dataset, and a differently structured study.

Alternatively, a much more intensive study could be done to optimize a model for the wind turbine industry specifically. The results of this thesis have shown that advertising is a valuable parameter, but it is certainly not the only one. Though the model which considers time variance and advertising performed the best, the outcomes still had large margins of error, that leave room for improvement. The errors may be reduced with the addition of more parameters. Creating such a model would require the identification and separate testing of many more variables, followed by re-assimilation and fitting of the entire new model as in the methods used here. Such a model is well beyond the scope of this thesis, but important to consider nonetheless.

#### **Chapter 8: Conclusion**

This study has indeed illuminated some aspects of the wind turbine manufacturing industry that are unique from typical large industries, and specifically some ways in which the Colorado wind market is unique even from the rest of the nation.

Question one demonstrated that despite theoretical expectations, smaller manufacturers in this industry are more innovative overall than their larger counterparts. It also showed that in general, innovation within those companies over time declines, as according to theory, but that some large companies such as GE do not always succumb to decreased innovation. Together, these conclusions work together to show that perhaps more than in typical industries, small and specialized turbine manufacturers utilize innovation as a means of competition in a very concentrated space, though larger firms maintain the market share.

Question three was also conclusive in demonstrating that adoption curves are a viable method for modelling wind turbine adoptions, just as in other industries. Furthermore, the results showed that higher order models, such as Simon and Horsky's advertising dependent curve are more effective than simpler models. While the atypical result of question one argues that government incentives may be affecting normal innovation, question three demonstrates that those incentives did not affect the industry's typical growth overall.

Finally, answers to question four illuminate some truths about Colorado's wind market specifically. The methods used here were able to confirm what other entities have claimed, that Colorado will have slower wind growth in the future than the rest of the United States, on average. The combined results of all sections in this paper point to several possible reasons for this lacking: decreasing advertising, an overly concentrated market, or an electric utility structure not conducive to growth.

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# Appendix A: Data Organization

## USGS WindFarm Dataset Example:

	А	В	С	D	Е	F	G	Н	1	J	К	L	М	N	0	Р	Q	R	S	Т	U
1	FID	unique id	site name	total turb or	n year	year r	ang on year s	manufac	model	type tow	e decommis	MW turbi	total cpcy	total ht	tower h	blade I	rotor dia	rotor s a	lat DD	long DD	state
2	17403	17685	Ponnequin	1 29	1999	no	1999	NEG Mico	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.98909	-104.837	со
3	17404	17686	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5 monopole	no	0.75	21.75	74	50	24	48	1809.56	40.98989	-104.835	со
4	17405	17687	Ponnequin	n 29	1999	no	1999	NEG Mico	NM48_75	5 monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99069	-104.834	CO
5	17406	17688	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5 monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99149	-104.833	со
6	17407	17689	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	6 monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99219	-104.831	CO
7	17408	17690	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99299	-104.83	со
8	17409	17691	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99379	-104.829	CO
9	17410	17692	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99459	-104.827	со
10	17411	17693	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99539	-104.826	CO
11	17412	17694	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99609	-104.825	CO
12	17413	17695	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99689	-104.823	CO
13	17414	17696	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99769	-104.822	CO
14	17415	17697	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99849	-104.821	CO
15	17416	17698	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.98699	-104.831	CO
16	17417	17699	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.98779	-104.83	CO
17	17418	17700	Ponnequin	n 29	1999	no	1999	NEG Mico	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.98859	-104.829	CO
18	17419	17701	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.98939	-104.827	CO
19	17420	17702	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99019	-104.826	CO
20	17421	17703	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99099	-104.825	CO
21	17422	17704	Ponnequin	n 29	1999	no	1999	NEG Mico	NM48_75	5(monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99179	-104.823	CO
22	17423	17705	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99259	-104.822	CO
23	17424	17706	Ponnequin	n 29	1999	no	1999	NEG Mico	NM48_75	6 monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99339	-104.821	CO
24	17425	17707	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5 (monopole	no	0.75	21.75	74	50	24	48	1809.56	40.99439	-104.819	со
25	17426	17708	Ponnequin	n 29	1999	no	1999	NEG Mico	NM48_75	6 monopole	no	0.75	21.75	79	55	24	48	1809.56	40.99509	-104.818	CO
26	17427	17709	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5 (monopole	no	0.75	21.75	79	55	24	48	1809.56	40.99579	-104.817	со
27	17428	17710	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	6 monopole	no	0.75	21.75	79	55	24	48	1809.56	40.99649	-104.815	CO
28	17429	17711	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	5( monopole	no	0.75	21.75	79	55	24	48	1809.56	40.99719	-104.814	со
29	17430	17712	Ponnequin	n 29	1999	no	1999	NEG Micc	NM48_75	o monopole	no	0.75	21.75	79	55	24	48	1809.56	40.99799	-104.812	CO

(WindFarm 2016)

# Energy Information Administration AEO2016 Data:

AEO2016 Market tre	ends - Figure d	ata - August 25	, 2016								
Figure MT-37. Renewable	electricity generatio	n by fuel type in all s	ectors in five cases,	2015 and 2040 (billion	kilowatthours)						
							201	5	204	0	
	Solar	Wind	Hydro	Geothermal	Biomass	MSW	Referen	e 🚬		4	
2015	37.62	189.63	246.80	16.68	32.12	23.51		-			
Reference	477.06	472.76	297.57	55.53	45.24	25.96	High Oil ar Gas Resource	d			
High Oil and Gas Resource	209.93	343.71	292.97	50.06	39.48	24.92	0401100041	-			
No CPP	388.56	398.91	294.97	55.63	40.97	26.39	No CF	P			
Low Oil Price	480.14	453.52	297.31	54.29	41.58	25.55					
Low Oil and Gas Resource	938.05	636.66	306.60	64.38	56.44	27.68	Law Oil Driv				Geothermal
							Low Oil Phi	8		4	Biomass
		Policy Case	Growth (2040 capacity	/ / 2015 capacity)			Low Oil or	Solar	Win	d Hydro	
		Reference (CPP)	2.493078517				Gas Resource	e,			
		No CPP	2.103629757					0 500	1 000	1 500	2 000 2 500
		Low Oil Price	2.391621446					0 300	1,000	1,000 1	,000 2,000

(EIA 2016)

	AT	AT
	(Windpower	(Google)
Year	Monthly)	
1998	23	66.7
1999	32	64.9
2000	39	82.5
2001	36	96.6
2002	39	104.2
2003	33	136.7
2004	33	137
2005	46	129.5
2006	23	118.6
2007	38	112.7
2008	35	95.7
2009	35	191.4
2010	117	128.1
2011	113	101.6
2012	169	147.8
2013	203	106.3
2014	188	105.3
2015	153	123.8
2008 2007 2008 2009 2010 2011 2012 2013 2014 2015	38   35   35   117   113   169   203   188   153	112.7 95.7 191.4 128.1 101.6 147.8 106.3 105.3 123.8

Aggregate Advertising Variable Proxy Data:

(Windpower 2016)

## Appendix B: Question 1 Results - Innovations



Colorado Innovation Time Rates:



















# Appendix C: Question 3 Results – Adoption Curves

## Section 1: Differentials

For each manufacturer, the four methods are organized as follows, clockwise from top left: Bass, Easingwood, Horsky with Google proxy, Horsky with Windpower proxy.
































## Section 3: Aggregated Data Results

The organization of the aggregated data graphs reads as such: all differential solutions are on the left, and cumulative solutions on the right. The order of models reads top to bottom: Bass, Easingwood, Horsky with Windpower proxy, Horsky with Google proxy.

<u>Colorado</u>



Iowa

