2019

SPECIAL PROBLEMS IN AGRICULTURAL ECONOMICS

Alexander Ogden Swartz
University of Kentucky, alexander.swartz@uky.edu
Digital Object Identifier: https://doi.org/10.13023/etd.2019.268

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

Alexander Ogden Swartz, Student

Dr. Tyler Mark, Major Professor

Dr. Carl Dillon, Director of Graduate Studies

SPECIAL PROBLEMS IN AGRICULTURAL ECONOMICS

THESIS

A thesis submitted in partial fulfillment of the
requirements for the degree of Master of Science in the College of Agriculture, Food and Environment at the University of Kentucky

By

Alexander Ogden Swartz

Frankfort, Kentucky

Director: Dr. Tyler Mark, Assistant Professor of Agricultural Economics

Lexington, Kentucky

2019

ABSTRACT OF THESIS

SPECIAL PROBLEMS IN AGRICULTURAL ECONOMICS

According to the USDA Economic Research service, farm-level prices are on the decline. This decline in prices particularly hurts smaller scale operators with many needing to rely on off-farm income in order to ensure they remain in operation. This thesis studies two problems of key interest to the Southeast region and the State of Kentucky by investigating dairy management practices and the environmental benefits of hemp production. As dairy prices have been on the decline and dairy co-ops have tightened their restrictions on somatic cell count (SCC) levels, dairy farmers and farm managers must decide the best course of action for maintaining milk quality in order to maintain their contract and profitability. Maintenance decisions as well as factors like sanitation and animal living conditions can all contribute to bulk tank SCC and depending on the type of incentives or penalties instituted by the co-op they can have an impact on net farm income. The objective of the dairy study is to determine which dairy management practices have the largest impact on SCC levels.

Industrial hemp is produced worldwide. Historically, the major producers of hemp have been China, Europe, and Russia. In 2014, the passage of the Farm Bill opened the door to the production of Industrial hemp through the development of state pilot programs. Then the 2018 Farm Bill removed industrial hemp from the Scheduled Drug list. This has further expanded the opportunities and excitement for this crop. The plant's versatility and the variety of products that can be made from it are coming to light. Sustainability is one of the key attributes touted concerning industrial hemp. Specifically, in the state of Kentucky, it is expected to be a replacement for tobacco and other traditional crops. However, how does the crop compare to tobacco production in terms of sustainability? The objective of the hemp study is to develop a life cycle analysis on the planting and harvesting of hemp and compare its impacts to more traditional crops.

Keywords: Somatic Cell Count, Dairy Management, Efficiency, Industrial Hemp, Life Cycle Analysis

_Alexander Ogden Swartz_____

_______June 26, 2019_______

SPECIAL PROBLEMS IN AGRICULTURAL ECONOMICS

By

Alexander Ogden Swartz

________________Tyler Mark_
(Director of Thesis)

_______________Carl Dillon_
(Director of Graduate Studies)

________ __June 26, 2019_
(Date)

Acknowledgements

I would like to thank Dr. Tyler Mark for allowing me to be a research assistant for two different and interesting grants and for helping to facilitate the research performed. Additionally, thank you to the members of my graduate committee, Dr. Kenneth Burdine and Dr. Will Snell for taking the time to review my thesis and offer their constructive criticisms during the defense process. I would like to express my gratitude to the Southeast Quality Milk Initiative and KY NSF EPSCoR, without whom funding for my graduate school education and the research contained in this thesis would not have been possible.

Thank you to my parents for their support of my graduate school endeavors as well as letting me live in their house the past two years. Lastly, thank you to Dr. Jay Gatrell for suggesting I take a look at pursuing a Master's degree and jumpstarting my graduate school journey.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

According to the USDA National Agricultural Statistics Service, the number of farms in the United States is on the decline. This decline in prices particularly hurts smaller scale operators with many needing to rely on off-farm income to ensure they can continue to operate their farm. In the time between 2016 and 2017, the United States lost approximately 12 thousand farms (NASS, 2018). Additionally, the land in farms decreased by 1 million acres despite average farm size increasing. The largest decreases for both the number of farms and the total amount of farmland were in the farm sales class between $1,000 and $9,999. What this indicates is that in the United States, small and midsize farms are declining, and the land is being consolidated into larger farms or being lost entirely. Figure 1.1 shows the national trends in the number of farms and the average farm size from 2010 to 2017.

Two ways to help mitigate the downturn of revenues would be to increase the quality of output or to diversify the crop portfolio. These strategies are what create the basis for this thesis. Chapter 2, “Dairy of a Madman: A Panel Stochastic Efficiency Model of the Relationship Between Somatic Cell Count and Dairy Farming Practices,” seeks to determine which dairy management practices have a significant impact on influencing somatic cell count in Kentucky dairies while chapter 3, “Hemper Tantrum: A Life Cycle Analysis on the Environmental Impact of Hemp Fiber,” looks at the life cycle of the hemp fiber production process to determine its environmental impact as compared to other crops such as hay and tobacco.

1.1 The Dairy Problem

Between 2017 and 2018 milk prices declined from $17.70 per cwt to $16.20 per cwt (ERS, 2019). Dairy producers within the United States often face price volatility from year to year which creates pressure for dairy managers to ensure they are getting the best price possible for their product so that their farm can remain profitable. Part of this goal is to ensure they are taking advantage of any incentives offered by their dairy processor, avoiding any penalties, and ensuring contract continuation. In the Southeast region, dairy processors judge dairies and provide price incentives/penalties based on the somatic cell count of the milk produced. A trend that has been occurring throughout the Southeast is a decrease in milk quality, exhibited by an increase in somatic cell count, and an overall decline in the number of dairies. With this in mind, the Southeast Quality Milk Initiative seeks to understand the factors that are contributing to these declines and address those factors. Using data gathered from SQMI surveys of 27 dairy farms throughout the southeast across multiple years, a panel stochastic efficiency model was developed to understand which management practices are significant in determining somatic cell count.

Two methods of calculating the efficiency frontier, a time-varying decay model with a truncated-normal distribution and a true random effects model with a half-normal distribution, were compared to determine which management practices produced the greatest effect. While this model is typically used with efficiency being defined in terms of quantity of output, this study defines efficiency as a lower somatic cell count, or rather the quality of output being produced. Both methods of calculating the model found that performing sanitation more frequently within the milking parlor and performing maintenance checks and repairs more frequently were significant in producing milk with a lower somatic cell count. It was also found that the true random effects model with a half-normal distribution is a more accurate representation of Kentucky dairies due to how the efficiency score would increase or decrease based on the behaviors of somatic cell count for the farm from year to year. This study implies that when dairy managers sanitize the milking parlor more frequently and perform maintenance checks and repairs more frequently, they improve their odds of producing milk with a lower somatic cell count and thus will be more likely to avoid any penalties or to take advantage of any bonuses offered by dairy processors.

1.2 The Hemp Problem

Industrial hemp is a crop which can be grown and used to produce a wide array of products such as rope, textiles, activated carbon, CBD oil, and food and beverages. Industrial hemp has been viewed as not only a viable monetary substitute to more traditional crops like tobacco but also a far more environmentally friendly alternative to many traditional crops. This eco-friendly reputation is based upon the characteristics of the plant like the fast growth, high biomass yield, and its ability to thrive against competitors which causes it to require fewer chemical inputs (Alberta Agriculture and Forestry, 2017). The passage of the 2018 Farm Bill allows for states to develop a “state plan” that regulates the cultivation of the crop. The state plans must include information on where in the state hemp is produced, procedures designed to verify hemp produced does not contain more than 0.3% THC, procedures for disposal of material which exceeds the 0.3% threshold, and the handling of violations to the 2018 Farm Bill and state plan (Mark & Shepherd, 2019). Additionally, in 2015, the total retail sales for hemp products of various categories in the United States total $573.3 million (Johnson, 2017). This emerging market and the relaxation of regulations has led to an increase in the number of industrial hemp acres planted. Between 2017 and 2018, the number of acres of industrial hemp planted in the United States increased from 25,713 acres to upwards of 78,000 acres while the acres in Kentucky increased from 3,271 acres to 6,700 acres (Mark & Shepherd, 2019). This is the foundation of the life cycle analysis performed in "Hemper Tantrum: A Life Cycle Analysis on the Environmental Impact of Hemp Fiber."

Using process and raw material data from the various libraries within the SimaPro software, University of Kentucky Industrial Hemp budgets, and outside research, a life cycle analysis was created to determine the environmental impact of planting and harvesting industrial hemp for fiber based on the metrics of global warming potential, human toxicity, land occupation, acidification, and freshwater exotoxicity. The process of hemp planting was created from information found in the industrial hemp budget as well as process data from SimaPro. The hemp planting process was then used as an input for the hemp fiber harvest process, which was created similarly to hemp planting, to study the overall impact of the entire life cycle from planting to harvest. It was found that the largest contributor to the overall environmental impact of industrial hemp fiber production was the planting process due to the agricultural machinery used. These results were then compared to LCA results on hay, a crop harvested in similar fashion whose data came from within SimaPro, and tobacco, a crop which hemp is often discussed as being a substitute. It was found that hemp is a more environmentally friendly crop than tobacco and hay in the metrics of global warming potential, acidification, and freshwater exotoxicity, hay was superior in human toxicity, and tobacco was superior in land occupation.

1.3 Thesis Objectives

The decline of dairies and the rise of hemp represent two special problems for agriculture; and the various disciplines which study it, moving into the future. The research found in this thesis represents efforts to understand and address these problems with a variety of methodology and areas of focus. This research will help to expand the knowledge base on the two subjects of interest through its novelty and the results generated. The insights found within the results will help agricultural decision makers at the farm level make more informed decisions when determining how best to run their operation.

1.4 Chapter 1 Tables and Figures

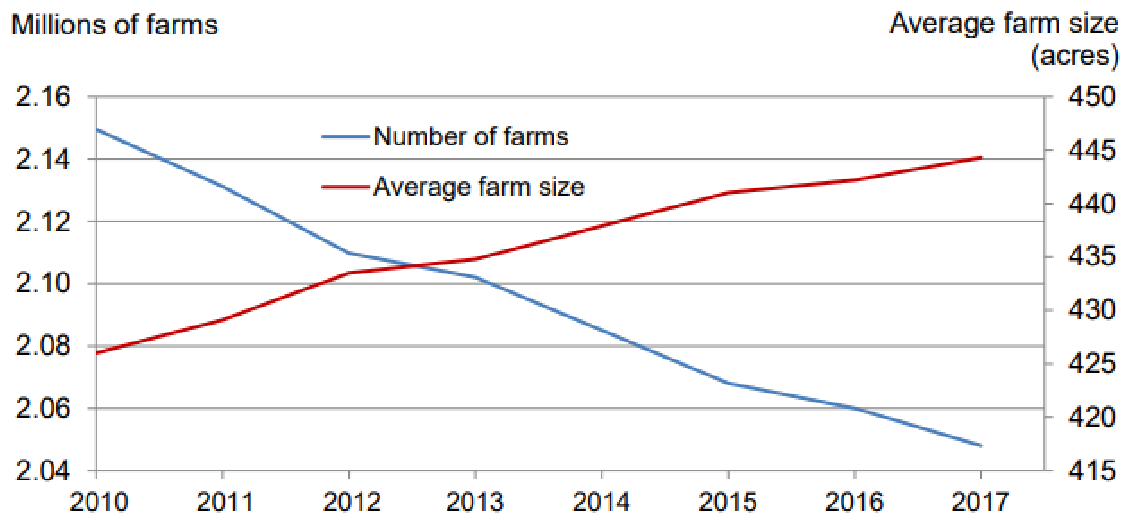


Figure 1.1: Number of Farms and Average Farm Size for the United States from 2010-2017. Source: USDA NASS, 2018

Chapter 2: Dairy of a Madman: A Panel Stochastic Efficiency Model of the Relationship Between Somatic Cell Count and Dairy Management Practices

2.1 Introduction

Dairy farmers in the United States face a large amount of price volatility from year to year and even month to month (Figure 2.1). In the years between the 2012 and 2017 USDA Census of Agriculture, the number of farms with dairy cows went from 64,098 in 2012 to 54,599 in 2017. However, the total number of dairy cows increased from 9,252,272 in 2012 to 9,539,631 in 2017 (USDA, 2019). The state of Kentucky recorded a slight increase in the 5 years moving from 1,564 in 2012 to 1,577 in 2017, although the number of cows in the state dropped from 71,783 in 2012 to 57,645 in 2017. Despite an increase in the census numbers, it has been found that in 2018, the state of Kentucky lost approximately 10% of its dairy farms (Estep, 2018). Most of the dairy farms in Kentucky are smaller operations with herd sizes of less than 100 (1,182 out of the 1,577 in the 2017 census) and most of those operations only have herds of one to nine cows (957 of the 1,577) (USDA, 2019). These smaller operations are the most vulnerable to shifts in pricing that occur within milk markets. With these trends in mind, it falls onto the dairy managers to determine how best to ensure they will manage this risk so that their enterprise remains profitable despite any negative price shifts.

One factor that dairy managers have to take into consideration is their bulk tank SCC (BTSCC). BTSCC "refers to the number of white blood cells (primarily macrophages and leukocytes), secretory cells, and squamous cells per milliliter of raw milk" (USDA 2012). The BTSCC refers to the combined SCC (SCC) of all cows which contributed to the milk in a tank, and is thus impacted by the SCC of milk produced by individual cows. Since milk with a high SCC leads to lower shelf life for milk products, many co-ops provide incentives and penalties based on the SCC content of the milk farmers provide. The question for dairy producers/managers becomes: what can be done in order to ensure BTSCC is below a certain level to ensure that any bonuses are taken advantage of and no penalties incurred?

The purpose of this study is to describe some of the dairy management decisions that can affect SCC to aid dairy producers and managers in the decision making process. The data comes from the Southeastern Quality Milk Initiative and is survey data from 27 farms throughout the southeast region across multiple years. Surveyors selected these farms because they were deemed to be representative of farms across the states in which they are located. The variables for this study come from survey questions grouped into four main categories: Animal Health, Sanitation, Operations Management, and Machinery Maintenance. These variables will be put through a panel stochastic efficiency frontier to determine which category constitutes the largest contributor to dairy farm inefficiency and SCC. Existing literature offers different views for the validity of each variable in keeping SCC low.

2.2 Literature Review

Esguerra et al. (2018) focused on the management practices of Brazilian dairy farms and how they relate to SCC. Utilizing survey data and SCC counts the research team studied farms that were both below and above specific SCC benchmarks to determine variation in management practices based on factors such as milking machine maintenance checks, employee motivation, owner participation, and technical knowledge of herd management processes. Their study found that the two largest contributors to SCC differences amongst the sample farms were the management practices and machinery upkeep. Their study found that the farms in the lower SCC range exhibited stronger management practices (such as using gloves, having a more intimate knowledge of milking conditions, and ownership being involved in milking for example) as well as more disciplined maintenance schedules and procedures (Esguerra et al. 2018).

One crucial factor to remember when determining which dairy management practices to implement to decrease SCC is that there is no single factor guaranteed to affect SCC but rather a combination of factors. Risvanli et al. (2017) found that on a farm with generally favorable management practices (access to water, bedding conditions, cleaning and scraping of milking area, proper machinery maintenance, etc.) for most of the year, there was still possible variation in SCC data. This could have been caused by factors such as the true random effects of moving animals to new housing areas or the season in which milking occurred (Risvanli et al. 2017). The Risvanli study helps to put this research into perspective in that rather than viewing the results as one factor being the most important; it highlights inefficiencies that are occurring and could be targeted in conjunction with the other efficient practices to help lower SCC.

One common theme in existing literature regarding dairy management practices and the SCC is the uses of survey data gathered from farmers across the areas of interest. Skrzypek et al. (2004) uses a survey consisting of questions regarding facilities for cows, milking practices, and matters of animal health and well-being to determine which factors contribute to SCC numbers. The other common theme is that stochastic efficiency modelling for this type of data is relatively non-existent, thus creating a case for the novelty of this study. Skrzypek's study alludes to factors such as herd size, the length of the dry period, time of the year, and foremilking as being indicators of SCC. Examining these factors is one way of studying this phenomenon. However, this study focuses on other factors not usually discussed.

Given the volatility in milk prices and increasing quality standards from dairy processors, dairy managers must find a way to ensure that they are taking advantage of premiums for milk quality and low BTSCC numbers. By focusing on factors like operations management, sanitation, machinery maintenance, and animal health, a producer can make decisions that will best increase their efficiency and thus their likelihood of receiving a premium and avoiding a penalty. The remainder of this paper will focus on the data and methods used for the study, the results of the stochastic efficiency model, and the implications these results have on decision makers.

2.3 Data

The data for this study comes from the Southeastern Quality Milk Initiative (SQMI, 2013) and a sample of 27 farms across the Southeast over the years spanning from as early as 2015 to 2018. The survey includes questions regarding demographic information (such as farm ID and year), animal health and living conditions, sanitation, operations management, and machinery maintenance. Answers to the questions were in words for participant response and then numbered for the survey conductor to record the answers (Figure 2.2). These numbers are the independent variables for analysis in this study. The dependent variable is the SCC recorded in the DHIA database for these farms. Due to the survey answers being recorded as one digit values, the natural log of the SCC value is taken to detect variability in the data. While taking the natural log actually causes there to be less variability with the dependent variable, it is better for comparing how the relatively small changes in the independent variables impact the actual SCC. Using the SCC as the dependent variable with each entry being multiple hundreds in value causes excess noise in the model and inaccuracy in the efficiency score calculation. One issue with using the stochastic panel frontier model is that the model considers larger numbers to be more efficient than lower numbers. In the case of SCC and milk quality, the opposite is true. To address this concern, the log of SCC was converted to a negative number and used as the dependent variable for this study (NegLogSCC). Due to data limitations, only SCC data from Kentucky were available and used for this study. The small dataset creates errors in the results. However, the framework of this study will be used for future research, as additional data becomes available.

The survey questions were not all organized in the same format, with some questions having larger numerical codes indicating more frequent/intensive practices and attitudes while other questions would be scaled the opposite. With this in mind, all survey questions were turned into dummy variables. The dummy process started by coding each item response as a variable and coding it with either a 1 or 0 depending on the answer. This creates a large number of independent variables with uneven amounts of variables depending on how many answer choices a question has. To address this concern, questions were further condensed to where ranges of answer choices became the variables. These ranges can be described as “more frequent/intensive,” “intermediate frequency/intensity,” and “less frequent/intensive.” From there, the answers were further condensed to where each question had two dummy variable choices, “more frequent/intensive” and “less frequent/intensive.”

By creating dummy variables, the imbalanced survey questions now have uniformity, and studying them is more feasible. To create further variability in the data, the questions were then grouped into categories which represent the kind of question being asked. The values for each category were then summed in order to create the independent variables to be put through the model. The groups became animal health more frequently (AHMF), animal health less frequently (AHLF), sanitation non-parlor more frequently (SNPMF), sanitation non-parlor less frequently (SNPLF), sanitation parlor more frequently (SPMF), sanitation parlor less frequently (SPLF), operations management more intensely (OMMI), operations management less intensely (OMMLI), milking two times per day (Milk2xDay), milking three times per day (Milk3xDay), maintenance more frequent (MMF), and maintenance less frequent (MLF). Figure 2.3 shows how the data was input for analysis, and table 2.1 shows the descriptions and summary statistics for each variable. Table 2.1 includes the summary statistics of the entire dataset except for

NegLogSCC, which is only for Kentucky data. It should be noted that except for non-parlor sanitation decisions and operations management decisions, all variables carry larger mean values for the more frequent categories. This could indicate that the more frequent variables are significant in determining the somatic cell counts for these farms and thus how efficient/inefficient the farms tend to be.

2.4 Methods

Stochastic frontier models are used to study and analyze efficiency in a variety of situations. The two pieces of the model are the stochastic production frontier; or the basis for how inefficiency is measured, and the error term that shows how far from the frontier a firm is operating (Liu, 2006). The output of a firm will be on or below the frontier (Aigner et al., 1977) and any deviation from this frontier is an inefficiency (Belotti et al. 2013). Stochastic frontiers have been used to study the efficiency of a variety of industries such as hotel management (Anderson et al., 1999 and Chen, 2007), investment strategies (Cebenoyan et al., 1993), and the relationship between information technology and production efficiency (Shao & Lin, 2001). Most literature in the agricultural space involves research on production outputs (Abdulai & Abdulai 2016 and Zaman et al. 2018) or the introduction of mechanization to a process (Abass et al. 2017). Within the subject of dairy economics, stochastic frontiers have been used to study the economic efficiency of New England dairies based on variables such as farm size and education (Bravo-Ureta & Reiger, 1991).

Most of the traditional stochastic frontier models only take into account cross-sectional data while this study uses panel data. Using panel data for a stochastic frontier creates the assumption that inefficiencies are a result of firm-specific variables and time (Batesse & Coelli, 1995). This ensures that inefficiencies can be attributed to specific firms as opposed to the entire population. To put this in the context of this study, the efficiency of individual firms can be calculated and observed as opposed to the efficiency of the entire dairy market. Stochastic panel frontiers also can be looked at as either a time decay model or time-invariant (Belotti et al. 2013). With a large amount of literature concerning stochastic efficiency and production output, a study such as this concerning the quality of what is being produced fills a largely non-explored avenue for research.

This study uses the STATA software command sfpanel described in "Stochastic frontier using STATA" by Belotti et al. (2013) to model the survey data acquired. The command's default model is used, and it is a time-decay model on a truncated-normal distribution in line with that of Battese and Coelli (1988). The model developed by Battese and Coelli is described by Crisci et al. (2016) as having the form:

Equation 2.1: $Y_{it}=\alpha_t + f(x'_{it}b) + v_{it} - u_{it} = \alpha_{it} + f(x'_{it}b) + v_{it} \quad i= 1,2, \ldots N, \quad t=1,2,\ldots T$

For this study, i is the farm in question during time t, x is the category being looked at (AHMF, AHLF, SNPMF, SNPLF, SPMF, SPLF, OMMI, OMLI, Milk2xDay, Milk3xDay, MMF, and MLF), and b is an unknown vector. The inefficiency is found in the term u, and while equation 1 is the general form for a panel data model, different models have a different estimation of u. This particular functional form was selected primarily because it varies with time as a dairy's management decisions would. Additionally, a truncated-normal distribution is suitable for the model because of the small dataset. The method of calculating the technical inefficiency score used for this study was developed by Jondrow et al. (1982) as being:

Equation 2.2: $E\ (u/\varepsilon)$

After running the initial sfpanel command, the predict command will use that equation to determine a technical inefficiency score which will then be compared with the other farms' and years' scores.

In addition to the truncated normal distribution of Battese and Coelli (1988), it is possible that a different model and distribution would better fit the data. With this in mind, the true random effects model of Greene (2005) will be used with a half-normal distribution. The model specification for the true random effects model is:

Equation 2.3: $Y_{it}=\alpha_i+x'_{it}\beta+\varepsilon_{it}$

In addition to the true random effects model having a different distribution (half normal vs. truncated normal), the model also has a different calculation for the efficiency of the farms. The true random effects model uses an efficiency score (as opposed to the inefficiency score calculated in the time-varying decay model) calculated by Battese and Coelli (1988). The efficiency score is specified as:

Equation 2.4: $E\{exp(-u/\varepsilon)\}$

By using two models to analyze the data, it creates a higher likelihood that the functional form which best represents that data will be utilized.

Calculating inefficiency based on the characteristics and decisions of a firm allows policy makers and researchers to examine better what determines the inefficiencies and make decisions and recommendations based on the findings (Liu, 2006). This idea is what allows this model to be used for this study. Traditionally, stochastic frontiers are used to determine the efficiency of a process using pure output or costs as the measure. It is inherently logical that the management decisions of a firm can have an impact on the outputs and costs of that firm. Taking this thought a step further, it becomes logical that the management decisions of a firm can also impact the quality of what is being produced. By using a panel stochastic efficiency frontier, a quality benchmark for lower SCC can be created and then the individual dairy farms can be compared to determine where their inefficiencies lie. Once it is known what causes the inefficiencies, and thus the higher SCC, management suggestions can be made in order to bolster farm efficiency and lower SCC. With this in mind, the two model specifications described above will be used on a subset of the SQMI data containing dairy farms from the state of Kentucky. The use of this small subset is due to data restrictions for the other states involved in the survey, but it will provide the foundation for future research on the complete dataset when the missing data becomes available.

2.5 Results

To address the collinearity issues which occur when using dummy variables, the model will be run as two different sets, the more frequent variable set, and less frequent variable set. These two sets will also be observed through the lens of the two different functional forms. After accounting for the collinearity, the time-varying decay model was run on the more frequent variables. It was found that the variables of SPMF (engaging in sanitation practices more frequently within the milking parlor) and MMF (performing maintenance more frequently) were significant at the five percent level in determining the NegLogSCC (Table 2.2).

It should also be noted that these variables have positive coefficients, which would indicate that an increase in these areas leads to an increase in the NegLogSCC and thus an increase in the efficiency of the dairy. This finding makes practical sense because if a milking machine is not properly maintained it can become a breeding ground for bacteria that will affect milk quality, as well as if the milking parlor and stalls are not cleaned then bacteria can grow there as well. After the model was run on the more frequent variables, it was run on the less frequent. This model returned no significant variables (Table 2.3).

The two models produced two significant variables between them in SPMF and MMF and these findings make practical sense because if a milking machine is not properly maintained it can become a breeding ground for bacteria that will affect milk quality, as well as if the milking parlor and stalls are not cleaned then bacteria can grow. While the findings of significance are helpful, the actual results of interest will be the inefficiency scores generated for the farms (which will be compared with those generated by the true random effects model later); although these findings also indicate variables which could be significant in the true random effects models.

The true random effects model was run on the two groups of variables like the time-varying decay model. The first model run was on the more frequent variable set, and it once again called SPMF and MMF significant in determining NegLogSCC (Table 2.4). This was not surprising. However, the alternative functional form still called them the only significant variables. Additionally, it should be noted that the results of the true random effects model and the time-varying decay model were virtually identical except for a few hundredths of a value. This could indicate that the truncated-normal and half-normal distributions fit the data in the same fashion. A true random effects model was also run on the less frequent variables, but because it also yielded no significant variables and was virtually identical to its time-varying decay counterpart a table containing the coefficient, standard error, z, and p-values is being omitted.

For each of the four models ran efficiency scores were calculated to be compared to determine which functional form better fits the data. For the time-varying decay models, the technical inefficiency is what is calculated so to make comparison easier the inefficiency score which was calculated will be subtracted from 1. Due to the fact that the less frequent models did not yield any significant results, their efficiency scores will be omitted and the focus placed on the differences between the more frequent time-varying decay and true random effects models. Table 2.5 shows the farm number, the date of the survey, the NegLogSCC, the SCC, the efficiency score for the time-varying decay model (score_HFtnorm), and the efficiency score for the true random effects model (score_HFtrue random effects).

The efficiency scores between the two functional forms are incredibly similar, both in relation to the farm scores within a particular functional form and between the two forms themselves. This similarity would indicate that the time-varying decay model with a truncated-normal distribution or the true random effects half-normal distribution fit the population of Kentucky dairies in the same fashion. Another facet of the efficiency score results that can be considered alarming is that all values are incredibly high. With every value starting with 0.997 and the variation coming from the digits that follow would mean that each dairy being surveyed is already over 99% efficient. Since the farms were selected for the survey by researchers because they were deemed as representative of the dairy farm population for the state, this would imply that the entire state of Kentucky has a highly efficient and well-functioning dairy industry. If this were the case, it is highly unlikely that 10% of Kentucky dairies would have shut down in 2018 (Estep, 2018). The questionable results are a direct result of the small dataset being utilized to test the model.

One other facet to consider in terms of the validity of the results would be how the efficiency scores change as SCC (and in the study NegLogSCC) changes. Table 2.6 shows the farm number, the date of the survey, the SCC, the change in SCC from year to year, the efficiency score for the time-varying decay model, the time-varying decay score change from year to year, the efficiency score for the true random effects model, and the true random effects score change from year to year.

The table shows the actual difference between the two functional forms. SCC differs from year to year and either increases or decreases. With this in mind, if SCC were to increase (a positive value in the SccChange column) then the efficiency scores in both functional forms should decrease and vice versa. What appears to occur is that no matter what actually occurs in the SCC, the efficiency score for the time-varying decay model with a truncated-normal distribution decreases from year to year. In contrast, the true random effects model with a half-normal distribution behaves as it should. When an increase in SCC from the previous year occurs, then the efficiency score decreases while a decrease from the previous year's SCC leads to an increase in efficiency score. This finding indicates that the true random effects model with a half-normal distribution is a better fit to represent the market of Kentucky dairy farms.

Putting the findings together, the true random effects model with a half-normal distribution fits the data better than the time-varying decay model. With this in mind, the true random effects model's findings of more frequent maintenance and more frequent sanitation within the milking parlor being the significant drivers of efficiency indicate that by making sure equipment is properly checked and maintained and facilities are adequately sanitized, the dairy manager can lower the risk of SCC numbers being above acceptable levels. By doing so, the farm manager will avoid any penalties and perhaps gain an incentive depending on the cost structure of the dairy processor. However, Risvali et al. (2017) points out that even when favorable management practices are being performed, there can still be variation in the SCC data and other aspects of dairy management should not be overlooked. While the efficiency scores are increasing and decreasing as SCCs decrease and increase respectively, it cannot be ruled out that there is a better functional form to fit the data. Additionally, the incredibly high-efficiency scores are cause for concern and could indicate that there is insufficient data to adequately perform the panel stochastic frontier analysis. An increased dataset and different functional forms would both be potential avenues for future research opportunities.

2.6 Conclusion

With dairy prices showing a downward trend and being volatile between periods, dairy managers have to make management decisions that will ensure the dairy operation remains profitable and can continue to operate. One of those decisions is how to ensure they are maintaining milk quality as measured by SCC. Many co-ops have incentive and penalty structures based on SCC so ensuring that the milk they are producing meets those standards to take advantage of incentives and avoid penalties is of major importance to the profitability of a dairy operation. While many studies have been done regarding the relationship between SCC and management practices, few have been done on dairies in the United States, and even fewer have taken the approach of using a panel stochastic efficiency model to investigate the relationship.

For this model, the STATA command sfpanel was used to calculate a stochastic frontier from panel data using the formulations of Battese and Coelli (1992 and 1988), Jundrow et al. (1982), and Greene (2005). The survey questions for this study formed the basis for the independent variables and were converted into dummy variables and then condensed and combined into topics of more frequency/intensity and less frequency/intensity. The independent variables for the study were more frequent animal health practices (AHMF), less frequent animal health practices (AHLF), more frequent sanitation in outside of the milking parlor (SNPMF), less frequent sanitation outside of the milking parlor (SNPLF), more frequent sanitation within the milking parlor (SPMF), less frequent sanitation within the milking parlor (SPLF), more intense operations management (OMMI), less intense operations management (OMLI), milking cows twice daily (Milk2xDay), milking cows three times per day (Milk3xDay), more frequent maintenance (MMF), and less frequent maintenance (MLF). The dependent variable of SCC was transformed into the negative log of SCC (NegLogSCC) to ensure the model considered a lower SCC as being more efficient. The data was put through the functional forms of a time-varying decay model with a truncated-normal distribution and the true random effects model with a half-normal distribution and separated into more frequent variables and less frequent variables in order to prevent issues with collinearity.

The four models run across the two functional forms found that the only significant variables were more frequent sanitation within the milking parlor and more frequent performing of maintenance. Practically speaking, this indicates that sanitation within the parlor and maintenance decisions are significant in generating lower SCC values and that by investing time into ensuring facilities are properly cleaned, and equipment is maintained the dairy manager will lower the risk of incurring a penalty for high SCC from the co-op. Additionally, the two functional forms yielded coefficient, standard error, z, and p-values that were nearly identical along with efficiency scores that were all incredibly high (each score was over 99% efficient) which could be indicative of problems with the data. Despite these similarities, the two functional forms differed in what is considered the critical finding of this study.

As SCC changed from year to year, it would either increase or decrease. In theory, if SCC were to grow, then the efficiency score that the model calculated would decrease and as SCC decreased, then the efficiency score would increase. The time-varying decay model with a truncated-normal distribution would show efficiency scores constantly decreasing as the years went on regardless of how SCC changed from year to year. In contrast, the true random effects model with a half-normal distribution had efficiency scores which would change depending on how the SCC changed, meaning as SCC decreased the efficiency score would increase and vice versa. This key difference between the two models indicates that the population of Kentucky dairies is better represented by a true random effects model with a half-normal distribution.

It should be noted that the model results could have been confounded by outside factors such as the stress of moving animals, undiagnosed infections, seasonal factors, or other factors that could cause herd distress. Additionally, not all questions from the SQMI survey were able to be transformed into dummy variables for the study and thus were excluded, which could lead to some omitted variable bias in the model. The number of data points was also low, with only nine different farms in the state of Kentucky being surveyed. A combination of these factors could be the cause of the abnormally high-efficiency scores generated by the models. A retooled survey combined with more data either from more Kentucky dairies or from dairies in other states would be changes that can influence future research. Additionally other functional forms could be the focus of future research on the subject. Finally, implementing changes to the current strategy creates costs for dairy producers. In the wake of declining profits, determining which costs are integral to maximizing profits and which can be ignored or delayed is vital to the management decision. Another avenue for future research would be to examine a cost approach to making changes depending upon the current milk quality level and pricing structure of processors.

2.7 Chapter 2 Tables and Figures

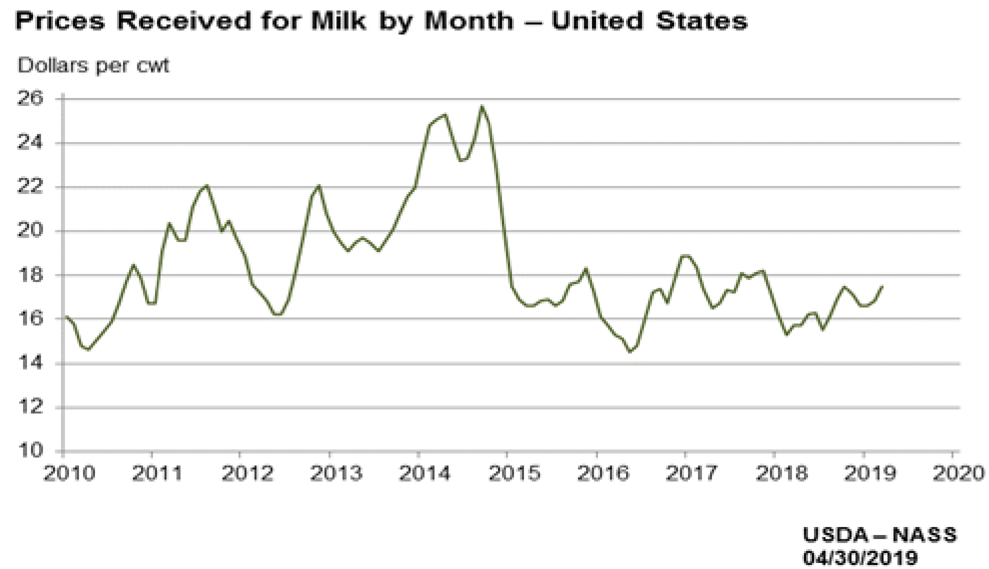


Figure 2.1: Price of Milk in dollars/cwt from 2010-2019. Note the volatility and large decline after 2014. Source: USDA NASS, 2019

Q70 How frequently is the milking system/pipeline washed?

- ❍ After each milking (1)
- ❍ Once daily (2)
- ❍ Other (3)

Figure 2.2: An example survey question regarding sanitation. Source: SQMI

Farm	Date	AHMF	AHLF	SNPMF	SNPLF	SPMF	SPLF	OMMI	OMLI	Milk2xDay	Milk3xDay	MMF	MLF
101	2/13/2016	3	2	1	2	2	0	3	0	1	0	1	0

Figure 2.3: An example of how the independent variables were input for analysis. The individual questions were turned to dummy variables and then condensed into more frequent and less frequent options which were then categorized and combined.

Table 2.1: The descriptions and summary statistics for each variable for all states.

Variable	Mean	St.Dev.	Min	Max	Description
Farm					Farm Identifier
Date					Year Identifier
NegLogSCC	-2.39	0.17	-2.67	-2.12	Dependent variable represent the negative log of SCC *KY data only
AHMF	2.645	0.97	0	4	Independent variable representing survey answers regarding matters of Animal Health being done More Frequently
AHLF	2.34	0.99	1	5	Independent variable representing survey answers regarding matters of Animal Health being done Less Frequently
SNPMF	1.06	1.14	0	3	Independent variable representing survey answers regarding matters of Non-Parlor Sanitation being done More Frequently
SNPLF	1.94	1.14	0	3	Independent variable representing survey answers regarding matters of Non-Parlor Sanitation being done Less Frequently
SPMF	1.31	0.50	0	2	Independent variable representing survey answers regarding matters of Parlor Sanitation being done More Frequently
SPLF	0.69	0.50	0	2	Independent variable representing survey answers regarding matters of Parlor Sanitation being done Less Frequently
OMMI	1.44	0.62	0	3	Independent variable representing survey answers regarding matters of Operations Management being done More Intensely
OMLI	1.56	0.62	0	3	Independent variable representing survey answers regarding matters of Operations Management being done Less Intensely
Milk2xDay	0.50	0.50	0	1	Independent variable representing survey answers regarding milking being done twice per day
Milk3xDay	0.50	0.50	0	1	Independent variable representing survey answers regarding milking being done three times per day
MMF	1.61	1.18	0	3	Independent variable representing survey answers regarding matters of Maintenance being done More Frequently
MLF	1.40	1.20	0	3	Independent variable representing survey answers regarding

Table 2.2: The coefficient, standard error, z, and p-values for the variables of AHMF, SNPMF, SPMF, OMMI, Milk3xDay, and MMF in the time-varying decay model with truncated-normal distribution.

Variable	Coefficient	Std. Error	Z	P-Value
AHMF	-0.003	0.028	-0.13	0.897
SNPMF	-0.043	0.034	-1.25	0.213
SPMF**	0.100	0.049	2.03	0.042
OMMI	0.055	0.046	1.20	0.231
Milk3xDay	-0.051	0.056	-0.91	0.362
MMF**	0.122	0.036	3.35	0.001

*=significant at 10%

**=significant at 5%

Table 2.3: The coefficient, standard error, z, and p-values for the variables of AHLF, SNPLF, SPLF, OMLI, Milk2xDay, and MLF in the time-varying decay model with truncated-normal distribution.

Variable	Coefficient	Std. Error	Z	P-Value
AHLF	0.015	0.033	0.44	0.658
SNPLF	0.003	0.037	0.07	0.944
SPLF	-0.065	0.057	-1.14	0.252
OMLI	-0.073	0.056	-1.30	0.195
Milk2xDay	0.046	0.066	0.70	0.484
MLF	0.025	0.036	0.69	0.487

*=significant at 10%

**=significant at 5%

Table 2.4: The coefficinet, standard error, z, and p-values for the variables of AHMF, SNPMF, SPMF, OMMI, Milk3xDay, and MMF in the true random effects model with half-normal distribution.

Variable	Coefficient	Std. Error	Z	P-Value
AHMF	-0.004	0.028	-0.13	0.896
SNPMF	-0.043	0.034	-1.24	0.215
SPMF**	0.100	0.049	2.02	0.043
OMMI	0.055	0.046	1.19	0.232
Milk3xDay	-0.051	0.056	-0.92	0.359
MMF**	0.122	0.036	3.38	0.001

*=significant at 10%

**=significant at 5%

Table 2.5: The farm number, survey date, NegLogSCC value, SCC value, efficiency score for the time-varying decay model (score_HFTnorm), and the efficiency score for the true random effects model (score_HFtrue random effects).

Farm	**Date**	**NegLogSCC**	**SCC**	**Score_HFtnorm**	**Score_HFtrue random effects**
101	2/13/2016	-2.16732	147	0.997262	0.9975415
101	6/13/2017	-2.1271	134	0.997256	0.9975595
101	8/2/2018	-2.66932	467	0.997253	0.9974982
102	2/13/2016	-2.21748	165	0.997346	0.9975743
102	5/9/2017	-2.65418	451	0.997342	0.9975103
102	8/2/2018	-2.43136	270	0.997337	0.9975543
103	3/26/2015	-2.40993	257	0.997282	0.9975272
103	9/17/2016	-2.60423	402	0.997279	0.9974731
103	5/8/2017	-2.44248	277	0.997278	0.9975425
103	8/1/2018	-2.20412	160	0.997273	0.997596
104	2/17/2016	-2.4216	264	0.997276	0.9975365
104	5/17/2017	-2.11727	131	0.997272	0.9975585
104	7/17/2018	-2.65514	452	0.99727	0.9975123
105	2/18/2016	-2.66087	458	0.99712	0.9974911
105	5/15/2017	-2.38202	241	0.997116	0.9975373
105	7/12/2018	-2.53529	343	0.997114	0.9975101
106	2/18/2016	-2.45025	282	0.997266	0.9975306
106	5/15/2017	-2.33846	218	0.997263	0.9975488
106	7/12/2018	-2.53275	341	0.997261	0.9975238
107	2/18/2016	-2.14613	140	0.997287	0.9975553
107	5/17/2017	-2.22531	168	0.997282	0.9975402
107	7/26/2018	-2.38917	245	0.99728	0.9975165
108	3/10/2016	-2.38382	242	0.997239	0.9975355
108	7/18/2018	-2.44091	276	0.997233	0.9975231
109	3/11/2016	-2.35793	228	0.99721	0.997527
109	5/11/2017	-2.20412	160	0.997208	0.9975449
109	7/18/2018	-2.40824	256	0.997205	0.9975058

Table 2.6: The farm number, date of survey, the SCC, the change in SCC from year to year, the efficiency score for the time varying-decay model, the time-varying decay score from year to year, the efficiency score for the true random effects model, and the true random effects score change from year to year

farm	date	SCC	SccChange	Hftnorm	TnormChange	Hftrue random effects	True random effectsChange
101	2/13/2016	147	-	0.997262	-	0.997542	-
101	6/13/2017	134	-13	0.997256	-5.8E-06	0.99756	1.8E-05
101	8/2/2018	467	333	0.997253	-3.2E-06	0.997498	-6.13E-05
102	2/13/2016	165	-	0.997346	-	0.997574	-
102	5/9/2017	451	286	0.997342	-3.6E-06	0.99751	-6.4E-05
102	8/2/2018	270	-181	0.997337	-5.1E-06	0.997554	4.4E-05
103	3/26/2015	257	-	0.997282	-	0.997527	-
103	9/17/2016	402	145	0.997279	-3.1E-06	0.997473	-5.41E-05
103	5/8/2017	277	-125	0.997278	-5E-07	0.997543	6.94E-05
103	8/1/2018	160	-117	0.997273	-5.3E-06	0.997596	5.35E-05
104	2/17/2016	264	-	0.997276	-	0.997537	-
104	5/17/2017	131	-133	0.997272	-4.7E-06	0.997559	2.2E-05
104	7/17/2018	452	321	0.99727	-1.6E-06	0.997512	-4.62E-05
105	2/18/2016	458	-	0.99712	-	0.997491	-
105	5/15/2017	241	-217	0.997116	-3.9E-06	0.997537	4.62E-05
105	7/12/2018	343	102	0.997114	-1.7E-06	0.99751	-2.72E-05
106	2/18/2016	282	-	0.997266	-	0.997531	-
106	5/15/2017	218	-64	0.997263	-3.7E-06	0.997549	1.82E-05
106	7/12/2018	341	123	0.997261	-1.6E-06	0.997524	-2.5E-05
107	2/18/2016	140	-	0.997287	-	0.997555	-
107	5/17/2017	168	28	0.997282	-4.2E-06	0.99754	-1.51E-05
107	7/26/2018	245	77	0.99728	-2.6E-06	0.997517	-2.37E-05
108	3/10/2016	242	-	0.997239	-	0.997536	-
108	7/18/2018	276	34	0.997233	-5.9E-06	0.997523	-1.24E-05
109	3/11/2016	228	-	0.99721	-	0.997527	-
109	5/11/2017	160	-68	0.997208	-2.1E-06	0.997545	1.79E-05
109	7/18/2018	256	96	0.997205	-3.3E-06	0.997506	-3.91E-05

Chapter 3: Hemper Tantrum: A Life Cycle Analysis on the Environmental Impact of Hemp Fiber

3.1 Introduction

With the passage of the Agricultural Improvement Act of 2018 allowing states to develop an individual "State Plan" that regulates the production of industrial hemp by farmers according to specific guidelines. The passage of the Farm Bill now brings into focus this controversial and misunderstood crop. Industrial hemp is a versatile crop which can be used to make a variety of products like textiles, rope, CBD oil, food and beverages, and activated carbon. Industrial hemp has been viewed as a way to revitalize struggling farms through diversification and being a substitute for declining crops like tobacco. Industrial hemp has also been touted as a more environmentally friendly crop due to its heartiness and lower need for fertilizers and pesticides. The environmental impacts of hemp cultivation are the focus of this study.

Life Cycle Analysis (LCA), also referred to as life cycle assessment, is a methodology used for determining the environmental impacts of a variety of processes and products. With studies ranging from the impact of different packaging materials, office building energy use, and the creation of activated carbon with agricultural byproducts, LCA is a versatile tool for investigating environmental impacts. While the focus of this study is the environmental impact of hemp planting and harvest and the creation of a life cycle inventory with the SimaPro software, it is essential to compare these impacts with other popular crops. For this purpose, tobacco and hay have been selected to compare their environmental impacts. Tobacco is a crop in decline, 180,000 tobacco growing farms in the 1980s to only approximately 10,000 in 2012 (CDC, 2018), and hemp has been suggested as a more profitable substitute and thus a natural subject for comparison while hay is harvested in the same manner as industrial hemp and thus shares many of the processes involved in harvest, creating another natural comparison.

3.2 Literature Review

Historically speaking, hemp was once one of the most highly traded commodities pre-1830, and today around 30 countries allow their farmers to produce the crop (Pal and Lucia, 2019). The most substantial reason for the popularity of hemp is the plant's ability to be used in the production of a large variety of products. As a non-food crop, hemp can be used to produce biofuels, construction materials, packaging, and pharmaceutical products in addition to being an additive in particular food and beverages (Simpson-Holley and Law, 2007). This versatility is what makes industrial hemp a viable economic alternative for older cash crops like tobacco becoming less popular (Pal and Lucia, 2019). Additionally, industrial hemp can be ecologically helpful due to "its low soil requirements and traces of cannabinoid content endowing it with antiseptic and fungicide properties, which makes them resistant to most diseases, thanks to which the application of fertilizers or herbicides is unnecessary" (Brzyski and Fic, 2017). Figure 3.1 shows a diagram of the hemp plant and the various uses each part has. This versatility and ease of growth are what have propelled hemp back into public discussion and even prompted the United States 2018 Farm Bill to allow American farmers to grow the crop.

Industrial Hemp is a dioecious (plants can be male or female), short day plant that comes in three varieties: oilseed, fiber, and hybrid. While hybrid plants can produce both oilseed and fibers, it does not produce as much as its specialized brethren (Purdue, 2015). Hemp being dioecious has been known to create problems with harvesting due to the fact the two genders have different maturity rates. To combat this, plants have been developed to be monoecious diploid which creates the added benefits of higher seed yield, more homogeneity in the crops, and easier harvest (Razumova et al., 2016). Known as a bast fiber plant, hemp is similar to plants like jute, kenaf, and flax. The interior of the hemp stalk is hollow and surrounded by a layer of fiber known as hurd. The hemp plant also contains bast fibers in the parenchyma layer. Hemp seeds are small and contain oil, which is similar to linseed oils (USDA, 2000). Despite having a variety of uses, in the United States, the growth of industrial hemp was prohibited after the 1937 Marijuana Tax Act prohibited all varieties of *Cannabis* plants. This incorrect classification is what has fueled misinformation regarding industrial hemp for years and is one of the largest barriers facing the expansion of industrial hemp production in the United States (Pal and Lucia, 2019). As time went on, it was recognized that not all *Cannabis* plants are created equal, and their THC[1] content differentiates industrial hemp and marijuana. With this difference in mind, varieties of industrial hemp grown must have a THC content of 0.3% or lower based on dry weight (Kim and Mark, 2018). Since marijuana is bred for its psychoactive qualities, plants carry a larger THC content. Another difference between the two plants is how they are grown. Marijuana plants are valued for their leaf and budding and thus

[1] Delta-9 Tetrahydrocannabinol, the psychoactive substance found in *Cannabis* plants

require larger row spacing than industrial hemp plants grown for their fiber content (USDA, 2000).

Tobacco is a popular cash crop facing decline. This decline has been attributed to factors like changing political attitudes regarding tobacco (Brown et al., 1999) and a deeper understanding of the health hazards of tobacco use (Cambala et al., 2019). In 2017 the World Health Organization conducted an environmental impact study on the growth, production, and consumption of tobacco products. This study found that in addition to the health consequences of tobacco use, the growth (which utilizes machinery and fertilizers) and harvest of tobacco have environmental impacts that should be considered. With this environmental impact in mind along with the prevailing theory of hemp being a substitute for tobacco, the LCA created for hemp will be compared with the findings of an LCA performed on tobacco. Zafeiridou et al. (2018) performed a life cycle analysis which sought to determine the environmental impacts of cigarette smoking from cradle-to-grave or, in other words, from planting to disposal of smoked cigarettes.

While the entirety of the study by Zafeiridou et al. (2018) is focused on cigarettes, it includes enough information on the impacts of the cultivation process to provide a comparison between the cultivation of tobacco and the cultivation of hemp. Table 3.1 contains their results for the farming process of their tobacco study (converted from per ton of tobacco to a per kg basis) and the effects it has on global warming potential, human toxicity, acidification, freshwater exotoxicity, and land occupation. The largest environmental impact comes from the land occupation needed to grow tobacco. Further discussion and analysis of these results as they compare to those of the hemp LCA will occur in the results section of this study. While tobacco is a crop most often discussed that hemp is a replacement for, there is another crop that more closely resembles the harvesting process of industrial hemp: hay. Much like hemp grown for fiber, hay must be swathed, raked, baled, and then stored in a barn or shed (Chartier, 2019). The similarities in harvest provide a natural comparison of the environmental impacts between the two crops, and thus, an LCA for hay will be performed and compared.

LCAs are often conducted on products or processes to determine the environmental impacts they carry. The LCA methodology can be applied to a variety of agricultural and non-agricultural topics such as the packaging material for apples (Manteuffel Szoege and Sobolewska, 2009), activated carbon production from coconuts (Arena et al., 2015), the energy usage of office buildings (Samnang and Jutidamrongphan, 2018), and ethanol production from miscanthus (Lask et al., 2019). Since industrial hemp is an emerging market, there is very little LCA literature regarding the production of hemp, thus illustrating the necessity for this study. LCA is typically done in a fashion referred to as "cradle-to-gate" meaning starting with the raw materials that are used for the process up to the finished product that will be put in the hands of consumers. Additionally, researchers have conducted life cycle analyses in cradle-to-grave fashion or gate-to-grave, both of which also take into account the disposal of the product after use (Schenck, 2000).

In her book *LCA for Mere Mortals: A Primer on Environmental Life Cycle Assessment* Rita C. Schenck (2000) describes the steps involved in conducting a life cycle assessment. The first steps in performing a life cycle analysis are to establish the goal and scope of the project. The goal and scope are necessary to ensure all researchers and stakeholders are on the same page in terms of what the LCA is supposed to look at. The next step is to create a life cycle inventory. The life cycle inventory is the collection of processes, raw materials, emissions, byproducts, etc. that are used or occur during the production of what is being analyzed. Once the inventory is established, the life cycle impact assessment (LCIA) can be performed. The LCIA takes into account all the data provided by the inventory and creates indicators for the impact of each raw material and process. "An indicator is not a measurement of actual environmental effects. Instead, it is a measurement of something that most environmental scientists believe will correlate well with the actual effects" (Schenck, 2000). The final step of the LCA is the interpretation of results in order to share with the stakeholders of the research.

3.3 Data

Most of the data from this study came from within the SimaPro software. The software contains various databases (referred to as libraries) containing large amounts of environmental impact data on different processes and raw materials. The libraries included in SimaPro and used for this study were ecoinvent v3, agri-footprint, USLCI, ELCD, EU and Danish input-output, industry data 2.0, and Swiss input-output (SimaPro.com). Ecoinvent is a life cycle inventory (LCI) database which contains over 15,000 different datasets for life cycle inventories over a variety of topics from agriculture, energy supply, packaging materials, construction materials, transport, biofuels, chemicals, metals, dairy, wood, and waste treatment (SimaPro.com). Agri-footprint is an LCI database focused on processes and materials involving agriculture in order to perform LCAs centered on agricultural matters. The database includes information on land use, water use, land use changes, fertilizers, and soil carbon content (SimaPro.com). ELCD is the European Life Cycle Database and includes datasets from the chemical and metal industries as well as energy production, transport, and end-of-life processes (SimaPro.com). USLCI is the United States Life Cycle Inventory database it contains life cycle inventory information on a variety of commonly used materials, products, and processes used in the United States (NREL.gov). The EU and Danish input-output and Swiss input-output databases serve the same purpose for their respective countries. The industry data 2.0 database collects data from a variety of industry associations, including PlasticsEurope, worldsteel, and European Detergents and Surfactants Industries (SimaPro.com).

These databases allow for the processes to be selected and their inputs, outputs, and environmental impacts to be measured without the researcher needing to select them separately. Despite their depth of knowledge, outside information is still needed for some processes. For this study, the hemp processes were created from outside data as well as processes contained within the SimaPro software. For the hemp crop process, data on inputs came from a combination of the SimaPro library information and the University of Kentucky Industrial Hemp Budgets (Shepherd and Mark, 2019). The industrial hemp budget gave information on the amount of hemp that would be produced, the fertilizers and amounts needed, and the farm machinery required to perform the process of planting and growing the hemp crop. The input values found in the industrial hemp budget were in the United States customary units and for input into the SimaPro system had to be converted to metric values. From there, the various inputs for the hemp crop were found within the collection of SimaPro libraries and the individual inputs of those materials and processes were automatically inserted and analyzed based on the amounts entered from the industrial hemp budget.

Data for the hay and tobacco comparisons was gathered from outside sources, and the processes were not manually designed for this study. Data for the hay impacts comes from the SimaPro collection of databases and is qualified as being the average inputs, processes, and outputs for alfalfa grass silage produced in the rest of the world (outside of Europe) in relation to producing 1kg of hay. The data for the tobacco results comes from the study "Cigarette Smoking: An Assessment of Tobacco's Global Environmental Footprint Across Its Entire Supply Chain" by Zafeiridou et al. (2018). Their study covers the life cycle of cigarettes, starting with the planting process up through used cigarette disposal. However, the information used for the comparison will be the environmental impact results they found for the farming process of the life cycle. It should be noted that the Zafeiridou et al. (2018) study does not specify whether or not the tobacco is flue-cured which could bias the results being compared. Additionally, "since very little reliable data is available on the illegal and unsustainable logging associated with tobacco curing…" the study by Zafeiridou et al. (2018) assumes sustainable logging practices, and thus the environmental impacts of deforestation associated with the tobacco cultivation and curing processes is minimized.

3.4 Methods

In order to conduct the life cycle analysis, the processes involved in hemp cultivation were programmed into the SimaPro LCA software. The first process created was the planting of hemp seeds, referred to as "Hemp Planting." The process is based on producing one hectare worth of hemp and uses various inputs found within the SimaPro libraries and the industrial hemp budget. The first part of the hemp planting process is to prepare the soil with a disk harrow. The process for using a disk harrow was taken from SimaPro and specified as being for preparation of one hectare of land (Figure 3.2). The next process is the actual planting, which is also based on one hectare of land. After the hemp is planted, fertilizers can be applied. The fertilizer information comes from the industrial hemp budget and has been adjusted to kg. 673kg of lime fertilizer, 56kg of urea containing 46% nitrogen, 50kg of potassium fertilizer, and 34kg of phosphorous fertilizer make up the fertilizer inputs for the hemp planting process. Table 3.2 shows the inputs involved in the hemp planting process. The hemp planting inputs each have their inputs and outputs/emissions. However, SimaPro automatically considers those when the particular input is selected, and thus, those do not have to be individually entered for analysis.

The next process after hemp planting is the hemp fiber harvest. One hectare of planted hemp (which is considered an input to the harvest process) will yield approximately 11,209 kg of hemp fiber. The harvesting process consists first of swathing via windrower over the 1 hectare of crop. The windrower both cuts the hemp plants (swathing) and arranges the mowed crop into windrows for drying before baling (windrowing). The next phase of the harvest process is to take a hay rake or similar implement and flip the hemp windrows to allow for drying on the other side. Because SimaPro does not contain information on this step, a second round of the swathing via windrower over the hectare will be added. This could skew the results slightly, but ultimately not enough to cause concern. The next step is the baling process. The hectare of planted hemp will yield approximately 28 round bales worth of hemp fiber for storage. Storage can be done in any preexisting space with enough volume to hold the number of bales produced. With this in mind, it is assumed that the farmer producing the hemp fiber already has a storage area such as a barn or shed suitable for storage of hemp and other crops. Due to the storage structure already being there as opposed to needing to be constructed, its environmental impact will not be considered because it is not impacting the environment in any additional fashion than it already did when it was constructed for a different enterprise. Table 3.3 shows the inputs involved in the hemp fiber harvesting process.

For the comparisons between hay and tobacco, outside resources will be used. In the case of hay, the SimaPro process for alfalfa grass silage (hay) produced under the standard practices of the rest of the world (outside Europe) and its associated inputs and outputs/impacts will be used to create the comparison results for hay. For the tobacco comparisons, the effects of "Cigarette Smoking: An Assessment of Tobacco's Global Environmental Footprint Across Its Entire Supply Chain" by Zafeiridou et al. (2018) will be used as the reference.

3.5 Results

The results of the life cycle analysis reveal the environmental impacts involved in planting and harvesting hemp fiber. The impacts of interest in this study are the global warming potential, human toxicity potential, land occupation, freshwater exotoxicity, and acidification. The EPA describes global warming potential as the amount of energy the emissions of 1 ton (or in this study, kg) of a gas will absorb over a given period relative to the emission of 1 ton (kg for this study) of carbon dioxide (EPA). It is measured in kg CO_2 equivalent. Human toxicity (which can be viewed as cancerous, non-cancerous, or combined) is an index which is calculated to reflect the potential harm of a unit of chemicals released into the environment, accounting for both the inherent toxicity of the compound and the dosage, and is measured in either kg 1,4-DB eq (as in the Zafeiridou study) or Comparative Toxic Units (CTU). This study uses CTU which is defined as being "the estimated increase in morbidity in the total human population, per unit mass of a chemical emitted" (Usetox). Land occupation discusses the amount of land used for the process and the impacts changing the land has and is measured in square-meter-years. Acidification potential measures the impacts on soil, groundwater, surface water, organisms, ecosystems, and materials that occur when acidifying substances are emitted into the air (NZME). Acidification is measured in kg SO_2 equivalent. Freshwater exotoxicity is the impact on freshwater ecosystems as a result of emissions of toxic substances to air, water, and soil (NZME). Freshwater exotoxicity is measured in this study by CTU but can also be measured in kg 1,4-DB eq. Table 3.4 shows the results of the life cycle analysis for hemp fiber production broken down by the processes involved in making 1 kg of hemp fiber.

According to the results of the LCA, the hemp planting process is the largest contributor to the five impact categories of interest to the study. In terms of the global warming potential for the hemp fiber process, hemp planting creates 0.0208 kg CO_2 eq when producing 1 kg of hemp fiber, just slightly over 50% of the impact category. Figure 3.3 depicts the results of the impact assessment in a segmented bar graph format. Note that the hemp planting process (orange portion) makes up the largest portion of the total impact across all categories. Closer examination of the process network of global warming potential (Figure 3.4) reveals the reason for this occurrence to be due to the existence and contributions of the sub-processes involved in hemp planting and the raw materials and processes which go into the manufacture of the fertilizers used. The red bars within each node and the thickness of the arrows connecting them serve as visual representations of the environmental impact contributed by each process or raw material. The cutoff for showing a node within the network is 7% contribution or higher, and thus only 20 nodes within the entire 11,618 node network are visible. The network shows the interconnectedness of the processes involved in hemp fiber production as well as their contribution to the overall global warming potential. Starting from the top and flowing down, the harvested hemp fiber makes up 100% of the global warming potential and the processes which directly yield the harvested fiber are broken down by their contribution. Flowing down further, the separate sub-processes and raw materials for the baling, planting, and swathing processes are broken down by their impact on their particular primary process. Each raw material or process had a node and then flows to the next node which uses it, with some materials or processes flowing to multiple other nodes. This serves to show the interrelatedness of each process as well as some of the raw materials which go into making the machines or chemicals required of each process to understand the impact a product or process has on the environment. Now the comparison between hemp, tobacco, and hay can be made.

Table 3.5 shows the impact assessment results for the three crops of hemp, tobacco, and hay. In terms of global warming potential, hemp carries the lowest environmental impact of the three crops. This implies that producing one kg of hemp produces less kg CO_2 eq than does one kg of either tobacco or hay, and producing one kg of hay will produce less than one kg of tobacco. Tobacco cannot be directly compared on the basis of human toxicity or freshwater exotoxicity due to the results of these impacts found in Zafeiridou et al. (2018) being measured in kg 1,4-DB eq while the LCAs performed on hemp and hay for this study use comparative toxic units, though hay and hemp can still be compared using these categories. Hay has a human toxicity measure of -1.992E-07 (caused by the non-cancerous measure of human toxicity) which implies it helps to absorb some of the harmful amounts human toxicity causing chemicals and creates a benefit to humans, thus making it more environmentally friendly in terms of human toxicity than hemp. This is most likely due to hay being able to absorb any CO_2 released into the air as a result of the planting and harvesting processes. Though in terms of freshwater exotoxicity hay has the largest impact of the three crops and hemp has the lowest. This is due to the properties of hemp, which make it heartier and less dependent on fertilizers or pesticides in comparison to other crops. Hemp also has the lowest acidification potential of the three crops examined and the second lowest land occupation. Tobacco was found to have the lowest impact on land occupation, meaning that to produce the raw materials needed as well as the crop itself there needs to be less transformation of land and other land impacts across years. It is possible that these results are skewed due to the assumption made by Zafeiriduo et al. (2018) that all wood was sustainably sourced and thus, the impacts of deforestation were minimized.

These comparative results imply that on the whole, hemp is a more environmentally friendly plant than either tobacco or hay. This is most likely attributable to the properties of hemp which allow it to need less fertilizer and pesticides for growth as opposed to other types of plants. Possible factors affecting these results could be incomplete data regarding some of the emissions and outputs involved in cultivating hemp, the lack of comparable units for human toxicity for tobacco, or conversion errors regarding the amount of inputs or outputs examined.

3.6 Conclusion

With legislation regarding the planting and cultivation of hemp in the United States becoming more relaxed, further study on the environmental impacts of planting and harvesting hemp is necessary. The three varieties of the crop (one grown for the fiber, one grown for the seeds, and one variety acting as a hybrid which can produce both) can provide a slew of different products which can be sold to consumers. These include rope, CBD oil, textiles, activated carbon, and food and beverages and has been seen as a viable alternative to declining staple crops such as tobacco. Additionally, hemp has been discussed as a viable means of diversification to allow for farming enterprises to boost farm income. Hemp has also been viewed as a more environmentally friendly crop because of the lower fertilizer and pesticide needs than most other crops. This study takes a life cycle analysis approach to determine whether this reputation as an eco-friendly alternative can be substantiated.

The life cycle analysis (also referred to as life cycle assessment) methodology has been employed to study the environmental impacts of different processes or products like packaging materials, building energy use, government projects, activated carbon production, and ethanol production. LCAs are typically performed as either cradle-to-gate, meaning beginning with the raw material extraction and going through all the processes associated with the creation of a finished product, or cradle-to-grave, going beyond the cradle-to-gate analysis and looking at factors such as the distribution of the product through consumer use and a disposal scenario. The steps of a life cycle assessment are to establish a goal and scope, create the life cycle inventory of the processes, raw materials, emissions, byproducts, etc. of what is being analyzed, perform the life cycle impact assessment, and finally interpret and share results with stakeholder of the research.

The data for this LCA comes from the databases included within the SimaPro life cycle analysis software (Ecoinvent v3, Agri-footprint, USLCI, ELCD, EU and Danish input output, Industry data 2.0, and Swiss input output), University of Kentucky industrial hemp budgets, and “Cigarette Smoking: An Assessment of Tobacco’s Global Environmental Footprint Across Its Entire Supply Chain” by Zafeiridou et al. (2018). The life cycle analysis was conducted by creating the processes for planting one hectare of hemp and then harvesting the grown hemp for its fiber. The planting process consisted of using a disk harrow to prepare the soil, a planter to plant the seeds, and then the use of nitrogen, potassium, phosphorous, and lime fertilizers to produce 11,209 kg of hemp fiber. The harvesting process consisted of the planting process, utilization of a windrower to swath the hemp plants and arrange them into windrows for drying, a second round of windrowing to flip the crop over to dry the other side, and then a collection of the fiber via baling. The results of the LCA were then compared to the results of an LCA of hay (due to the similarities in the harvesting process) contained within the SimaPro software and an LCA of tobacco (due to the comparisons drawn between the two crops as substitutes) performed by Zafeiridou et al. (2018). The impact categories of interest for the study were global warming potential, human toxicity, land occupation, acidification, and freshwater exotoxicity.

It was found that the largest contributor to the overall environmental impact of hemp fiber production was the planting process. In terms of global warming potential, the overall process totaled 0.0411 kg CO_2 eq per production of one kg of hemp fiber. Of that total, 0.0208 kg CO_2 eq, or just over 50%, was attributed to the planting process. This can be attributed primarily to the planter machine as well as the preparation of soil via disk harrow. The fertilizers had a relatively minuscule impact with only the 46% nitrogen solid urea being over the 7% impact cutoff to appear as a node in the process network.

When compared against tobacco and hay across the five impact categories, hemp was found to have the lowest impact for global warming potential, acidification, and freshwater exotoxicity (compared to only to hay). Hay was found to have a positive impact on human toxicity (compared only to hemp) which was due to its non-cancerous toxicity properties. Lastly tobacco was found to have the lowest impact on the land occupation. These findings imply that hemp could be a more eco-friendly alternative to conventional crops.

Possible shortcomings to this research could be incomplete data regarding the emissions and byproducts/other outputs involved with cultivating hemp, a lack of comparable units for the toxicity impact categories for tobacco, or data input errors. Future research would include refinement and expansion of the processes included in this model, as well as the expansion of the analysis to include a product made from hemp fiber (such as textile products or activated carbon) or a comparison between the fiber and seed hemp varieties and their impacts. Further research could also tie in monetary benefits/pitfalls to the implementation of hemp for an enterprise as well as the environmental impacts or the environmental impact of starting a hemp operation from scratch and the increased transformation of land that would occur.

3.7 Chapter 3 Tables and Figures

Table 3.1: The results of the farming portion of the LCA conducted by Zaferidou et al. (2018), which will be compared to the results of the hemp LCA conducted in this study. Source: Zafeiridou et al., 2018

Impact Category	Unit	Amount
Global Warming Potential	kg CO_2 eq	3.49
Human Toxicity	kg 1,4-DB eq	1.19
Land Occupation	m^2a	7.04
Acidification	kg SO_2 eq	0.0199
Freshwater Exotoxicity	kg 1,4-DB eq	0.0309

Table 3.2: the inputs, their amount, and their unit for the Hemp Planting process

Input	Amount	Unit
Disk Harrow*	1	ha
Planting*	1	ha
Urea**	56	kg
Potassium**	50	kg
Phosphorous**	34	kg
Lime**	673	kg

*=a process included within SimaPro

**=a raw material included within SimaPro whose amount comes from the industrial hemp budget

Table 3.3: The inputs, their amount, and their unit for the Hemp Fiber Harvesting process.

Input	Amount	Unit
Hemp Planting**	1	ha
Baling*	28	bales
Swathing/windrowing* x2	1	ha/repetition

*= a process included within SimaPro

**= a process created for this study

Table 3.4: The results of the LCA for Hemp Fiber Production broken down by the processes involved in creating 1kg of hemp fiber.

Impact Category	Unit	Total	Baling	Hemp Planting	Swathing & windrowing x2
Global Warming Potential	kg CO_2 eq	0.0411	0.0171	0.0208	0.003199
Human Toxicity	CTU	5.21E-8	1.44E-08	3.18E-08	5.89E-09
Land Occupation	M^2a	0.000743	0.000217	0.000382	0.000143
Acidification	kg SO_2 eq	0.000235	9.22E-5	0.00012	2.21E-05
Freshwater Exotoxcitity	CTU	0.216	0.0781	0.1116	0.021825

Table 3.5: Impact assessment results for hemp, tobacco, and hay. Tobacco data source: Zafeiriduo et al., 2018.

Impact Category	Unit	Hemp	Tobacco	Hay
Global Warming Potential	kg CO_2 eq	0.0411	3.49	0.368
Human Toxicity	kg 1,4-DB eq	5.21E-8 CTU	1.19	-1.922E-07 CTU
Acidification	kg SO_2 eq	0.000743	7.04	0.00387
Freshwater Exotoxicity	kg 1,4-DB eq	0.000235 CTU	0.0199	0.951 CTU
Land Occupation	M^2a	0.216	0.0309	1.74

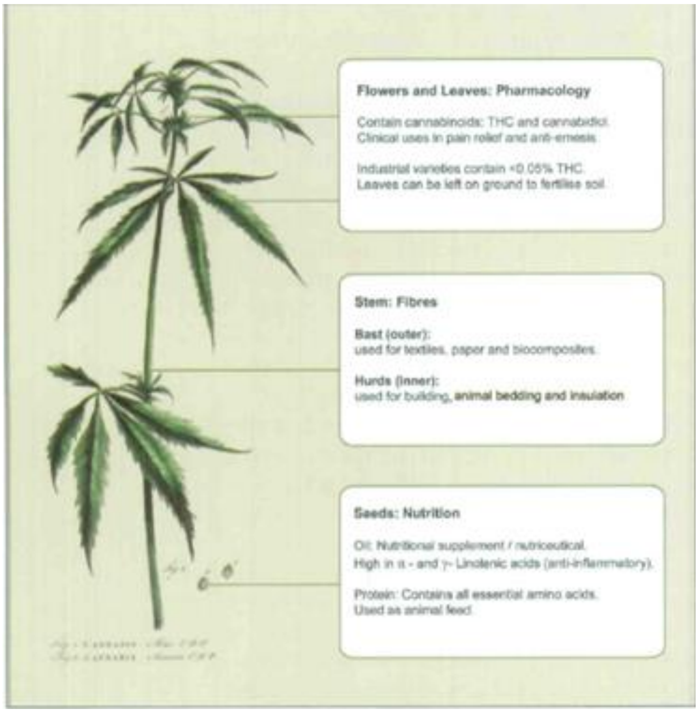
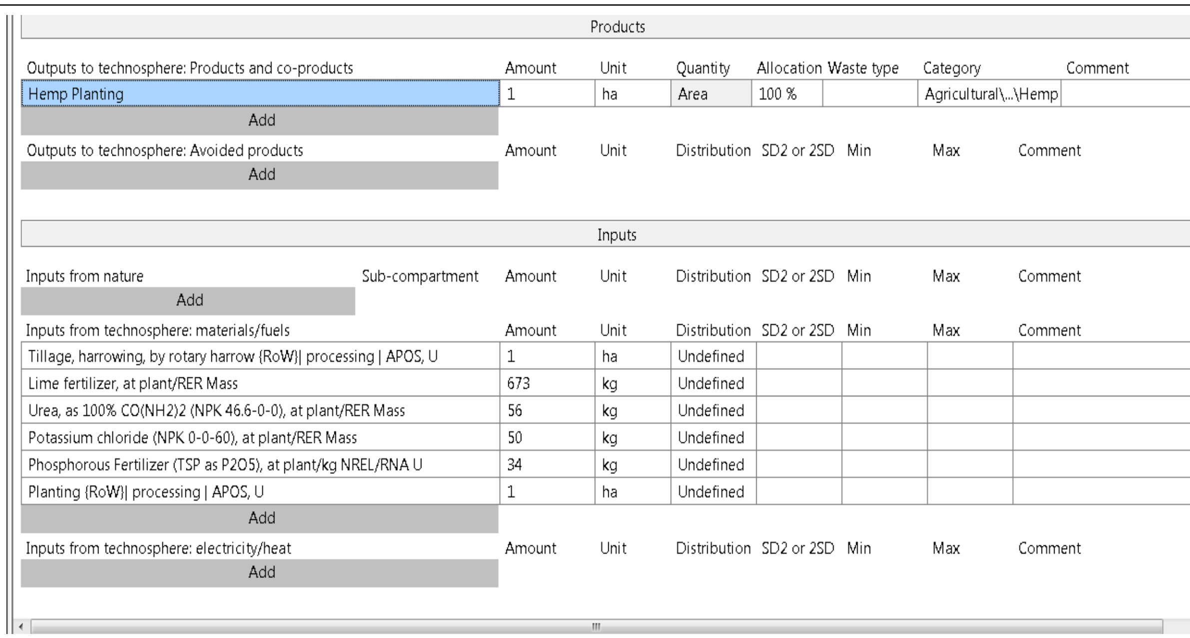


Figure 3.1: A diagram of the parts of a hemp plant and the uses for those parts. Source: Simpson-Holley and Law, 2007.



Products

Outputs to technosphere: Products and co-products	Amount	Unit	Quantity	Allocation	Waste type	Category	Comment
Hemp Planting	1	ha	Area	100 %		Agricultural\...\Hemp	
Add							

Outputs to technosphere: Avoided products	Amount	Unit	Distribution	SD2 or 2SD	Min	Max	Comment
Add							

Inputs

Inputs from nature	Sub-compartment	Amount	Unit	Distribution	SD2 or 2SD	Min	Max	Comment
Add								

Inputs from technosphere: materials/fuels	Amount	Unit	Distribution	SD2 or 2SD	Min	Max	Comment
Tillage, harrowing, by rotary harrow {RoW}| processing | APOS, U	1	ha	Undefined				
Lime fertilizer, at plant/RER Mass	673	kg	Undefined				
Urea, as 100% CO(NH2)2 (NPK 46.6-0-0), at plant/RER Mass	56	kg	Undefined				
Potassium chloride (NPK 0-0-60), at plant/RER Mass	50	kg	Undefined				
Phosphorous Fertilizer (TSP as P2O5), at plant/kg NREL/RNA U	34	kg	Undefined				
Planting {RoW}| processing | APOS, U	1	ha	Undefined				
Add							

Inputs from technosphere: electricity/heat	Amount	Unit	Distribution	SD2 or 2SD	Min	Max	Comment
Add							

Figure 3.2: An example of the input menu for the Hemp Planting process in SimaPro.

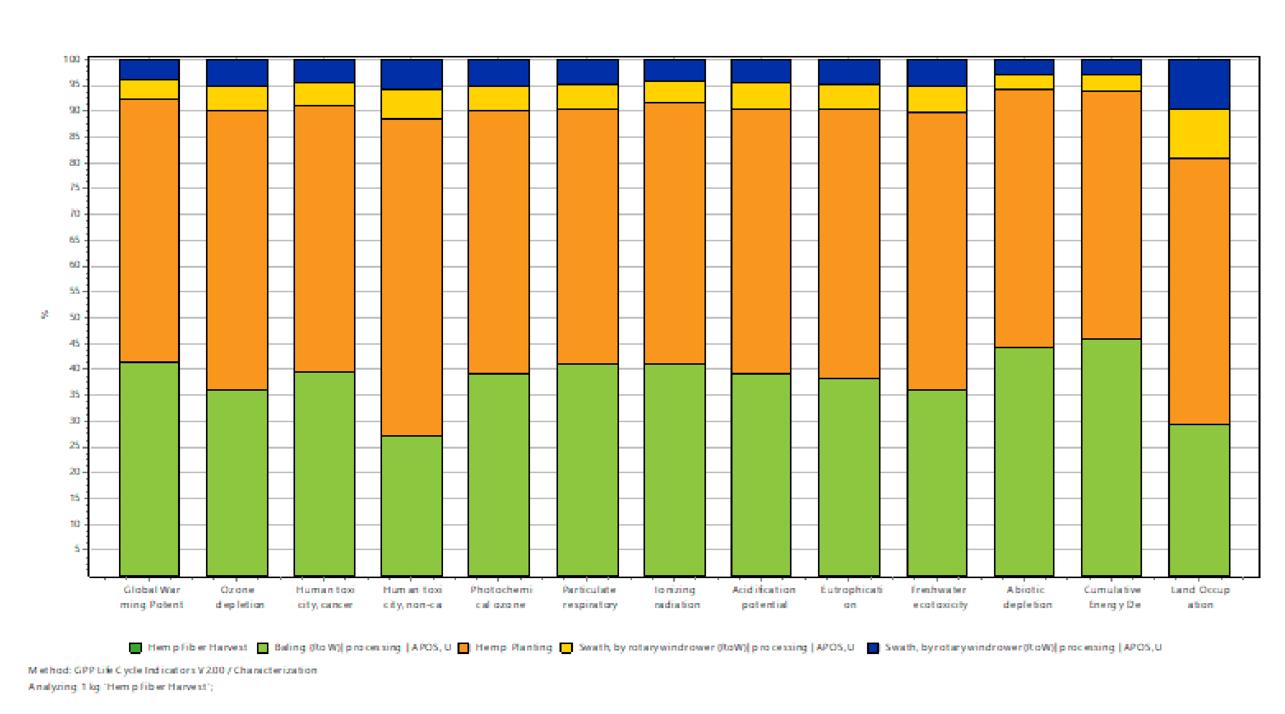


Figure 3.3: Results of the impact assessment in segmented bar form. Baling is depicted in light green, hemp planting in orange, and the two swathing and windrowing processes in yellow and blue.

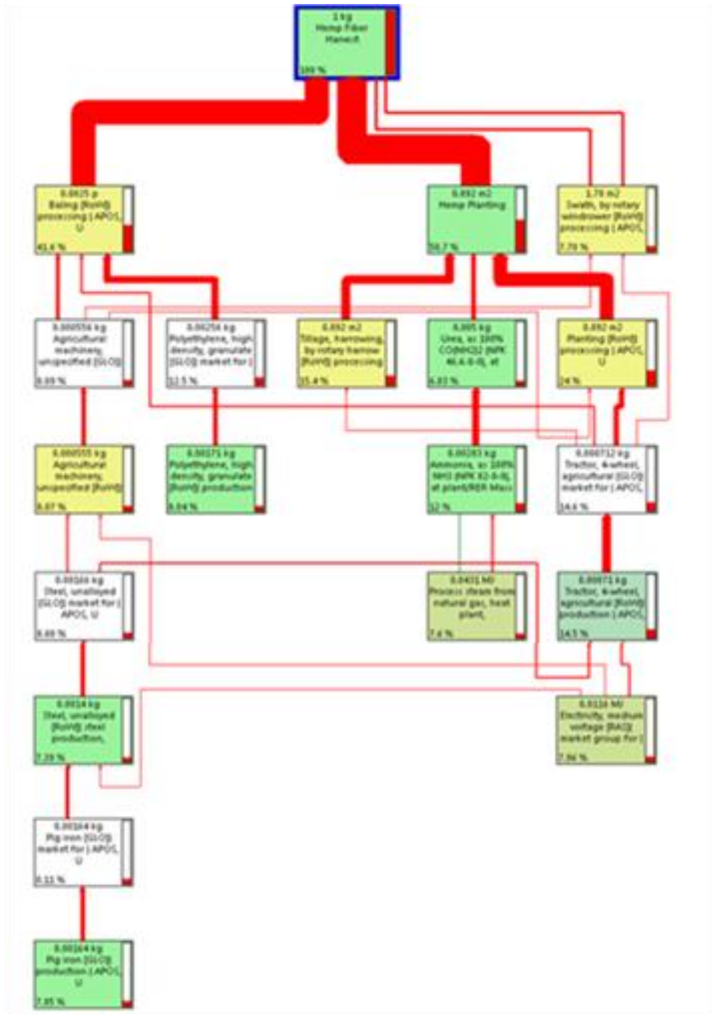


Figure 3.4: The process network for hemp fiber harvest. Thickness of arrows and red bars within nodes indicate a larger contribution to the overall environmental impact.

Chapter 4: Conclusion

Farmers in the United States are facing new challenges as time goes on. From declining prices to an overall decline in the number of farms, finding ways to improve farm productivity is paramount to farm managers to ensure the continued profitability of the farm. In addition to profits, producers must ensure that what they are doing will cause as little harm to the environment as is possible. These two issues are the drivers of this study. With dairies on the decline across the southeast and Kentucky in particular, dairy managers must find ways to lower the somatic cell count of the milk they are producing to ensure they can get the highest price possible. The panel stochastic efficiency model in "Dairy of a Madman: A Panel Stochastic Efficiency Model of the Relationship Between Somatic Cell Count and Dairy Farming Practices" seeks to answer the question of which dairy management practices have a significant impact on somatic cell count.

Additionally, with the passage of the 2018 Farm Bill allowing for the increased production of Industrial Hemp, the environmental impacts of the crop have come under scrutiny to truly test the claim of it being an eco-friendly alternative to traditional crops. In order to determine hemp's environmental impact and compare it to traditional crops such as hay and tobacco, "Hemper Tantrum: A Life Cycle Analysis on the Environmental Impact of Hemp Fiber Production" uses a life cycle analysis model to determine what part of the hemp fiber production process contributes the largest environmental impact and how the overall process compares to hay and tobacco.

"Dairy of a Madman: A Panel Stochastic Efficiency Model of the Relationship Between Somatic Cell Count and Dairy Farming Practices" uses dairy management survey data collected by the Southeastern Quality Milk Initiative from the same 27 dairy farms throughout the southeast across multiple years. With questions spanning multiple topics such as animal health, operations management, sanitation, and machinery maintenance, the survey data were transformed into dummy variables. The data for Kentucky were input into two different panel stochastic efficiency models, a time-varying decay model with a truncated-normal distribution and a true random effects model with a half-normal distribution, to determine which management decisions impact somatic cell count more significantly as well as the efficiency scores of the farms. It was found that performing sanitation within the milking parlor more often and performing maintenance checks and repairs more often were significant in determining somatic cell count. Based on the efficiency scores calculated by the two methods, it was found that the true random effects model with a half-normal distribution best fits the Kentucky dairy data.

The implications of this research are that dairy managers should make sure that they are correctly sanitizing the milking parlor more frequently and should conduct routine maintenance checks and repairs more frequently in addition to their other practices in order to ensure that the somatic cell count of the milk taken to co-ops is lower and they will avoid penalties. For future research on this topic, a larger dataset should be used with the true random effects model with a half-normal distribution as well as investigating other ways of calculating a panel stochastic efficiency frontier in order to determine the most accurate way of describing the efficiency levels of the farms.

“Hemper Tantrum: A Life Cycle Analysis on the Environmental Impact of Hemp Fiber Production” uses data from the various databases within the SimaPro software, the University of Kentucky industrial hemp budget, and outside research to perform a life cycle assessment on the production of industrial hemp fiber. Data on fertilizer and cultivation practices was taken from the industrial hemp budget and combined with the process information contained within SimaPro to determine the overall environmental impact of hemp fiber production as well as the impacts of individual processes and how they contributed to the total across the measures of global warming potential, acidification, freshwater exotoxicity, human toxicity, and land occupation. It was found that the largest contributor to the overall environmental impact of hemp fiber production was the planting process. The results were then compared to LCA results on hay and tobacco to determine if industrial hemp was a more eco-friendly alternative to the more traditional crops. According to the LCA results, industrial hemp carries less global warming potential, acidification, and freshwater exotoxicity than the other crops while hay and tobacco were superior in human toxicity and tobacco, respectively.

This research implies that hemp is, in fact, a more environmentally friendly crop than more traditional ones such as hay and tobacco. Further, most of this impact came from the machinery used in planting and was mitigated by hemp’s natural characteristics, which cause it to require less fertilizer and pesticides than other crops. Future research on the subject would refine the LCA process data as well as expand the model to include the manufacture of one of hemp’s various products. Further research could also focus on comparing the environmental impacts of hemp fiber production vs. hemp seed production.

As agricultural markets and practices change, producers must be ready to adapt. This could entail making changes to dairy management practices to achieve higher milk quality or embracing a new plant for its eco-friendly qualities and lower fertilizer dependence. As the legislative landscape for both industries continues to shift (with milk quality requirements becoming more stringent for producers and the regulations of hemp becoming less stringent), producers must keep in mind the costs associated with managing a dairy operation and producing hemp. The panel stochastic efficiency model of "Dairy of a Madman: A Panel Stochastic Efficiency Model of the Relationship Between Somatic Cell Count and Dairy Farming Practices" and the life cycle assessment of "Hempter Tantrum: A Life Cycle Analysis on the Environmental Impact of Hemp Fiber Production" serve as foundations which can be used to create a management index for both industries, which can serve as future avenues of research for both studies, particularly in Kentucky where dairies are on the decline, and industrial hemp research is on the rise.

References

Abass, Adebayo, Paul Amaza, Beatrice Bachwenkizi, Kelly Wanda, Ambrose Agona, and Nicolaus Cromme. 2017. “The Impact of Mechanized Processing of Cassava on Farmers’ Production Efficiency in Uganda.” *Applied Economics Letters* 24 (1–3): 102–6.

Abdulai, Abdul Nafeo, and Awudu Abdulai. 2016. “Allocative and Scale Efficiency among Maize Farmers in Zambia: A Zero Efficiency Stochastic Frontier Approach.” *Applied Economics* 48 (55–57): 5364–78.

Aigner, Dennis, C.A. Knox Lovell, and Peter Schmidt. 1977. “Formulation and Estimation of Stochastic Frontier Production Function Models.” *Journal of Econometrics* 6: 21-37.

Alberta Agriculture and Forestry Information Management. 2017. “Industrial Hemp Enterprise.” *Alberta Government.*

Anderson, Randy I., Mary Fish, Yi Xia, and Frank Michello. 1999. “Measuring Efficiency in the Hotel Industry: A Stochastic Frontier Approach.” *International Journal of Hospitality Management* 1: 45-57.

Arena, Noemi, Jacquetta Lee, and Roland Clift. 2016. “Life Cycle Assessment of Activated Carbon Production from Coconut Shells.” *Journal of Cleaner Production* 125: 68-77

Battese, G. E., and T. J. Coelli. 1988. “Prediction of Firm-Level Technical Efficiencies with a Generalized Frontier Production Function and Panel Data.” *Journal of Econometrics* 38: 387-399.

Battese, G. E., and T. J. Coelli. 1992. “Frontier Production Functions, Technical Efficiency, and Panel Data: With Application to Paddy Farmers in India.” *Journal of Productivity Analysis* 3: 159-169.

Battese, G. E., and T. J. Coelli. 1995. “A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data.” *Empirical Economics* 20: 325.

Belotti, Federico, Silivo Daidone, Giuseppe Ilardi, and Vincenzo Atella. 2013. “Stochastic Frontier Analysis Using Stata.” *The Stata Journal* 13 (4): 719-758.

Bing Wang, Yongang Li, Hongyu Si, Huiyuan Chen, Ming Zhang, and Tao Song. 2018. “Analysis of the Physical and Chemical Properties of Activated Carbons Based on Hulless Barley Straw and Plain Wheat Straw Obtained by H3PO4 Activation.” *BioResources* 13 (3): 5204-12.

Bravo-Ureta, Boris E., and Laszlo Rieger. 1991. “Dairy Farm Efficiency Measurement Using Stochastic Frontiers and Neoclassical Duality.” *American Journal of Agricultural Economics* 73 (2): 421-428.

Brown, A. Blake, William M. Snell, and Kelly Tiller. 1999. “The Changing Political Environment for Tobacco- Implications for Southern Tobacco Farmers, Rural Economies, Taxpayers, and Consumers.” *Journal of Agricultural and Applied Economics* 31 (2): 291-308.

Brzyski, Przemyslaw, and Stanislaw Fic. 2017. “The Application of Raw Materials Obtained from the Cultivation of Industrial Hemp in Various Industries.” *Economics and Regional Studies* 10 (1): 100-113.

Cambala, Akanksha D., Radhika Arjun Kumar, and Thamaraiselvan Murugan. 2019. “Comparative Study of the Severity of Periodontal Destruction in Chronic Periodontitis Patients with Habits of Smoking Tobacco versus Chewing Smokeless Tobacco.” *Drug Invention Today* 11 (1): 173-76.

Cebenoyan, A. Sinan, Elizabeth S. Cooperman, Charles A. Register, and Sylvia C. Hudgins. 1993. “The Relative Efficiency of Stock versus Mutual S&Ls: A Stochastic Const Frontier Approach.” *Journal of Financial Services Research* 7 (2): 151-170.

Chartier, Jeremy. 2019. “Baling Hay on the Homestead.” *Countryside & Small Stock Journal* 103 (2): 28.

Chen, Ching-Fu. 2007. “Applying the Stochastic Frontier Approach to Measure Hotel Managerial Efficiency in Taiwan.” *Tourism Management* 28(3): 696-702.

Crisci, Anna, Lucio Siviero, and Luigi D’Ambra. 2016. “Technical Efficiency with Several Stochastic Frontier Analysis Models Using Panel Data.” *Electronic Journal of Applied Statistical Analysis* 9 (4): 736–59.

Economic Research Service. 2019. “Dairy Situation at a Glance.” *United States Department of Agriculture.*

Elga LabWater. 2019. “Activated Carbon.” *ElgaLabWater.com*

Environmental Protection Agency. “Understanding Global Warming Potentials.” *Epa.gov.*

Estep, Bill “Kentucky’s Dairy Farms are Disapperaing; Most Milk at Stores isn’t Local. Why?” *Lexington Herald Leader* December 31, 2018 issue.

Esguerra, Juan C., Laerte D. Cassoli, Oscar D. Múnera-Bedoya, Mario F. Cerón-Muñoz, and Pablo F. Machado. 2018. “Milk Quality: Milking Personnel Associated Factors.” *Revista MVZ Córdoba* 23 (1): 6461–73.

Greene, William. 2005. “Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model.” *Journal of Econometrics* 126: 269-303.

Johnson, Renee. 2017. “Hemp and an Agricultural Commodity.” *Congressional Research Service.*

Jondrow, James, C.A. Knox Lovell, Ivan S. Materov, and Peter Schmidt. 1982. "On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Function Model." *Journal of Econometrics* 19: 233-238.

Kim, GwanSeon, and Tyler Mark. 2018. "Who are Consuming Hemp Products in the U.S.? Evidence from Nielsen Homescan Data." *Southern Agricultural Economics Association 2018 Annual Meeting* Selected Paper.

Hertwich, EG, SF Mateles, WS Pease, and TE McKone. 2001. "Human toxicity potentials for life-cycle assessment and toxics release inventory risk screening." *Environmental Toxicology and Chemistry* 20 (4): 928-39.

Lask, Jan, Moritz Wagner, Luisa M. Trindade, and Iris Lewandowski. 2019. "Life Cycle Assessment of Ethanol Production from Miscanthus: A Comparison of Production Pathways at Two European Sites." *GCB Bioenergy* 11 (1): 269-88.

Liu, Yanyan. 2006. "Model Selection in Stochastic Frontier Analysis: Maize Production in Kenya." *American Agricultural Economics Association Annual Meeting.* Selected Paper.

Mark, Tyler, and Jonathan Shepherd. 2019. "Farm-Level Economics of Hemp." *University of Kentucky College of Agriculture Department of Agricultural Economics.*

Mark, Tyler, and Jonathan Shepherd. 2019. "Industrial Hemp Budgets 2019." *University of Kentucky College of Agriculture Department of Agricultural Economics.*

Manteuffel Szoege, Henryk, and Agnieszka Sobolewska. 2009. "Life Cycle Analysis with Regard to Environmental Impact of Apple Wholesale Packaging." *Problems of World Agriculture* 6 (21): 59-68.

National Agricultural Statistics Service. 2018. "Farms and Land in Farms 2017 Summary." *United States Department of Agriculture.*

National Agricultural Statistics Service. 2019. "Prices Received: Milk Prices Received by Month, US." *United States Department of Agriculture.*

National Renewable Energy Laboratory. "U.S. Life Cycle Inventory Database." *United States Department of Energy*.

New Zealand Ministry of the Environment. "Appendix A: Impact Category Descriptions." *Mfe.govt.nz.*

Office on Smoking and Health. 2018. "Economic Trends in Tobacco." *Center for Disease Control*.

Pal, lokendra, and Lucian Lucia. 2019. "Renaissance of Industrial Hemp: A Miracle Crop for a Multitude of Products." *BioResources* 14 (2): 2460-64.

Purdue University Hemp Project. 2015. "Hemp Production." *PudueHemp.org*

Razumova, Olga V., Oleg S. Alexandrov, Mikhail G. Divashuk, Tatiana I. Sukhorada, and Gennady I. Karlov. 2016. “Molecular Cytogenetic Analysis of Monoecious Hemp (Cannabis Sativa L.) Cultivars Reveals Its Karyotype Variations and Sex Chromosomes Constitution.” *Protoplasma* 253 (3): 895-901.

Risvanli, Ali, Ibrahim Seker, Nevzat Saat, Burcu Karagulle, Abdurrahman Koseman, and Erdal Kaygusuzoglu. 2017. “The Management Practices and Microbiological Quality of a Dairy Farm with Low Bulk Tank Milk Somatic Cell Count.” *Pakistan Veterinary Journal* 37 (2): 175–79.

Samnang Tim, and Warangkana Jutidamrongphan. 2018. “Life Cycle Cost Analysis and Energy Performance of President’s Office, Prince of Songkla University, Thailand.” *Songklanakarin Journal of Science & Technology* 40 (2): 440-48.

Schenck, Rita C. 2000. “LCA for Mere Mortals: A Primer on Environmental Life Cycle Assessment.” *Institute for Environmental Research and Education.*

Shao, B.B.M., and W.T. Lin. 2001. “Measuring the Value of Information Technology in Technical Efficiency with Stochastic Production Frontiers.” *Information and Software Technology* 43 (7): 447-456.

SimaPro Databases. *SimaPro.com.*

Simpson-Holley, Martha, and Ian Law. 2007. “Renewable in More Ways than One: Hemp Returns to UK Farming. (Cover Story).” *Biologist* 54 (1): 18-23.

Skrzypek, R., J. Wójtowski, and R.-D. Fahr. 2004. “Factors Affecting Somatic Cell Count in Cow Bulk Tank Milk – A Case Study from Poland.” *Journal of Veterinary Medicine Series A* 51 (3): 127–31.

Southeast Quality Milk Initiative. 2013. *Agriculture and Good Research Initiative Competitive Grant number 2013-68004-20424.*

United States Department of Agriculture. 2000. “Industrial Hemp in the United States: Status and Market Potential.” *USDA Economic Research Service* Report.

United States Department of Agriculture. 2019. “2017 Census of Agriculture.” *United States Department of Agriculture.*

USDA Center for Epidemiology and Animal Health. 2012. “Determining U.S. Milk Quality Using Bulk Tank Somatic Cell Counts, 2011.” *APHIS Info Sheet.*

USDA Economic Research Service. 2018. “U.S. Dairy Situation at a Glance (Monthly and Annual).” *Dairy Data.*

Usetox. “How to Use Characterization Factors.” *Usetox.org*

World Health Organization. 2017. “Tobacco and its Environmental Impact: an Overview.” *World Health Organization.*

Xinxin Ma, Lee M. Smith, Liping Cai, Sheldon Q. Shi, Hui Li, and Benjua Fei. 2019. “Preparation of High-Performance Activated Carbons Using Bamboo through One-Step Pyrolysis.” *BioResources* 14 (1): 688-99.

Zafeiridou, Maria, Nicholas S Hopkinson, and Nikolaos Voulvoulis. 2018. “Cigarette Smoking: An Assessment of Tobacco’s Global Environmental Footprint Across Its Entire Supply Chain.” *Environmental Science and Technology* 52 (15): 8087-8094.

Zaman, Ronaq, Shahid Ali, and Inam Ullah. 2018. “Technical Efficiency of Broiler Farms in District Mansehra, Pakistan: A Stochastic Frontier Trans-Log Production Approach.” *Sarhad Journal of Agriculture* 34 (1): 158–67.

Vita

Alexander O. Swartz

Education

B.A. Economics and Accoutning, Bellarmine University, Louisville, KY

Professional History
Data Analyst- LG&E and KU Energy. Louisville, KY. May 2019 – Present

Banquet Manager – Culbertson West Events. New Albany, IN. June 2013 – Present

Graduate Research Assistant – UK Dept. of Agriculture Economics. Lexington, Ky. August 2017 – April 2019

Business Research Analyst Intern - Kentucky Farm Bureau Insurance Agency. Louisville, KY. May 2018 – August 2018

Math Teacher – Summerbridge Louisville. Louisville, KY. June 2017 – July 2017

Presentations
"A Life Cycle Analysis on the Environmental Impact of Hemp Fiber." *KY NSF EPSCoR Super Collider.* Lexington, KY April 19, 2019. *Poster*.

"Udder Efficiency: A Panel Stochastic Efficiency Model of the Relationship between Somatic Cell Count and Dairy Farming Practices." *Southern Agriculture Economics Association*. Birmingham, AL February 2-5, 2019. *Selected Paper.*

"A Regression of the Impact the Crop Intensification Program and Other Factors have had on Real Per Capita GDP in Rwanda." *Bellarmine University Undergraduate Research Fair*.
Louisville, KY April 2017. *Poster.*