Evaluating The Performance Of Animal Shelters: An Application Of Data Envelopment Analysis

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EVALUATING THE PERFORMANCE OF ANIMAL SHELTERS: AN APPLICATION OF DATA ENVELOPMENT ANALYSIS

by

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ABSTRACT

The focus of this thesis is the application of data envelopment analysis to understand and evaluate the performance of diverse animal welfare organizations across the United States. The results include identification of the most efficient animal welfare organizations, at least among those that post statistics on their operations, and a discussion of various partnerships that may improve the performance of the more inefficient organizations.

The Humane Society of the United States estimates that there are 4000 - 6000 independently-run animal shelters across the United States, with an estimated 6-8 million companion animals entering them each year. Unfortunately, more than half of these animals are euthanized. The methods shared in this research illustrate how data envelopment analysis may help shelters improve these statistics through evaluation and cooperation.

Data envelopment analysis (DEA) is based on the principle that the efficiency of an organization depends on its ability to transform its inputs into the desired outputs. The result of a DEA model is a single measure that summarizes the relative efficiency of each decision making unit (DMU) when compared with similar organizations. The DEA linear program defines an efficiency frontier with the most efficient animal shelters that are put into the model that "envelops" the other DMUs. Individual efficiency scores are calculated by determining how close each DMU is to reaching the frontier.

The results shared in this research focus on the performance of 15 animal shelters. Lack of standardized data regarding individual animal shelter performance limited the ability to review a larger number of shelters and provide more robust results. Various programs are in place within the United States to improve the collection and availability of individual shelter performance. Specifically, the Asilomar Accords provide a strong framework for doing this and could significantly reduce euthanasia of companion animals if more shelters would adopt the practice of collecting and reporting their data in this format. It is demonstrated in this research that combining performance data with financial data within the data envelopment analysis technique can be powerful in helping shelters identify how to better deliver results. The addition of data from other organizations will make the results even more robust and useful for each shelter involved.

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LIST OF ACRONYMS/ABBREVIATIONS

DEA	Data Envelopment Analysis
DMU	Decision Making Unit
FIREPAW	Foundation for the Interdisciplinary Research & Education Promoting Animal Welfare
KPI	Key Performance Indicator

1. INTRODUCTION

Why Should Animal Shelter Performance be Measured?

The numbers are astounding. The Humane Society of the United States estimates that there are 4000 - 6000 independently-run animal shelters across the United States, with an estimated 6-8 million companion animals entering them each year (Humane Society, 2006).

Although the Humane Society posted statistics in 2006, the most widely recognized pet overpopulation study was done by the National Council on Pet Population Study and Policy in 1997. Study results showed that about half of the animals entering a shelter have been relinquished by owners, and the other half are picked up by animal control. It is from these numbers that estimates have been derived to understand what is occurring nationwide. Approximately 9.6 million animals are euthanized annually in the United States (American Humane, 2002), and less than 2% of cats and 15% of dogs are actually reunited with their owners. About 24-25% of the animals are adopted. These statistics help explain why it is so important to focus on the continuous improvement of shelter performance. A reduction of just one percentage of the animals that are euthanized would result in 96,000 fewer animals' lives being cut short each year.

The statistics from the 1997 study done by the National Council on Pet Population Study and Policy were compiled by studying 1000 shelters who responded to a survey. These shelters handled 4.3 million animals, of which 2.7 million, or 64%, were euthanized. Approximately 56% of dogs that entered a shelter were euthanized versus 71% of cats, mostly due to the fact that more cats arrive without owner identification, such as a collar or microchip (American Humane, 2002). Animals may be euthanized for many reasons; overcrowding is just one of these reasons. Some animals may be sick or injured or considered too aggressive to be placed in a home.

The true magnitude of these numbers is hard to pinpoint because there is no formal structure in place in the United States to measure the operational statistics of various shelters and animal welfare societies. Although most individual groups do collect data on their operation, formats vary and most agencies do not tend to actively publish their statistics widely. Therefore, almost all knowledge that exists on an aggregate, national level comes from studies that are done specifically to collect data from various shelters and provide a comprehensive analysis based on the samples. Throughout the past two decades there have been many organizations and movements put in place to help address this problem, including the National Council on Pet Population Study and Policy, the Asilomar Accords, and Maddie's Fund® guidelines.

The National Council on Pet Population Study and Policy was established in 1993 by a group of animal-related groups that came together for a common cause:

> “The mission of the National Council is to gather and analyze reliable data that further characterize the number, origin, and disposition of pets (dogs and cats) in the United States; to promote responsible stewardship of these companion animals; and based on the data gathered, to recommend programs to reduce the number of surplus/unwanted pets in the United States.” (The National Council on Pet Population Study and Policy, 2007)

The council conducted surveys in 1994, 1995, 1996, and 1997 to better understand the national pet population and, specifically, animal traffic through shelters. The studies were done by sending survey cards to each of the approximately 5000 shelters believed to be in the United States at the time. The study was eventually halted because of the low number of survey respondents. The focus of the council’s studies switched to better understand the population of pet owners and why they purchase and dispose of their animals, as well as the characteristics of animals that have been relinquished. One study explains why most animals are relinquished to shelters. Among the top reasons are owners moving, landlord issues, cost of maintenance, and too many pets in the home (National Council for Pet Population Study and Policy, 2008).

In addition to the National Council for Pet Population Study and Policy, the Asilomar Accords were created in August 2004 to foster a more consistent method for collecting and reporting operational shelter data. These records seemed to introduce a new way of thinking about and addressing pet overpopulation. The guiding principles encouraged shelters to become more liberal with sharing private information and to work together to reduce overall euthanasia on a community-wide basis. They put together specific definitions for how data should be classified and introduced these definitions to all of the shelters that decided to follow this method of collecting data. They built standardized tables to collect and display the information, as well as common formulas to calculate key performance indicators. By doing so, they began to create a common method for reporting information and built the foundation needed to use data from the various shelters in order to build an aggregate picture of shelter operations. A desired outcome is for all of the shelters involved to more effectively run their operations and cross-utilize their resources with other shelters around them (Asilomar Accords, 2004).

Richard Avanzino, Maddie's Fund® President, was one of the founders of the Asilomar Accords. Maddie's Fund® is a charitable foundation that was started in 1999 when the founders of PeopleSoft were inspired to start the group in the name of their beloved miniature schnauzer, named Maddie. An excerpt from the mission statement for Maddie's Fund® is:

> The Maddie's Fund® mission is to revolutionize the status and wellbeing of companion animals. Maddie's Fund®, the Pet Rescue Foundation (www.maddiesfund.org), is a family foundation established in 1999 to help fund the creation of a no-kill nation. The first step is to help create programs that guarantee loving homes for all healthy shelter dogs and cats throughout the country. The next step is to save the sick, injured and poorly behaved pets in animal shelters nationwide (Maddie's Fund®, 1999).

Maddie's Fund® is the largest animal welfare nonprofit organization, in terms of financial assets, in the United States. It focuses on community-wide initiatives and projects (Frank, 2007). Maddie's Fund® awards money through grants every year to shelters across America who are working toward the "no-kill" goal by reducing the number of healthy and treatable animals that are euthanized each year. In order to receive a Maddie's Fund® grant, a shelter must provide its data in the format set forth in the Asilomar Accords. Maddie's Fund® makes a strong statement in support of a more unified process for collecting and reporting shelter data. It seems to be having an impact on the shelters who have applied for the grants. Through an Internet search and calls to various animal welfare agencies, 17 shelters were found to have recorded and published their data in the Asilomar Accords format. There may be more shelters that have done so, but their data have not been discovered. Hopefully the number of shelters releasing these data will continue to grow as more and more shelters recognize the benefit of and/or apply for a Maddie's Fund® grant.

What Is Data Envelopment Analysis?

Businesses are constantly looking for new ways to measure their performance and understand how to improve upon their current operational practices. They often compare themselves to other businesses performing similar functions in an effort to understand how well each business is performing. Individual businesses have opportunities to identify not only how well they are doing but also to learn ways to continuously improve. Such a comparison is not only useful to individual businesses that are looking to learn from their peers, but it is also useful to analysts who are responsible for looking at a macro-view of how an industry is performing, how specific units within in the industry are faring, and what may be forecasted for the future.

Analysts often look for metrics that allow them to quickly gauge operational efficiency and calculate how well an entity is performing. Operational, or resource, efficiency is easy to calculate in situations in which only one output is being measured against one input. In these situations, efficiency is simply the ratio of output to input. For example, this could be the number of items produced per staff member or the number of customers served per labor hour. Unfortunately, most businesses cannot look at just one input and one output to determine how well they are performing. Efficiency becomes much more difficult to measure when multiple inputs and outputs are being examined simultaneously. A simple ratio no longer tells the story and multiple ratios are hard to build into a consistent message. Data envelopment analysis (DEA) is one method that can be used to evaluate multiple decision making units (DMU) on various inputs and outputs simultaneously.

A DMU is an entity that has the responsibility for deciding how to use various resources (or inputs) to produce outputs. By collecting resource usage and output data on multiple DMUs with the same operational goals, a DEA linear programming model can be formulated. Such a model can then be used to identify how efficiently each DMU is utilizing its resources in comparison with the other DMUs being evaluated. A version of the model is run for each DMU, allowing each DMU to uniquely choose the weights that are assigned to each of its inputs and outputs in order to maximize its efficiency score. When run, the model identifies best-in-class DMUs that most efficiently utilize their input resources to produce output. These best-in-class DMUs provide a comparison point for the other units. Mathematically, this works by creating an efficiency (or production) frontier with the best DMUs "enveloping" the other units in a multi-dimensional space. The efficiency score for each DMU is calculated by determining how much less input or more output the unit would need to produce to become a part of the production frontier.

Utilizing the theory of DEA to help better understand the operational efficiency of multiple animal shelters could be a very powerful tool to help quantify and address the problem of pet overpopulation. A DEA model that contains an abundant amount of shelter data will identify best-in-class shelters that utilize their resources to most efficiently place animals into adoption or return them to their owners. The unique benefit that DEA brings is that it allows shelter efficiency to be determined relative to other shelters that operate with a similar or dissimilar magnitude of inputs and outputs. In addition, the solution to the model will help direct the focus of a specific shelter to the inputs or outputs that most significantly impact its overall performance.

The remainder of this document is organized as follows. Chapter 2 is a summary of relevant literature about animal welfare and DEA. Then, Chapter 3 outlines the steps to build the proposed DEA model for analyzing the performance of animal shelters. Chapters 4 and 5 present results of the model and conclusions.

2. LITERATURE REVIEW

Animal Welfare

FIREPAW, Inc.

The Foundation for the Interdisciplinary Research & Education Promoting Animal Welfare (FIREPAW) was established as a charitable, nonprofit organization focused on research, analysis, and education to stop animal suffering (FIREPAW, 2007). This group uses data associated with Maddie's Fund® to do its analysis.

According to Frank and Frank (2007), Americans are highly inclined to support animal welfare programs. Twenty percent of Americans have contributed money to an animal welfare organization, and 10-15 million Americans belong to at least one animal welfare group. Congress receives more letters regarding animal welfare than any other topic. In effect, there are major efforts underway in the United States to decrease shelter deaths, and many organizations and individuals have adopted the belief that the U.S. should move toward a "no-kill" society.

Asilomar Accords

The Asilomar Accords were written in August 2004 by a group of animal welfare specialists from all over the United States. This group met at Asilomar in

Pacific Grove, California to work together toward the goal of reducing the euthanasia of healthy and treatable companion animals in the United States (Asilomar Accords, 2004). There were 20 people in that original meeting from various animal welfare societies including The Humane Society of the United States, Maddie's Fund®, The National Council on Pet Population Study and Policy, American Society for the Prevention of Cruelty to Animals, the Society of Animal Welfare Administrators (SAWA), the American Humane Association, and various privately run animal shelters.

One of the most significant guiding principles in the Asilomar Accords is the belief that euthanasia of healthy and treatable animals can only be addressed by a community-wide focus and community-based solutions. They recognize the fact that euthanasia is a sad responsibility of some organizations that neither desired nor wanted the task.

The most relevant guiding principle of their work that aligns with our work is the belief that all organizations should openly share accurate, complete animal-sheltering data and statistics in a method that is clear to both the animal welfare community and the public. In addition, they should utilize a uniform method for collecting and reporting shelter data so that analysis can be done easily. The Asilomar Accords include an "Animal Statistics Table" that provides an outline for reporting shelter data and calculating key indicators. We used data from 15 shelters that posted their information in the format of the "Animal Statistics Table" in this research.

The following definitions are used to categorize dogs and cats in the various organizations that report their data according to the Asilomar Accords (Asilomar Accords, 2004).

Healthy: The term "healthy" means and includes all dogs and cats eight weeks of age or older that, at or subsequent to the time the animal is taken into possession, have manifested no sign of a behavioral or temperamental characteristic that could pose a health or safety risk or otherwise make the animal unsuitable for placement as a pet, and have manifested no sign of disease, injury, a congenital or hereditary condition that adversely affects the health of the animal or that is likely to adversely affect the animal's health in the future.

Treatable: The term "treatable" means and includes all dogs and cats who are "rehabilitatable" and all dogs and cats who are "manageable."

Rehabilitatable: The term "rehabilitatable" means and includes all dogs and cats who are not "healthy," but who are likely to become "healthy," if given medical, foster, behavioral, or other care equivalent to the care typically provided to pets by reasonable and caring pet owners/guardians in the community.

Manageable: The term "manageable" means and includes all dogs and cats who are not "healthy" and who are not likely to become "healthy," regardless of the care provided; but who would likely maintain a satisfactory quality of life, if given medical, foster, behavioral, or other care, including long-term care, equivalent to the care typically provided to pets by reasonable and caring owners/guardians in the community; provided, however, that the term "manageable" does not include any dog or cat who is determined to pose a significant risk to human health or safety or to the health or safety of other animals.

Unhealthy and Untreatable: The term "unhealthy and untreatable" means and includes all dogs and cats who, at or subsequent to the time they are taken into possession,

(1) have a behavioral or temperamental characteristic that poses a health or safety risk or otherwise makes the animal unsuitable for placement as a pet, and are not likely to become "healthy" or "treatable" even if provided the care typically provided to pets by reasonable and caring pet owners/guardians in the community; or

(2) are suffering from a disease, injury, or congenital or hereditary condition that adversely affects the animal's health or is likely to adversely affect the animal's health in the future, and are not likely to become "healthy" or "treatable" even if provided the care typically provided to pets by reasonable and caring pet owners/guardians in the community; or

(3) are under the age of eight weeks and are not likely to become "healthy" or "treatable," even if provided the care typically provided to pets by reasonable and caring pet owners/guardians in the community.

Table 2-1 was developed as part of the Asilomar Accords. It shows the preferred format for presenting data for animal shelters.

Table 2-1: Asilomar Accords Annual Animal Statistics Table

		Dogs	Cats	Total
A	BEGINNING SHELTER COUNT (date)			
	INTAKE (Live Dogs & Cats Only)			
B	From the Public			
C	Incoming Transfers from Organizations within Community/Coalition			
D	Incoming Transfers from Organizations outside Community/Coalition			
E	From Owners/Guardians Requesting Euthanasia			
F	Total Intake [B + C + D + E]			
G	Owner/Guardian Requested Euthanasia (Unhealthy & Untreatable Only)			
H	ADJUSTED TOTAL INTAKE [F minus G)			
I	ADOPTIONS			
J	OUTGOING TRANSFERS to Organizations within Community/Coalition			
K	OUTGOING TRANSFERS to Organizations outside Community/Coalition			
L	RETURN TO OWNER/GUARDIAN			
	DOGS & CATS EUTHANIZED			
M	Healthy (Includes Owner/Guardian Requested Euthanasia)			
N	Treatable – Rehabilitatable (Includes Owner/Guardian Requested Euthanasia)			
O	Treatable – Manageable (Includes Owner/Guardian Requested Euthanasia)			
P	Unhealthy & Untreatable (Includes Owner/Guardian Requested Euthanasia)			
Q	Total Euthanasia [M + N + O + P]			
R	Owner/Guardian Requested Euthanasia (Unhealthy & Untreatable Only)			
S	ADJUSTED TOTAL EUTHANASIA [Q minus R]			
T	SUBTOTAL OUTCOMES [I + J + K + L + S] Excludes Owner/Guardian Requested Euthanasia (Unhealthy & Untreatable Only)			
U	DIED OR LOST IN SHELTER/CARE			
V	TOTAL OUTCOMES [T + U] Excludes Owner/Guardian Requested Euthanasia (Unhealthy & Untreatable Only)			
W	ENDING SHELTER COUNT (date)			

Charity Ratings Agencies

Throughout the past decade, technology has helped us make smarter decisions in all aspects of our lives. Charity donations are not an exception to this trend. As Americans make decisions on which charities they will support, they look to various sources to first educate them about how their money will be used. An article written in the Stanford Social Innovation Review evaluates the three groups that rank charities (Lowell, Trelstad & Meehan, 2005). This article states that these organizations have competed over the past few years to establish themselves as the main source for donors who are seeking information to guide their decisions, and it seems to be working. Many nonprofit organizations cite the successful ratings that they receive from these various agencies on their websites or within their marketing materials. However, this study highlighted three major weaknesses of the ratings agencies that would support the use of a more robust analysis tool such as DEA. First, they rely too heavily on simple analysis and ratios derived from poor-quality financial data. Second, they overemphasize financial efficiency while ignoring the question of program effectiveness. Third, they generally do a poor job of conducting analysis in important qualitative areas such as management strength, governance quality, or organizational transparency.

Charity Navigator

Charity Navigator seems to be the most widely mentioned organization currently providing rating information to consumers. Their primary focus is on financial statistics. They share revenue and expense statistics for over 5,300 American nonprofit organizations (Charity Navigator, 2006). They not only show aggregate numbers but also the breakdown of the various revenue streams and exactly how the money is spent. In addition, they share historical financial data, key contacts, and provide links to organizations' websites. Although the mere fact that Charity Navigator provides a centralized repository for all of these data is extremely valuable to the end user, they provide additional insight beyond this point to those who are interested. They analyze the financial data for the various organizations, and provide ratings for the effectiveness of each group.

These ratings allow people to search quickly through multiple choices for making donations and evaluate the organizations before they make a decision. Users are able to build an individual user ID for the website that allows them to customize the view that they see each time they return to the site. In doing so, they can track specific charities to see how their money is being used, or how their favorite charities continue to compare to each other and their peers.

Charity Navigator currently provides efficiency scores for 247 animal rights, animal welfare, or animal services groups spread widely across the United States (Charity Navigator, 2006). Seventy-seven (or 31%) of the 247 organizations received the highest efficiency score of four stars, 102 (or 41%) of these organizations received three stars, 48 (or 20%) received two stars, and the remaining 20 (or 8%) received the lowest score of one star. The methodology used to calculate these scores focuses on two areas of evaluation: organizational efficiency and organizational capacity.

Organizational efficiency is meant to be a measure of effectiveness in day-to-day operation. Charity Navigator's philosophy is that efficient organizations spend less to raise more. Financially this means that they keep fundraising expenses to goal, administrative expenses reasonable, and spend most of their money directly on the services they provide (Charity Navigator, 2006). The four areas used to measure organizational efficiency are program expenses, administrative expenses, fundraising expenses, and fundraising efficiency.

Organizational capacity is a measure of an organization's ability to sustain its performance throughout economic change, as well as a prediction of its ability to do so in the future. Charity Navigator rates charities that have shown consistent growth and financial stability with a high score in organizational capacity. Financial stability means that an organization makes a large enough profit to continue to focus on strategic projects and grow its ability to influence the end state of the service it is trying to provide. To be considered functionally stable, the charity cannot have its focus on fundraising only to meet all of its administrative bills each year. Three categories are used to determine the financial-stability measurement: primary revenue growth, program expenses growth, and working capital ratio.

The evaluation by Charity Navigator is calculated entirely from financial information that is provided on the annual tax return, IRS Form 990, completed by each organization. Seven major categories are used to develop scores for each organization, and then a process is used to normalize the scores in each of these categories against other organizations with a similar focus (Charity Navigator, 2006). Once the scores for the organizations have been normalized, three other categories are used to provide ratings on the individual organizations. These ratings are for the charity's organizational efficiency, organizational capacity, and overall financial health. The following describes each rating category.

Program expenses are evaluated by dividing the total program expenses by the total functional expenses to develop a ratio for the proportion of operating budget that is spent on actual services provided by the charity. This ratio is then used to develop a score for how well the charity performs. In general, Charity Navigator believes that any organization that does not spend at least one-third of its operating budget on the services it provides is not adequately performing to its mission. Organizations that meet this threshold are then rated in conjunction with how well they beat that threshold. They have found that seven out of ten charities spend at least 75% of their budget on the services and programs that they are in place to provide, and only one out of ten spends less than 65%.

Administrative expenses encompass the money needed to recruit, develop, and retain talented people to make sure that the organization delivers upon its mission. Administrative expenses are also evaluated by comparing them to the total functional expenses. The proportion of expenses used on administrative expenses is then used to develop a rating for this category, with lower proportions receiving higher scores because these groups have been able to best manage their total administrative costs.

Fundraising expenses are measured because charities exist to provide services and deliver upon their mission. Charities are not in place to grow their profit margin. So fundraising expenses are compared to total spending to determine what proportion of funds is used in fundraising. This measurement is used to develop a category score, with lower fundraising percentages converting to higher category scores.

In addition to the pure expense ratios, a measure for fundraising efficiency is calculated to determine how much money is spent to generate $1 of charitable contributions. The calculation is simply the total dollars spent on fundraising divided by the total dollars of contributions. Again, the result of this calculation is converted to a score. The lower the calculated value, the higher the score because this means that less money is spent to generate each dollar of contributions.

Adjustments are made to these scores if an organization tends to operate with a deficit in its total operating budget. This appears to be done to “normalize” organizations that may show positive proportions in each of the categories described above yet operate overall with more money than they actually have to spend. Obviously, this practice is not healthy on a long-term basis.

Similar to other businesses, charities want to continue to grow over time and provide even more abundant service and help to the community. Charity Navigator identifies two key areas of growth measured through the financials. The first is primary revenue growth. This type of growth is defined by Charity Navigator to include contributions from corporations, foundations, individuals, government grants, program service revenue, contracts and fees, and revenue from membership dues and fees. In addition to revenue growth, growth can be recognized in continuing to provide more programs and services, the second key area of growth measured by Charity Navigator. Each of these growth areas is measured by looking at the most recent three to five years and following a standardized formula for computing annualized growth. The results of these formulas are then converted into a category score with larger growth percentages corresponding to larger scores.

The seventh category, working capital ratio, is used to evaluate how prepared an organization is to face economic downturn. Financially this is done by looking at the liquid assets and liabilities as reported on the most recent Form 990. These include cash, savings, accounts receivable, grants receivable, pledges receivable, investments in securities, accounts payable, accrued expenses, and grants payable. To measure working capital, Charity Navigator looks at how long a charity could sustain its current programs without generating new revenue. An organization's working capital is divided by the total expenses to calculate this ratio, which is then converted into a score with higher ratios receiving higher scores.

Once all seven categories have been transformed into scores ranging from 0-10, totals are calculated. The sum of the first four categories, focused on operational efficiency, is calculated. Then the sum of the last three categories, focused on operational capacity, is calculated. These sums are then compared to a predetermined table that assigns star ratings to ranges of total scores. The combination of star rating for operational efficiency and star rating for operational capacity results in the final star rating for the organization.

Charity Navigator's methodology seems sound and is easy to explain. However, rather than having a holistic method for looking at various inputs and outputs simultaneously, Charity Navigator calculates multiple ratios and then uses an ad hoc method which they have devised to combine those ratios into a single overall rating. This is where data envelopment analysis becomes a useful tool in nonprofit performance analysis and can be a very useful tool in measuring the relative performance of animal welfare groups.

GuideStar and BBB Wise Giving Alliance

In addition to Charity Navigator, other nonprofit evaluation groups exist to help document the importance and need for this type of performance measurement and evaluation. Other large organizations include GuideStar and BBB Wise Giving Alliance. GuideStar provides analysis on 1.7 million nonprofit organizations (GuideStar, 2008). When searching for "animals", the website returns over 34,000 options for nonprofit organizations that are associated with animals. GuideStar appears to be less focused on rating charities than Charity Navigator; however, it provides basic information for a significantly larger number of nonprofit organizations. The primary purpose of GuideStar appears to be to provide data regarding specific organizations or groups of organizations, rather than analysis of how each is performing. The goal is to provide data that can then be used for analysis of performance. There are three subscription options available for GuideStar users with each option including more data at a higher cost. The model described in this paper uses financial data found with the basic option.

BBB Wise Giving Alliance was formed in 2001 through the merger of the National Charities Information Bureau with the Council of Better Business Bureaus' Foundation (BBB Wise Giving, 2007). Similar to the organizations described above, the Alliance shares various information about individual charities, however it tends to provide more qualitative information on various aspects of the organization in addition to the basic financials. Their focus is to share whether the charity meets a predetermined set of standards based on encouraging fair and honest solicitation practices, promoting ethical conduct by charitable organizations, and advancing support of philanthropy. Charities are not ranked against each other.

These evaluation groups all focus on evaluating charities by examining their financial statements. However, more holistic insight into performance can be gained by including a larger variety of data. In studying animal welfare groups, these data could include operational measures such as the number of animals that are put into adoption households, the number of animals that are euthanized, the number of workers, or the average length of stay for the animals. It could also include facility measures such as the number of cages or square footage of facilities.

The example shared in this paper is limited to data that were publicly available for various animal welfare organizations at the time this paper was written. A combination of Asilomar Accord, Charity Navigator and GuideStar data was used to build the models. We were limited 15 organizations which collected and published Asilomar Accord reports and were included in either Charity Navigator or GuideStar's data (Table 2-2). Financial data were available for 40% of those organizations with Charity Navigator, and the remaining 60% with GuideStar.

Table 2-2: Shelters and Financial Data Source

	Shelter	Charity Navigator	Guidestar	Charity Navigator Score
1	San Fran SPCA	x		***
2	Richmond SPCA	x		****
3	Dubuque HS		x	
4	Allen Cty SPCA		x	
5	Indy Southside		x	
6	SPCA Monterray	x		**
7	Animal Friends		x	
8	Boulder Valley	x		***
9	Table Mountain		x	
10	Tompkins County		x	
11	Arizona HS	x		***
12	North Cty San Diego		x	
13	San Diego HS/SPCA		x	
14	El Cajon AS		x	
15	Escondido HS	x		**
		40%	60%	

The data prepared under the Asilomar Accord guidelines include the total number of dogs and cats to enter a shelter, the total number put into adoption, the total number returned to their owners, the total number euthanized, and the total number that died in shelter care. This gives an overall view of the operational performance throughout the year being studied. One can derive the percentage of animals saved and the percentage of animals euthanized from these numbers.

Other Groups Citing the Need for Standardized Data

Various organizations and people have tried to conduct studies on animal welfare in the past; however, many found that the overwhelming lack of data limited what they could do. Many animal-welfare activists and organizations continually discuss the difficulty that arises when trying to find shelter data for analysis. One effort put forth to better understand the animal welfare population was the creation of the National Council on Pet Population and Study that conducts nation-wide surveys to continually understand the activity of surplus or unwanted pets in the United States. Their studies appear to be the most commonly cited in literature describing the significance of animal welfare issues, and they are the only known statistics that the American Humane Society has recognized to date (Swan, 2006). The method of data collection includes the distribution of surveys to various shelters and agencies to gather data. The results of their most recent study, conducted in 1997, were shared in the Introduction of this paper.

Wenstrup and Dowidchuk were contracted to do an analysis of the economics and implications of pet overpopulation in 1999. They gathered data through surveys, interviews, tours and existing literature. The results of their study support the same issues that were found when we approached this work. They found that there was no widespread standardized reporting process across shelters, and detailed analysis was sparse and often anecdotal. Interesting findings of their study include that shelters only have capacity to handle an average of 2.6% of the animals that enter annually, half of the animals euthanized were considered “not adoptable”, and of those deemed “adoptable”, 70-80% that were euthanized were done so because of inadequate space. This study supports the need for better tools to help shelters partner to utilize their resources, especially the space they have available. In addition to limited capacity, this study found that focusing on “best practice” shelters yields insight into successful policies that could be implemented in other organizations. We believe the results of this study heavily support the use of DEA to better understand animal shelter performance and ultimately aid in the efficiency of various animal shelters across the United States.

Data Envelopment Analysis

Basic Explanation of DEA

According to Zaleski and Zech (1997), the concept behind DEA is simple: The efficiency of an organization depends on its ability to transform its inputs into the desired outputs. The result of a DEA model is a single measure that summarizes the relative efficiency of each DMU when compared with other organizations providing similar outputs with similar inputs. One significant benefit of the DEA model is that the relative efficiency is calculated without an assumption of *a priori* weights or specification of the relationship between the inputs and outputs. The result of the DEA model not only provides a relative efficiency score, but identifies the sources and amounts of inefficiency for each DMU. Having this information available provides insight into decisions that management of the DMU can make to improve efficiency.

In addition to providing an efficiency rating for each DMU, we get other insightful pieces of information from the solution. We can locate the sources of inefficiency for a DMU by looking for its inputs and outputs that have a positive slack value in the associated constraint. A slack value for an input in our model tells us the amount of the excess input being used. An example of an excess input is a shelter that spends more dollars for expenses than comparable shelters. A shelter with a positive slack value for expenses could become more efficient if it reduced the dollars it spends to operate. Likewise, a slack value for an output in our models tells us the amount the DMU falls short in delivering that output. A shelter with a positive slack value for the number of cats placed into adoption could become more efficient if it increased the number of cats that it places. Slack values will either take a positive value or the value zero. Inefficient DMUs will often have results that have many constraints with a positive slack value. A shelter that is utilizing an input amount less than or equal to the most efficient shelter will have a slack value of zero for the corresponding constraint. Contrastingly, a positive slack value for an output constraint means that the shelter produces less output than the best shelter to which it is being compared. The shelter could improve its efficiency score by generating more of this output.

Limits of Applying DEA

Although DEA provides many benefits in doing efficiency analysis, Zaleski and Zech (1997) point out some drawbacks. First, DEA only provides relative efficiency for each DMU. Because DEA uses a comparison of DMUs to determine an efficiency score, it assigns the highest possible score to the DMUs that perform the best. This provides a *relative* efficiency for each of the other DMUs in the model; however, it does not necessarily mean that an efficient DMU would always be judged efficient at using its inputs to produce outputs. The DMU's efficiency score is dependent upon the other DMUs in the model. It is possible that none of the DMUs are actually efficient at utilizing their resources, yet the design of the DEA tool would show that they are. An additional drawback to determining *relative* efficiency with DEA is that the efficiency score of each DMU is dependent upon the other DMUs that have been chosen to be a part of the model. If one were to change the DMUs being used in the model, the efficiency score for each DMU may change as well.

Second, a DEA model will often have many DMUs that are given the highest efficiency score of 1.000. This requires the user to have substantially more DMUs than inputs and outputs in order to produce a highly relevant model with insightful results.

Origin and History of DEA

The first DEA model was introduced in 1978 by Charnes, Cooper and Rhodes. This model is called the CCR Model, in recognition of its developers, and is still the basic model used today by many people to formulate and solve DEA problems. The model was built on the earlier work of Farrell, who focused on developing methods for evaluating productivity in 1957. Over time, discoveries were made regarding the model formulation that provide the ability to solve the problem more easily and gain more insight out of the solution. The following progression of formulations explains how researchers were able to arrive at the most current methodology used for the CCR Model.

The most basic version of the CCR Model is in a ratio form, and is described as follows. The objective is to maximize the ratio of output to input by determining the optimal weight to apply to each input and output measure for the specific DMU being measured. These weights are determined by using performance data for other DMUs that are performing the same function. The linear program requires the weights to be greater than or equal to zero and the efficiency ratio for each DMU to be less than or equal to one.

Parameters:
n = the number of DMUs included in the model
j = the DMU being referenced (j = 1..n)
j = o for the DMU being evaluated in the model
s = the number of outputs
m = the number of inputs
y_{rj} = units of output r for DMU j
x_{ij} = units of input i for DMU j

Decision Variables:
u_r = weight placed on output r (r = 1..s)
v_i = weight placed on input i (i = 1..m)

$$\max \quad \frac{\sum_r u_r y_{ro}}{\sum_i v_i x_{io}}$$

subject to

$$\frac{\sum_r u_r y_{rj}}{\sum_i v_i x_{ij}} \leq 1 \quad \text{j=1,2,…,n}$$

$$u_r, v_i \geq 0 \qquad \text{r=1,…,s; i=1,…,m}$$

Figure 2-1: Model #1 - Original CCR Formulation - Ratio Format

This type of mathematical program is referred to as a linear fractional program. According to Bazaraa et al. (1993), a linear fractional program is a problemin which the objective function is the ratio of two linear functions and the constraints are linear. In the model above, we can transform the constraints into linear functions by multiplying each side of the equation by the denominator in the ratio on the left side of the equation.

According to Cooper et al. (2004), this formulation delivers an infinite number of solutions because the values found for the variables u and v can all be multiplied by a positive scalar α and still provide a feasible solution to the problem. Charnes and Cooper developed a transformation in 1962 that can be used to address this issue, and change the model into a formulation that can be solved with the simplex method. Their transformation results in the formulation in Figure 2-2, in which a ratio is no longer calculated in the objective function because the inputs are moved into a new constraint in the model. This is done under the assumption that you can continue to maximize the objective function if the denominator containing the inputs is held constant. The variable μ replaces u in this formulation. This is the main input-oriented CCR model used in practice today.

New Decision Variables:
μ_r = weight placed on output r (r = 1..s)

$$\max \sum_{r=1}^{s} \mu_r y_{ro}$$

subject to

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad \text{j=1,2,…,n;}$$

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

$$\mu_r, v_i \ge 0$$

Figure 2-2: Model #2 - Primal CCR Model – Input-Oriented

In practice, it is recommended that a DEA model have a significantly larger number of DMUs than inputs and outputs being used. A general rule of thumb is to have enough DMUs to cover the maximum of the multiplicative product of the inputs and outputs or three times the sum of the inputs and outputs.

Because the corresponding primal and dual models result in the same value for the objective function, considering the dual of the CCR model gives us the ability to more easily solve for the efficiency score. The dual model typically has fewer constraints, corresponding to the inputs and outputs, than the primal model, which has constraints corresponding to each DMU. λ_j is the variable used to denote the weight applied to each DMU.

<u>New Decision Variables:</u>
λ_j = weight placed on DMU j
θ = efficiency of DMU being evaluated

$$\begin{aligned}
&\min\ \theta \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{io} \quad && i=1,2,\ldots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro} \quad && r = 1,2,\ldots,s; \\
&\lambda_j \ge 0 && j = 1,2,\ldots,n.
\end{aligned}$$

Figure 2-3: Model #3 - Dual CCR Model (Input – Oriented)

Once solved, this linear program may have DMUs that receive a θ, or objective function, value equal to 1 but actually still have room to improve. Graphically, the DMUs that still have room to improve are located on the production frontier but another DMU either produces the same output with less input or more output with the same input. It is possible to identify these DMUs by solving a two-step linear program. When the two-step program is solved, you can tell by the fact that the DMU with room to improve will have slack values that are greater than zero. If a DMU has results of $\theta = 1$ in Step One and all slack values equal to zero in Step Two, it is considered to be "fully efficient". However, if a DMU has results of $\theta = 1$ and slack values that are greater than zero, it is considered "weakly efficient". If $\theta < 1$, the DMU is considered inefficient. The possible outcomes are summarized in Table 2-3.

Table 2-3: Fully vs. Weakly Efficient

	$\theta = 1$	$\theta < 1$
$S = 0$	Fully efficient	Inefficient
$S > 0$	Weakly efficient	Inefficient

The second step of the linear program forces the slack variables to their maximum value while holding θ equal to 1. That program is shown below. It modifies the dual model to put the slacks into the objective function and constraints. There is one slack variable for each input and output, thus one for each constraint. The value of θ is forced to equal 1.000.

New Decision Variables:

s_i^- = surplus of input i

s_r^+ = slack of output r

$$\max \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$

subject to

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io} \quad \text{i=1,2,…,m;}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro} \quad \text{r = 1,2,…,s;}$$

$$\theta = 1$$

$$\lambda_j, s_i^-, s_i^+ \geq 0 \quad \forall i, j$$

Figure 2-4: Model #4 - Maximum Slacks Dual CCR Model (Input – Oriented)

To determine whether a DMU is fully efficient, one must solve both Model #3 to calculate θ and Model #4 for any DMU with θ = 1 to determine whether the slack values are equal to zero. The next linear program (Model #5) is designed to show the combination of the two steps in one linear program; however, the program still needs to be solved in two steps. The first step is to solve the linear program to minimize theta. The second step is to solve the linear program a second time for the shelters that received an efficiency score of 1.000. The second step is completed by setting θ equal to 1.000 for these shelters and running the linear program to maximize the slack values.

Step 1: min θ

Step 2: max $\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$

subject to

$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta x_{io}$ i=1,2,…,m;

$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{ro}$ r = 1,2,…,s;

$\lambda_j, s_i^-, s_i^+ \geq 0 \quad \forall i, j$

Figure 2-5: Model #5 - Combined 2-step Dual CCR Model (Input – Oriented)

Each of the linear programming formulations shown above is built to solve an input-oriented problem. Input-oriented means that the problem will look for ways that the DMU can continue to provide the same output with less input by locating other DMUs that are able to do this. Another method for determining a DMU’s ability to become more efficient is to look at how it can produce more output with the same level of input. A linear program that does this is considered to be output-oriented.

The following two models correspond to Models 3 and 5 and provide the output-oriented version of the formulations.

$$
\begin{aligned}
&\text{min} \quad \sum_{i=1}^{m} v_i x_{io} \\
&\text{subject to} \\
&\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0 \quad \text{j=1,2,…,n;} \\
&\sum_{r=1}^{s} \mu_r y_{ro} = 1 \\
&\mu_r, v_i \geq \varepsilon \quad \forall r, i
\end{aligned}
$$

Figure 2-6: Model #6 - Primal CCR Model (Output – Oriented)

$$
\begin{aligned}
&\text{Step 1: max } \phi \\
&\text{Step 2: max } \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_{ij} \lambda_j + s_i^- = x_{io} \qquad \text{i=1,2,…,m;} \\
&\sum_{j=1}^{n} y_{rj} \lambda_j - s_r^+ = \phi y_{ro} \quad \text{r = 1,2,…,s;} \\
&\lambda_j \geq 0 \qquad\qquad\qquad \text{j = 1,2,…,n.}
\end{aligned}
$$

Figure 2-7: Model #7 - Combined 2-step Dual CCR Model (Output – Oriented)

In summary, we have proceeded through the evolution of the CCR model from a basic ratio form input-oriented formulation to a combined 2-step output-oriented formulation. Table 2-4 summarizes the qualities of each model that was discussed.

Table 2-4: CCR Models

Model	Objective	Decision Variable	Primal or Dual	Input or Output Oriented	Basic or 2-step
1	max ratio (h)	U_j v_i	Primal	Input	Basic
2	max output (z)	μ_r v_i	Primal	Input	Basic
3	min efficiency (θ)	λ_j	Dual	Input	Basic
4	max slacks	λ_j s_i^-, s_i^+	Dual	Input	Basic
5	min θ & max slacks	λ_j s_i^-, s_i^+	Dual	Input	2-step
6	min input (q)	μ_r v_i	Primal	Output	Basic
7	max φ & max slacks	λ_j s_i^-, s_i^+	Dual	Output	2-step

DEA Applied to Nonprofit Organizations

According to Zaleski and Zech, DEA has been applied to nonprofit organizations for approximately 20 years because it has been recognized as a tool that allows for the comparison of businesses that do not operate to make a profit. The technique is most popular in economic analysis of organizations such as banks, schools, or libraries. Although DEA has been used to analyze various nonprofit organizations, it seems that it has never been applied to animal-welfare societies.

One notable use of DEA was a study completed by Zaleski and Zech in 1997. This study focused on applying DEA to religious organizations to measure both efficiency and resource allocation. The specific focus of their work was to look at the critical problem of a shortage of priests within the Catholic Church. They used DEA to analyze the distribution of priests across a diocese. They studied how priests are allocated, and found that the Church would benefit from a better distribution of priests and that the use of deacons and priest-less parishes can be effective in some circumstances. The model results showed that some dioceses had both an excess of priests and priest-less parishes. This provided an easy target for improvement because these dioceses should be able to easily improve their efficiency scores by reallocating their priests.

The analysis presented in this manuscript uses techniques for understanding resource allocation from the Zaleski and Zech study. The same techniques are applied to the analysis of the animal welfare model results to look at resource allocation of the shelters.

3. **METHODOLOGY**

We can use the information on animal welfare organizations and DEA to begin formulating CCR linear programs to determine the relative efficiency of the animal welfare organizations for which we have data.

Choice of Output-Oriented Model

As discussed, there are two types of data envelopment analysis models that can be run to determine DMU efficiency. The first is an input-oriented model. This type of model calculates efficiency by determining how to minimize the DMU's inputs in order to deliver the same outputs. In applying this method to the shelters for which we have data, we would focus on decreasing the number of dogs or cats to enter a shelter or society and the total expenses used to run the shelter or society. While maintaining the same number of animals placed in adoptive homes or returned to their owners, an animal shelter can impact the number of animals entering through educational programs, partnerships with other shelters, or programs such as spaying and neutering. However, the number of dogs or cats entering the shelter or society is not completely within the organization's control. Although they may be able to impact these totals with various programs, they do not have complete power over the total intake.

Because the volume entering the shelter or society is not completely within its control, the second type of model, output-oriented, has been used in this paper. This model is called an output-oriented model because it focuses on calculating efficiency by determining how well the shelter maximizes its outputs with the same inputs that it currently has. For shelters or animal welfare societies, this means measuring the ability to maximize the number of dogs or cats saved without changing the number coming in or the money spent to do so.

The primal problem is solved by determining the weight that will be applied to each input and output in the problem. The dual problem is solved to minimize the efficiency score and the slacks by determining the weight that will be applied to each DMU while building the composite (or virtual) DMU used for comparing relative efficiency.

Data Envelopment Analysis Model for Animal Welfare Groups

Data Set (Asilomar Accords, Charity Navigator and GuideStar)

Combining the Asilomar Accord, Charity Navigator, and GuideStar data gives the dataset listed in Table 3-1 that is used to complete a data envelopment analysis model for the 15 shelters. Identifying the inputs and outputs is critical to data envelopment analysis. Typically, an exhaustive list of potential inputs and outputs will be created before choosing what will be used in the model. Too few inputs and outputs will cause the DMUs to appear similar; however, an increase in the number of inputs or outputs may result in more DMUs with the relative efficiency score 1.000. We are limited to the inputs and outputs available with the Asilomar Accord, Charity Navigator, and GuideStar data. Therefore, it is assumed that the inputs and outputs are correctly identified for this model, and the DMUs are independent of one another.

Table 3-1: Inputs and Outputs Used in Model

Type	Data	Source	Metric
Input	Total Expenses	Charity Navigator/GuideStar	$
Input	Number of Dogs to Enter Shelter	Asilomar Accords	Total volume
Input	Number of Cats to Enter Shelter	Asilomar Accords	Total volume
Output	Number of Dogs Adopted	Asilomar Accords	Total volume
Output	Number of Cats Adopted	Asilomar Accords	Total volume
Output	Number of Dogs Returned to Owner	Asilomar Accords	Total volume
Output	Number of Cats Returned to Owner	Asilomar Accords	Total volume

Figure 3-1 displays an aggregate version of the outputs. Along the x-axis we show the number of dogs either put into adoption or returned to their owner. On the y-axis, we show the number of cats either put into adoption or returned to their owner. By looking at this graph, we can see that Shelter 11, the Arizona Humane Society of Phoenix, puts more dogs and cats into adoption or returns them to their owners than any other shelter. However, note that this point is based on pure volume, not as a proportion of the animals that enter the shelter. Figure 3-2 shows the number of dogs and cats adopted and returned to their owners as a proportion of the total number of dogs and cats that enter the shelter. Arizona Humane Society of Phoenix is now the lowest performer.

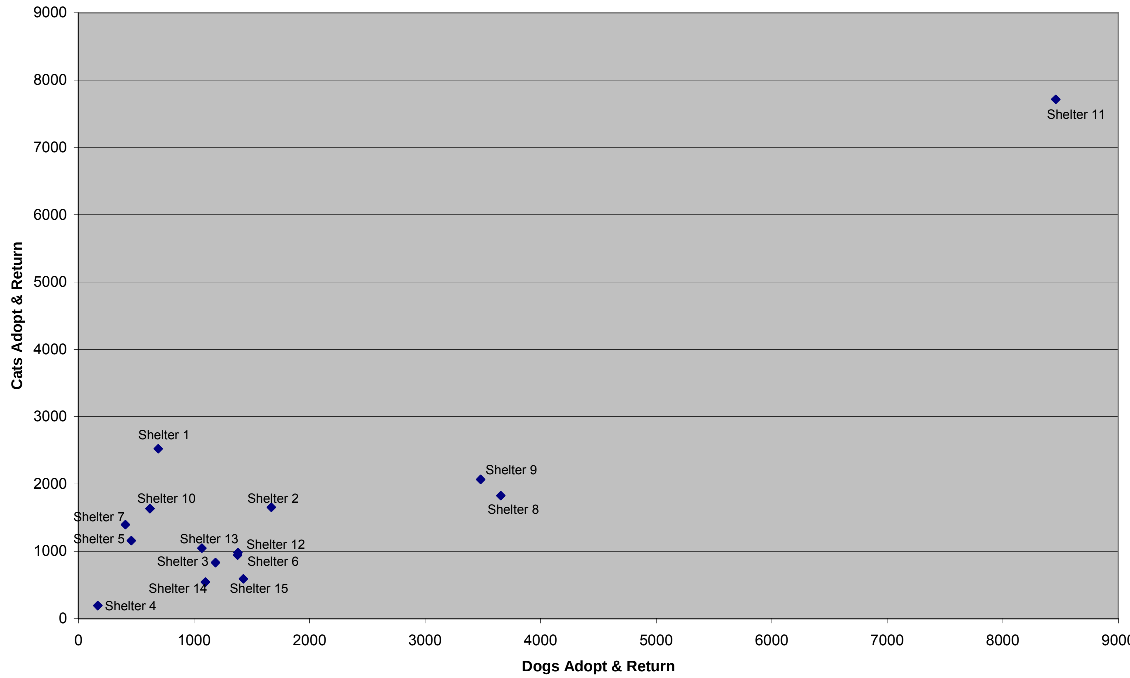

Figure 3-1: Outputs for Each DMU

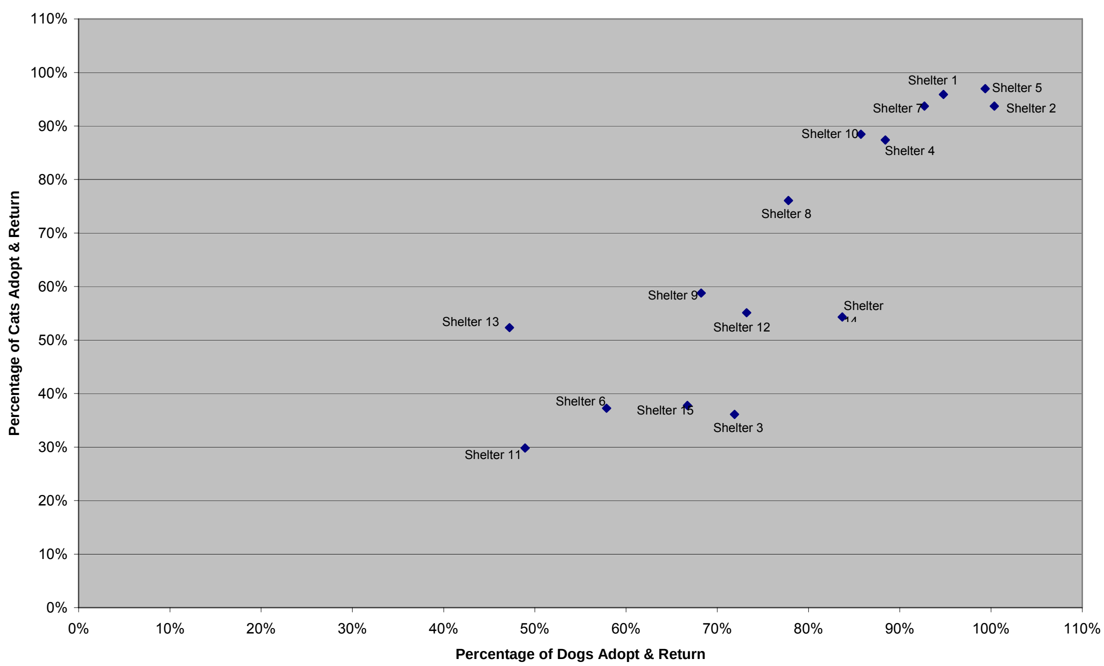

Figure 3-2: Proportional Outputs for Each DMU

Figure 3-3 displays the financial input (expenses) that will be used for each shelter. Shelters 1, 11, and 13 spend the most money, while Shelters 3, 4, 5, 9 and 14 spend the least.

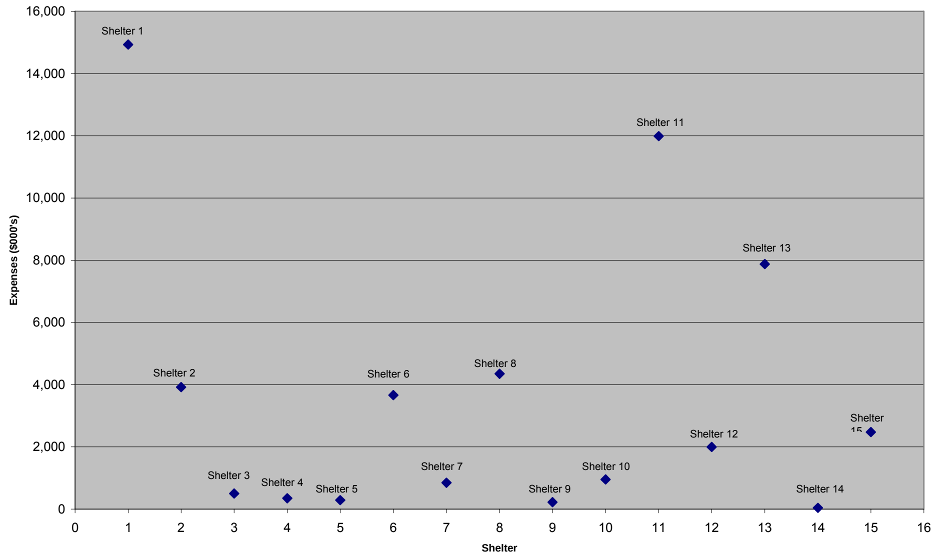

Figure 3-3: Expenses for Each DMU

Output-Oriented Primal Model (Step 1)

The formulation for the first step of the CCR Primal model containing this data is shown below. It is based on Model 3, which was presented earlier in this document. The input and output data for the 15 shelters are shown in Table 3-2.

<u>Parameters:</u>
n = 15
s = 4 (the number of outputs)
m = 3 (the number of inputs)
y_{rj} = units of output r for shelter j
x_{ij} = units of input i for shelter j

<u>Decision Variables:</u>
μ_r = weight placed on output r (r = 1..4)
v_i = weight placed on input i (i = 1..3)

$$\max \sum_{r=1}^{s} \mu_r y_{ro}$$

subject to

$$\sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0 \quad \text{j=1,2,…,n;}$$

$$\sum_{i=1}^{m} v_i x_{io} = 1$$

$$\mu_r, v_i \ge 0$$

Figure 3-4: CCR Primal Model (Step 1)

Table 3-2: Input and Output Data for Each Shelter

		INPUTS			OUTPUTS			
		i = 1	i = 2	i = 3	r = 1	r = 2	r = 3	r = 4
j	Shelter	Total Intake (# dog)	Total Intake (# cat)	Expenses ($ in 000's)	Total Adoptions (# dog)	Total Adoptions (# cat)	Return to Owner/Guardian (# dog)	Return to Owner/Guardian (#cat)
1	San Fran SPCA	728	2632	14933	677	2485	13	39
2	Richmond SPCA	1663	1763	3919	1656	1637	13	15
5	Indy Southside	461	1195	286	458	1159	0	0
7	Animal Friends	439	1492	845	407	1398	0	0
8	Boulder Valley	4699	2402	4347	2393	1556	1262	271
9	Table Mountain	5100	3520	222	1414	1941	2066	128
10	Tompkins County	722	1847	954	382	1441	237	193
14	El Cajon AS	1312	1002	39	512	515	586	29
4	Allen Cty SPCA	190	222	347	168	194	0	0
3	Dubuque HS	1651	2305	498	873	783	314	49
12	North Cty San Diego	1885	1780	1995	846	943	534	38
15	Escondido HS	2137	1565	2475	743	558	683	33
6	SPCA Monterray	2380	2528	3661	1098	900	279	42
11	Arizona HS	17282	25869	11991	7655	7429	802	284
13	San Diego HS/SPCA	2262	2003	7875	955	998	113	50

Output-Oriented Dual Model (Step 1)

The dual model will seek to find the best efficiency score possible by creating a composite or virtual DMU. The composite DMU will be determined by finding the optimal weight to be applied to each of the 15 shelters. This composite is built for each of the inputs and outputs, and then used to calculate the efficiency level of the DMU being evaluated.

<u>New Decision Variables:</u>
λ_j = weight placed on shelter j
θ = efficiency of shelter being evaluated

$$\begin{aligned}
&\min\ \theta \\
&\text{subject to} \\
&\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{io} \qquad && i=1,2,\ldots,m; \\
&\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro} \qquad && r=1,2,\ldots,s; \\
&\lambda_j \ge 0 \qquad && j=1,2,\ldots,n.
\end{aligned}$$

Figure 3-5: CCR Dual Model (Step 1)

Output-Oriented Dual Model (Step 2)

The objective function value of the CCR primal and dual models will be equal for each shelter's primal and dual formulations. Step 1 is complete when the objective function value is computed. This value is the efficiency score for the specific shelter being studied. We can now move on to Step 2 of the process: forcing the model to maximize the slack variables for all shelters that received an efficiency score of 1.000. To do this, we design the linear program to force the efficiency score to equal 1.000 and replace its objective with the goal of maximizing the slacks. We will use the following formulation to complete Step 2. The results will tell us which shelters are fully efficient and which are weakly efficient.

Parameters:
ϕ = efficiency of DMU being evaluated (set equal to 1)

Decision Variable:
s_i^- = surplus of input i
s_r^+ = slack of output r

$$\max \quad \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right)$$

subject to

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{io} \qquad \text{i=1,2,…,m;}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = \phi y_{ro} \qquad \text{r = 1,2,…,s;}$$

$$\phi = 1.000$$

$$\lambda_j \geq 0 \qquad \text{j = 1,2,…,n.}$$

Figure 3-6: CCR Dual Model (Step 2)

The linear programs were solved using ILOG OPL Development Studio to confirm that the results were correct. Accurate results were found with OPL, showing that the Management Scientist results for the three models in question were actually inaccurate. Therefore, all models were written in OPL and solved again. This includes the Primal CCR model and both Steps One and Two of the Dual CCR model. The results of the OPL models are summarized in this paper.

The “SheetConnection” function within OPL was used to make the models easier to solve. Because solving a DEA problem requires multiple iterations of models that are slightly different for each DMU, a Microsoft Excel spreadsheet that easily changed the model parameters was built in order to be run for each DMU. The Excel spreadsheet was designed to update the linear program for each DMU, based on just one cell that shows the number of the DMU to be modeled. This program design allowed the programs to be run very quickly. Each model required less than five seconds to run Step One or Step Two. In total, the dual model for each of the 15 DMUs could be run in less than an hour. After the models were completed, it was easy to make changes to the Excel spreadsheet in order to conduct various sensitivity analyses quickly.

4. RESULTS

Most Efficient Shelters with Singular Key Performance Indicators

Each of the 15 shelters for which we have data is different in size and physical location throughout the United States. The locations of the shelters are shown on the map below. They are heavily-weighted toward locations in California. This may be because the Asilomar Accords were written in Pacific Grove, California.

Figure 4-1: Location of Model Shelters

The volume of animals entering each shelter, being put into adoption or returned to their owners, and euthanized is shown in Table 4-1. We can see by looking at these volumes that Arizona Humane Society of Phoenix handles the largest volume of animals, while the Allen County SPCA in Fort Wayne, Indiana handles the least. The Indianapolis Southside Animal Shelter euthanized the lowest number of animals, yet its intake is smaller than the average of the 15 shelters.

Table 4-1: Summarized Operational Performance Data

Shelter	Shelter Name	Total Intake	Total adopt or return	Total Euthanized
1	San Fran SPCA	3360	3214	71
2	Richmond SPCA	3426	3321	33
3	Dubuque HS	3956	2019	1793
4	Allen Cty SPCA	412	362	30
5	Indy Southside	1656	1617	25
6	SPCA Monterray	4908	2319	2192
7	Animal Friends	1931	1805	30
8	Boulder Valley	7101	5482	1477
9	Table Mountain	8620	5549	2382
10	Tompkins County	2569	2253	211
11	Arizona HS	43151	16170	28615
12	North Cty San Diego	3665	2361	562
13	San Diego HS/SPCA	4265	2116	1627
14	El Cajon AS	2314	1642	334
15	Escondido HS	3702	2017	1185

Looking at the raw data to determine the efficiency of the shelters is difficult. For instance, we may look at each shelter's cash flow. The percentage of revenue used toward expenses last year for each shelter is shown in the table below. Using total revenue toward expenses is not necessarily a bad thing for nonprofit organizations; however, having some money in reserves that is not used toward expenses makes an organization more stable. The San Diego Humane Society & SPCA and the Richmond SPCA use the least amount of their total revenue on expenses, and thus have the highest proportion of their revenue available for additional projects or unforeseen situations. Looking at this metric alone would lead us to believe that these two shelters are the best performers. The Allen County SPCA clearly performs the worst. However, looking at just one metric to make conclusions is unwise.

Table 4-2: Cash Flow KPI Results

Shelter	Shelter Name	Proportion of revenue used for expense	Cash Flow Rank
13	San Diego HS/SPCA	75%	1
2	Richmond SPCA	81%	2
8	Boulder Valley	86%	3
14	El Cajon AS	89%	4
1	San Fran SPCA	89%	5
3	Dubuque HS	94%	6
5	Indy Southside	99%	7
10	Tompkins County	102%	8
9	Table Mountain	105%	9
12	North Cty San Diego	105%	10
11	Arizona HS	109%	11
15	Escondido HS	109%	12
6	SPCA Monterray	113%	13
7	Animal Friends	113%	14
4	Allen Cty SPCA	194%	15

Rather than profitability, we could look at operational performance to determine which shelter is the best. One metric for doing this would be to look at the percentage of animals put into adoption or returned to their owners. The results for this metric for the 15 shelters are shown in the table below. The Indianapolis Southside Animal Shelter, Richmond SPCA, and San Francisco SPCA perform the best according to this metric. The Arizona Humane Society of Phoenix receives the worst score. The Richmond SPCA is the only organization that has consistently ranked at the top of the list of both metrics. Allen County SPCA is ranked fifth on this metric. Reviewing these two metrics does not tell us much; however, it does allow us to begin to believe that the Richmond SPCA may be the top performing shelter.

Table 4-3: Animals Adopted & Returned KPI Results

Shelter	Shelter Name	% into adopt or return	% Adopt/Return Rank
5	Indy Southside	98%	1
2	Richmond SPCA	97%	2
1	San Fran SPCA	96%	3
7	Animal Friends	93%	4
4	Allen Cty SPCA	88%	5
10	Tompkins County	88%	6
8	Boulder Valley	77%	7
14	El Cajon AS	71%	8
12	North Cty San Diego	64%	9
9	Table Mountain	64%	10
15	Escondido HS	54%	11
3	Dubuque HS	51%	12
13	San Diego HS/SPCA	50%	13
6	SPCA Monterray	47%	14
11	Arizona HS	37%	15

We can add another metric to this list, the percentage of animals that are not euthanized in each shelter. When we do this, we get slightly different results. The Richmond SPCA again falls into the top performer ranks. The San

Francisco SPCA ranks third; however, there is a new shelter mentioned in our discussion: the Animal Friends Rescue Project, which performs the best. What is very interesting about looking at this metric is that the Allen County Humane Society, which was ranked as the worst in performance on the basis of cash flow, is ranked highly in the percentage of animals that are not euthanized. Some would argue that this is the most important metric of all the metrics.

Table 4-4: Animals Euthanized KPI Results

Shelter	Shelter Name	% No Kill	% No Kill Rank
7	Animal Friends	98%	1
2	Richmond SPCA	97%	2
1	San Fran SPCA	97%	3
4	Allen Cty SPCA	92%	4
10	Tompkins County	92%	5
5	Indy Southside	91%	6
14	El Cajon AS	85%	7
12	North Cty San Diego	83%	8
8	Boulder Valley	79%	9
9	Table Mountain	72%	10
15	Escondido HS	63%	11
13	San Diego HS/SPCA	61%	12
6	SPCA Monterray	55%	13
3	Dubuque HS	53%	14
11	Arizona HS	32%	15

So how do we come to a conclusion about which shelters are truly performing the best? Each of these metrics provides a slightly different indicator of each shelter's performance, and with the various indicators, ranks the shelters differently. Data envelopment analysis provides a means for helping us better understand what is happening.

Data Envelopment Analysis Results

Efficiency Scores for Each Shelter

The results of the CCR DEA models give us the ability to combine the various key indicators and determine which shelters are the most efficient. The efficiency score for each shelter is shown in Table 4-5 and Figure 4-2. Eight shelters were given the highest efficiency score of 1.000. These shelters are considered "best in class". Seven shelters received scores that are less than 1.000, with the Allen County SPCA being the closest to the efficiency frontier and the San Diego Humane Society & SPCA being the farthest away from the frontier.

Table 4-5: KPI and DEA Model Results

Shelter	Shelter Name	Cash Flow Rank	% Adopt/Return Rank	% No Kill Rank	Efficiency Score	Reference Set
1	San Fran SPCA	5	3	3	1.000	1
2	Richmond SPCA	2	2	2	1.000	2
5	Indy Southside	7	1	6	1.000	5
7	Animal Friends	14	4	1	1.000	7
8	Boulder Valley	3	7	9	1.000	8
9	Table Mountain	9	10	10	1.000	9
10	Tompkins County	8	6	5	1.000	10
14	El Cajon AS	4	8	7	1.000	14
4	Allen Cty SPCA	15	5	4	0.980	2, 5, 14
3	Dubuque HS	6	12	14	0.920	5, 8, 10, 14
12	North Cty San Diego	10	9	8	0.835	2, 5, 10, 14
15	Escondido HS	12	11	11	0.801	2, 8, 14
6	SPCA Monterray	13	14	13	0.620	2, 10, 14
11	Arizona HS	11	15	15	0.614	2, 5, 8, 14
13	San Diego HS/SPCA	1	13	12	0.582	2, 8, 10

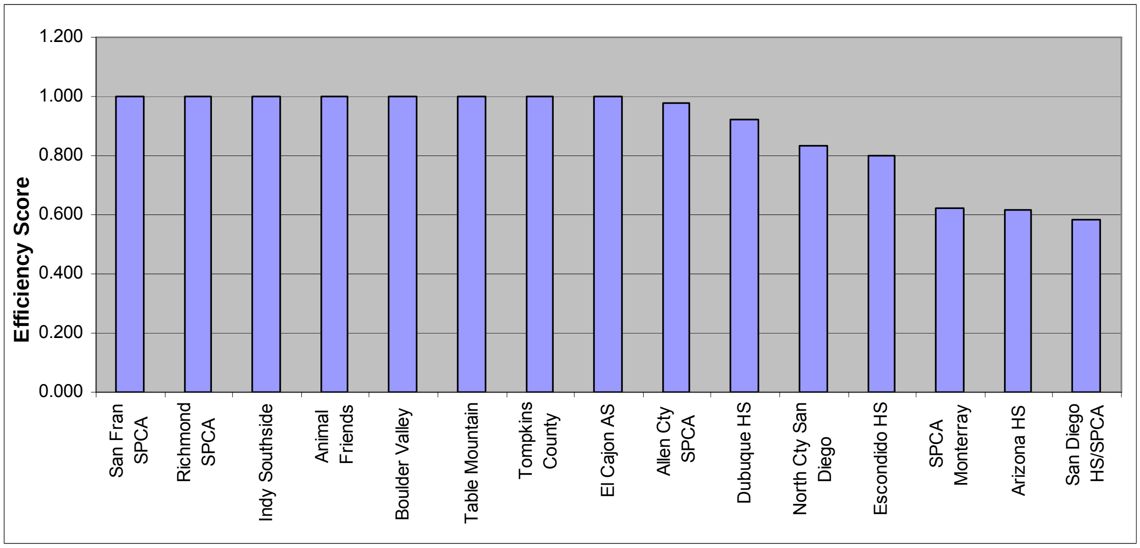

Figure 4-2: Shelter DEA Efficiency Scores

DEA gives us the ability to see other shelters that are actually performing well that we may not have recognized in looking at just one metric at a time. By examining the results in Table 4-5 for the dual model, we can learn which shelters each DMU used for its reference group in calculating the efficiency. The frequency with which a shelter is used as a reference for other shelters shows how often it has been chosen as the best in class reference point for the other DMUs. A shelter that has been chosen as a reference point by multiple DMUs is potentially displaying strong performance. For example, El Cajon Animal Shelter ranked 4th on cash flow, 8th on the percentage of animals put into adoption or returned to their owner, and 7th on the percentage of animals that were not killed. These rankings were better than half of the peers, yet we would not have listed this shelter as a top performer. However, when we look at the DEA results, we see that El Cajon Animal Shelter was given an efficiency score of 1.000 and was actually used as a reference point for more shelters than any other shelter. This means that they are actually performing well overall. A similar pattern can be seen for Indianapolis Southside Animal Shelter, Boulder Valley Humane Society, and Tompkins County Society for the Prevention of Cruelty to Animals.

The primal model can help us determine which inputs and outputs most influence a DMU's efficiency. Table 4-6 displays the inputs and outputs used by each shelter. If we use Richmond SPCA for our example, we see that the shelter puts most emphasis on the number of dogs to enter the shelter, the number of dogs to be adopted, and the number of cats to enter the shelter. This shows us that of the pet population, dogs weigh more heavily in impacting Richmond SPCA's efficiency score than cats. However, if we look at columns v2, m2, and m4, we see that some shelters have more weight on cats than dogs. For example, although the San Francisco SPCA model puts emphasis on the number of dogs that enter, it puts more emphasis on the number of cats placed into adoption or back with their owner to determine its efficiency. Indianapolis Southside, Animal Friends Rescue Project, Table Mountain Animal Center, and the Tompkins County SPCA have similar results in which placement of cats is the most important output.

Table 4-6: Input and Output Inclusion Model Results

Shelter	Shelter Name	Efficiency Score	i1	i2	i3	r1	r2	r3	r4
1	San Fran SPCA	1.000	x				x		x
2	Richmond SPCA	1.000	x	x		x			
3	Dubuque HS	0.920	x	x	x	x			x
4	Allen Cty SPCA	0.980	x	x	x	x			
5	Indy Southside	1.000	x		x		x		
6	SPCA Monterray	0.620	x			x		x	x
7	Animal Friends	1.000	x	x	x		x		
8	Boulder Valley	1.000		x		x			
9	Table Mountain	1.000		x	x				x
10	Tompkins County	1.000	x	x					x
11	Arizona HS	0.614	x	x	x	x			x
12	North Cty San Diego	0.835	x			x	x	x	x
13	San Diego HS/SPCA	0.582		x		x	x		x
14	El Cajon AS	1.000	x					x	x
15	Escondido HS	0.801	x	x		x		x	

Fully Efficient Shelters vs. Weakly Efficient Shelters

As mentioned before, running the model to determine the efficiency score alone does not give us the entire picture of a shelter's performance. A shelter may be on the efficiency frontier and receive a score of 1.000; however, it may still be inferior to another shelter on the frontier. It is possible to produce output to the level of the best shelters, yet still be reaching the output by consuming more inputs than another shelter. If a DMU is using more inputs, it is only weakly efficient.

We ran the second step of the CCR model (maximize slacks while holding efficiency equal to 1.000) for the eight DMUs that were found to have a score of 1.000. This includes the following shelters: San Francisco SPCA, Richmond SPCA, Indianapolis Southside Animal Shelter, Animal Friends Rescue Project, Boulder Valley Humane Society, Table Mountain Animal Center, Tompkins County SPCA, and El Cajon Animal Shelter. The results are shown in Table 4-7.

Table 4-7: Fully and Weakly Efficient Shelter Results

Shelter	Shelter Name	Efficiency Score	Full or Weak
1	San Fran SPCA	1.000	Weak
2	Richmond SPCA	1.000	Full
3	Dubuque HS	0.920	
4	Allen Cty SPCA	0.980	
5	Indy Southside	1.000	Full
6	SPCA Monterray	0.620	
7	Animal Friends	1.000	Weak
8	Boulder Valley	1.000	Weak
9	Table Mountain	1.000	Full
10	Tompkins County	1.000	Full
11	Arizona HS	0.614	
12	North Cty San Diego	0.835	
13	San Diego HS/SPCA	0.582	
14	El Cajon AS	1.000	Weak
15	Escondido HS	0.801	

Richmond SPCA, Indianapolis Southside Animal Shelter, Table Mountain Animal Center, and Tompkins County SPCA are the fully efficient shelters in our dataset. This means that these shelters have the strongest overall performance when we look at their expenses, the number of animals taken in, and the animals put into adoption or returned to their owners. The San Francisco SPCA, the Animal Friends Rescue Project, the Boulder Valley Humane Society, and the El Cajon Animal Shelter perform well, but not as well as the other four fully efficient shelters.

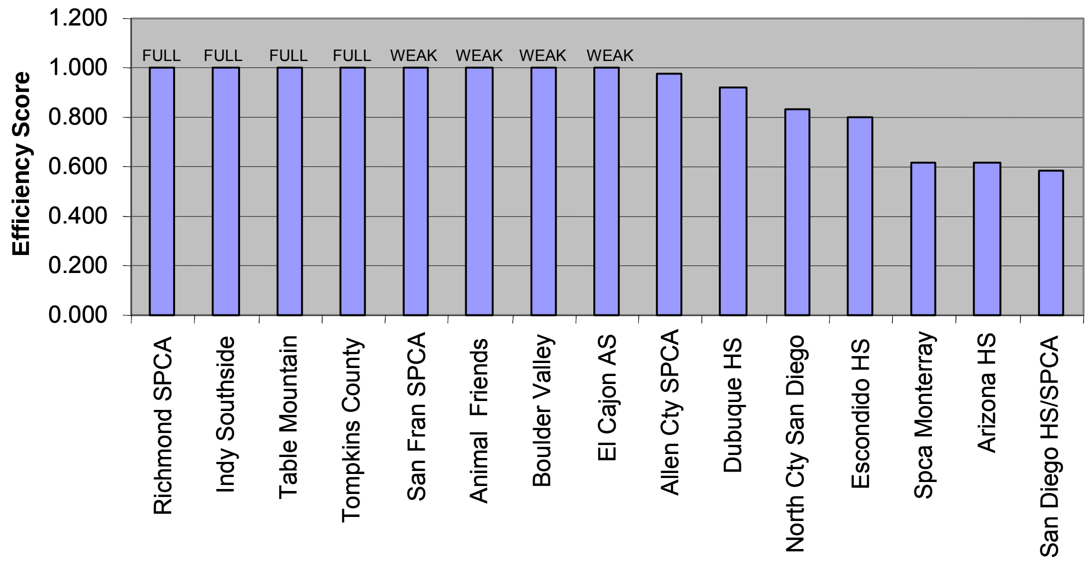

Figure 4-3: Shelter Full Efficiency and Weak Efficiency Results

The results of these two models display why DEA can be a very useful tool in developing true relative performance of multiple DMUs. When looking at isolated key indicators as we did above, we would have come to the conclusion that the San Francisco SPCA, the Richmond SPCA, and the Animal Friends Rescue Project were the best performing agencies. However, we are able to gather much more in-depth insight by using DEA. In doing so, we learn that these three shelters are indeed good performers; however, they are not necessarily the best, and this list is not exhaustive of all top performers. DEA helps bring to light three additional shelters that are also top performers.

Charity Navigator Shelter Score Comparison

Only 6 of the 15 shelters used in this model were also ranked by Charity Navigator. A comparison of their Charity Navigator and DEA scores are shown in Table 4-8. Richmond SPCA is shown to have the highest score given by Charity Navigator as well as the highest ranking given in the DEA model. However, there are three shelters that were given Charity Navigator's second highest score of three stars. Of those three shelters, only two of them received an efficiency score of 1.000 in the DEA model. The third, Arizona Humane Society of Phoenix actually received a low DEA score. This comparison of the scores allows us to see the value gained from a DEA model because it separates the rankings of the shelters as well as gives insight into results dependent upon more than just financial metrics.

Table 4-8: Charity Navigator and DEA Comparison

j	Shelter	Org Efficiency	Org Capacity	Total Score	DEA Score
1	San Fran SPCA	**	****	***	1.000
2	Richmond SPCA	***	****	****	1.000
3	Dubuque HS				
4	Allen Cty SPCA				
5	Indy Southside				
6	SPCA Monterray	**	***	**	0.620
7	Animal Friends				
8	Boulder Valley	**	****	***	1.000
9	Table Mountain				
10	Tompkins County				
11	Arizona HS	***	****	***	0.614
12	North Cty San Diego				
13	San Diego HS/SPCA				
14	El Cajon AS				
15	Escondido HS	0	****	**	0.801

Interpretation of Slack Values

The slack values for the input and output constraints of each DMU's model can be used to look for opportunities to improve the efficiency score. A positive slack value indicates a potential means of improvement. For example, if a positive slack value exists for the number of dogs that enter a shelter, the shelter will improve its efficiency score by reducing this input. Similarly, if the output constraint for the number of dogs that are returned to their owners includes a positive slack value, the efficiency score will improve if more dogs are returned to their original owners. The following lists show detail of why each of the seven shelters are inefficient and where they can focus to improve.

Dubuque Humane Society
- Increase the number of cats put into adoption
- Increase the number of dogs returned to their owners

Allen County SPCA
- Increase the number of cats put into adoption
- Increase the number of dogs returned to their owners
- Increase the number of cats returned to their owners

SPCA Monterrey County
- Decrease the number of cats that enter the shelter
- Decrease the amount of money used on expenses
- Increase the number of cats put into adoption

Arizona Humane Society of Phoenix
- Increase the number of cats put into adoption
- Increase the number of dogs returned to their owners

North County Humane Society and SPCA
- Decrease the number of cats that enter the shelter
- Decrease the amount of money used on expenses

San Diego Humane Society and SPCA
- Decrease the number of dogs that enter the shelter
- Decrease the amount of money used on expenses
- Decrease the number of dogs returned to their owners

Escondido Humane Society

- Lessen the amount of money used on expenses
- Increase the number of cats put into adoption
- Increase the number of cats returned to their owners

5. **CONCLUSION**

We can use the results of the model to understand each shelter's efficiency, the source of inefficient performance for those that are measured to be relatively inefficient, and the potential for redistribution of resources. This chapter describes a detailed review of applying these techniques to the results shared in Chapter 4.

Most Efficient Shelters with Data Envelopment Analysis

The results of the analysis shown above indicated that eight out of the 15 shelters studied are considered relatively efficient while the remaining seven shelters are relatively inefficient. Of the eight shelters, half of them are considered fully efficient. Although the other half received an efficiency score of 1.000, they are considered weakly efficient because their peers were able to produce more output with the same resources.

The slack values for the input and output constraints gave us the ability to identify means of improvement for the seven inefficient shelters. The most common method for improvement in inputs is to reduce the amount of money spent on expenses. The most common method for improvement in output is to increase the number of cats that are placed into adoption.

Resource Allocation for Multiple Shelters

Shelters located in general proximity to each other could partner to better utilize their resources and potentially save more companion animals. To start, the means of improvement listed in Chapter 4 by identifying positive slack values for each shelter can be reviewed.

Of the seven shelters that were inefficient, one of them, San Diego Humane Society & SPCA, had a positive slack value for the number of dogs entering. This means that they had an excess in the number of dogs coming into the shelter and would be more efficient if less dogs entered. The San Diego Humane Society & SPCA is in close proximity to El Cajon Animal Shelter. This shelter “consumes” all of the dogs that enter and received the highest efficiency score of 1.000. Therefore, there is a possibility that San Diego Humane Society & SPCA could improve its efficiency score by partnering with El Cajon Animal Shelter to transfer dogs when they enter their facility.

Generally, the dual price for each input and output constraint would be used to determine the impact of the partnership described above on the shelters involved. Unfortunately, the methods typically used for sensitivity analysis in linear programming are not appropriate for DEA, as found in research initiated by Charnes et al. in 1985. Their research was the first to note that these methods are not appropriate because variations in the data of a DEA model could alter the inverse matrix that is typically used to approach this type of work (Cooper, Seiford and Zhu, 2004). Therefore, rather than using the linear program output to conduct sensitivity analysis in this paper, the models for San Diego Humane Society and El Cajon Animal Shelter were run again with the variations in the data to measure the true impact of this partnership.

If we pretend that a little more than half (1,151) of the dogs that enter the San Diego Humane Society & SPCA are shifted to the El Cajon Animal Shelter upon entry, we can rerun the models with these numbers. The result is that the San Diego Humane Society & SPCA receives an improved efficiency score of 1.000 while the El Cajon Animal Shelter maintains its efficient score of 1.000. Although this indicates that the partnership could be helpful to San Diego Humane Society without harming El Cajon Animal Shelter, we cannot be certain of the true overall impact on the two shelters involved. There may be other operational constraints that we cannot see through this linear program; however, this gives insight into a place to start looking for improvement.

A similar process can be done by looking at the slack values for the number of cats that enter a shelter. Two shelters, SPCA Monterrey and North County San Diego, had a positive slack value for the number of cats entering. This means that they had an excess in the number of cats coming into the shelter and could improve by lessening this number.

Four shelters, SPCA Monterrey, North County San Diego, San Diego Humane Society & SPCA, and Escondido Humane Society, also had an excess in their expenses. Therefore, these shelters could become more efficient if they spent less money.

In addition to studying the slack values for the inputs, partnerships to improve output could also drive improvement in the efficiency score for the inefficient shelters. There are no shelters that have a shortage for the number of dogs that are put into adoption when compared to the shelters that perform the best. However, four of the inefficient shelters have a positive slack value for the constraint that represents the number of dogs that are returned to their owners. The Dubuque Humane Society, the Allen County Humane Society, the Arizona Humane Society of Phoenix, and the San Diego Humane Society & SPCA all could improve their efficiency score by returning more dogs to their owners. An even larger proportion of the inefficient shelters, five of them, could benefit from focusing on the number of cats that they put into adoption.

The five shelters that struggle with the number of cats put into adoption are the Dubuque Humane Society, the Allen County SPCA, the SPCA Monterrey County, the Arizona Humane Society of Phoenix, and the Escondido Humane Society. They would each need to improve by the amounts shown in Table 5-1 to achieve an efficiency score of 1.000.

Table 5-1: Improvement Needed in the Number of Cats Adopted

	Shelter	Current Efficiency Score	Current # of cats adopt	% Improvement to be efficient	New # of cats adopt
4	Allen Cty SPCA	0.980	194	8%	16
3	Dubuque HS	0.920	783	143%	1903
15	Escondido HS	0.801	558	90%	1060
6	Spca Monterray	0.620	900	154%	2286
11	Arizona HS	0.614	7429	229%	24441

Because we designed the data envelopment analysis model to be easily adjusted within Microsoft Excel and OPL Studio, this type of sensitivity analysis can easily be done for the various DMUs and combinations of the other inputs and outputs in the model. An individualized strategy could be designed for each shelter to begin working toward an efficient status.

Additional Insight That Could be Gained with Improvements in Data

Additional Insight Due to More Shelters with Data

The significance of the results from a data envelopment analysis grows with an increased number of DMUs. The ability to use our model to truly measure the efficiency of the shelters is limited because we were only able to find complete datasets for 15 shelters. There is no standardized system for measuring and reporting data in the animal welfare world. Although the animal welfare groups that operate as nonprofits are required by the government to submit a Form 990 each year, the means for computing the numbers which go into the Form 990 are not standardized. Therefore, it is difficult to use the data to develop comparisons of multiple shelters. In addition to this shortfall in the financial means of measuring activity, no formal record system exists for measuring operational activity. The group that developed the Asilomar Accords attempted to put forth such a framework. The Asilomar Accords include a method for measurement and a standardized way of reporting. It would be extremely helpful and beneficial for more animal welfare societies to adopt this system. If they were to do so, we could use the data to do many types of analysis, with just one of them being a more holistic and actionable data envelopment analysis model.

Additional Insight Due to More Inputs and Outputs

In addition to more shelters collecting data, an increased number of inputs and outputs would help us better identify where a shelter should focus on improvement. As mentioned in the Chapter 3 of this paper, it is desirable to have a significantly larger number of DMUs in a DEA model than the number of inputs and outputs. A general rule of thumb is to have enough shelters to cover the maximum of three times the sum of the inputs and outputs or the product of the inputs and outputs. In our model, three times the sum of the inputs and outputs is 3(3+4) = 21. The product of the inputs and outputs is (3x4) = 12. With 15 DMUs, we have enough to cover the second guideline; however, we do not have enough to cover the first guideline.

If we had been able to find data for more inputs and outputs and more DMUs, we would have liked to include the following.

Table 5-2: Potential Inputs and Outputs for Model Improvement

Inputs	Outputs
Number of workers	Average length of stay
Labor hours	Animals return to shelter after adoption
Number of cages	
Square footage of building	
Demographic of location	
Human Population of location	
Estimated Animal Population of location	
Dollars from government	
Dollars from donations	
Age of animals	
Type/Breed of animals	

Statistics such as those in the table above would give us more insight into why the performance measures for the various shelters differ. Information such as the labor resources used to manage a shelter or place animals into adoption could be useful if one shelter does more than another with the same resources, or, the same thing could be said for the number of cages. We may find that a shelter with more cages than its peers should be able to produce proportionately more output than its peers. The DEA model would help us identify what level of output should be feasible for the given DMU, based on the number of cages and level of output in the other shelters included in the model. Additional inputs and outputs ultimately help us better target specific tactics that a shelter could use to improve its efficiency.

Additional Insight Due to More Years of Historical Data

Another area in which this analysis would benefit from a more structured process of collecting data in animal shelters is by having multiple years of recorded information. An average of 3-5 years for each of the numbers put into our model would most likely yield more accurate results. This would help ensure that unusual occurrences do not as significantly impact the results of the analysis. For example, this would be applicable to shelters that are impacted by a natural disaster such as a hurricane or forest fire during a year in which they provide data for the analysis. If their operational statistics are unusual, more years of data will be less likely to impact that shelter's efficiency score or the efficiency of other shelters in the model.

Sensitivity Analysis that could be Done with Additional Data

According to Cooper, Seiford, and Zhu (2004), the topic of sensitivity analysis in DEA has taken many forms throughout DEA literature since the discovery of Charnes et al in 1985. One part of this literature studies the response of the data when DMUs are added or eliminated from the model. Another technique called “window analysis” focuses on changes in DMU performance over time. Other methods of sensitivity analysis focus on the impact of increasing or decreasing the number of inputs or outputs in the model, while even more methods examine the sensitivity of the results to various types of DEA models that can be used. Unfortunately, the ability to use these sensitivity analysis techniques in this manuscript were limited due to the lack of animal shelter performance data that was found. The basic model required the use of all of the DMUs that were found to have full sets of data and as many outputs and inputs as possible. Alternative models were calculated; however, they provided even less differentiation between the shelters being studied.

Future Research Recommendations (Using DEA or for Shelters)

Since the original DEA model was created by Charnes, Cooper and Rhodes, there have been many advances in the methods used to formulate the linear programs for DEA. One of the most famous models was developed in 1984 by Banker, Charnes, and Cooper. According to Cooper, Seiford, and Zhu (2004), this so-called BCC model allows for variable returns to scale because it bends the efficiency frontier more tightly around all of the boundary points and makes it easier for DMUs enveloped inside the frontier to reach the frontier. This adjustment can be made to the model very easily by adding just one new constraint which forces the sum of the weights placed on each shelter to build the composite shelter in the dual model to equal one. The efficiency score found with the BCC model will be higher than the score found with the CCR model because it lessens the distance needed to get to the frontier.

In addition to the BCC model, many researchers have published improvements or variations to the original models. Many people continue to study DEA and participate in groups to share their insights. There are new formulations that could be applied to the animal welfare data to see if the results change. However, before newer models are applied to the data, it is more important to gather complete datasets for more shelters to be used in the comparisons. According to Jill Grand, on behalf of the Asilomar Accords, Maddie's Fund® is currently in the process of building a public database with information for the animal welfare groups that have received their grants. This database will include data in the Asilomar Accords format. Currently, grants have been awarded to 150 organizations and a database is expected to be available for Internet searches in the coming months. Once this data is made available, a more holistic DEA model can be built which includes more shelters and thus should provide more insightful results.

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