ESTIMATING MATERIAL CONVERGENCE: FLOW OF DONATIONS FOR HURRICANE KATRINA

by

Lisa Destro

A Thesis Submitted to the Graduate

Faculty of Rensselaer Polytechnic Institute

in Partial Fulfillment of the

Requirements for the degree of

MASTER OF SCIENCE

Major Subject: TRANSPORTATION ENGINEERING

Approved:

____

José Holguín-Veras, Thesis Adviser

Rensselaer Polytechnic Institute
Troy, New York

May, 2010
(For Graduation May 2010)

CONTENTS

LIST OF TABLES

LIST OF FIGURES

ACKNOWLEDGMENT

I would like to thank Dr. Jose Holguín-Veras, he has been my adviser, my boss my teacher, and my mentor in these last few years of my life. I am grateful because I had the chance to work with him and learn from him, and most importantly I got to know a truly inspirational man. Because of him I got to enter his world of humanitarian logistics and with the tools of transportation engineering and social science he provided I made this exciting, complex, multidisciplinary field my research work. I want to acknowledge all the Undergraduate Research Program students who contributed in the data collection for this thesis, especially Robyn Marquis and Jessica Gillett. Finally, I would like to thank my mom and dad for their endless support and understanding all through my graduate studies.

ABSTRACT

In the aftermath of an extreme event such as Hurricane Katrina, the delivery of critical supplies (e.g., food, water) to the disaster site often becomes a difficult task because such events originate a convergence process, which is the movement of personnel, information, and material towards the disaster site. From the humanitarian logistics standpoint, material convergence is an important issue since donations—particularly of non-priority items—can severely hamper the flow of critical supplies by distracting resources from critical tasks. The main problem is that the logistic system has a limited capacity and there is a high volume of low priority goods and a low volume of high priority supplies trying to use the system simultaneously, therefore the efficiency of the flow of critical supplies depends on the flow of low priority supplies.

This research focuses on the quantification of the material convergence. One of the most critical issues in disaster response is the overwhelming inflow of donations to the disaster site and the lack of planning for handling and distributing the donations. In order to contribute to the understanding of this complex problem, a database of donations made in the aftermath of Hurricane Katrina has been assembled. These data are based on post-processing of newspaper articles and web publications to be used for econometric modeling to quantify convergence. These data are used to investigate the donations' patterns taking Hurricane Katrina as a case study, with the objective of trying to figure out if donations can be explained in terms of the socioeconomic characteristics of the geographical locations of the event and the donors. Developing such models is important because it might improve the efficiency of humanitarian relief agencies, giving them an idea of what to expect in the event of a disaster and thus helping the agencies to be ready for the management of donations in the response process.

1. INTRODUCTION

In the aftermath of an extreme event, such as a natural or manmade disaster, humanitarian logistics plays a key role in the disaster response. Humanitarian logistics is the process of planning and managing the relief flows into the disaster site in order to meet the needs of the affected population and minimize human suffering. However, due to the inherent nature of disasters, humanitarian logistics is a challenge yet to be overcome. Holguín-Veras, et al. (2007) characterize these challenges in the following main facets: (1) infrastructure and communication systems may have been impacted and unable to fully function; (2) large (and dynamic) volumes of critical supplies must be transported; (3) there is a short timeframe to respond and prevent loss of lives and property; and, (4) there is a huge amount of uncertainty about what is actually needed, where it is needed, and what is available at the site; among other complications.

As described in Holguín-Veras, et al. (2007) the research in logistics in general mainly focuses on private sector practices, in the process of planning, implementing, and controlling the flow and storage of commercial goods and services from the point of origin to the point of consumption; yet, it rarely discusses humanitarian logistics. On the other hand, the disaster research in the social science field has studied institutional planning and multi-organizational responses to extreme events, but little attention has been given to the impact of such planning on logistics. This suggests the need for research in humanitarian logistics with a multidisciplinary approach, using both the social science knowledge and experience in disaster response and the engineering modeling techniques in logistics to undertake the unique challenges of humanitarian logistics (Holguín-Veras et al., 2007).

The occurrence of an extreme event triggers a massive influx of personnel, information and materiel to the impacted area (Fritz and Mathewson, 1956). Convergence behavior has been identified in almost all extreme events; however the amount of research that has been conducted in this subject is not proportional to its importance (Holguín-Veras et al., 2007). This was highlighted by Scanlon (1991) who emphasized the lack of research on convergence. The publications on this topic have mostly focused on personnel convergence, Neal (1994) is among the few publications that have focused solely on materiel convergence.

Nevertheless, materiel convergence is an especially important subject since it impacts the delivery of critical supplies to the site of an extreme event. As it has been seen in recent disasters such as the World Trade Center in 2001, the Asian Tsunami in 2004 and Hurricane Katrina in 2005, unsolicited donations can cause unexpected problems to the emergency logisitc system. Donations, particularly of non-priority items, can severely hamper the flow of critical supplies by distracting resources from critical tasks. The main problem is that the logistic system has a limited capacity and there is a high volume of low priority supplies and a low volume of high priority supplies trying to use the system simultaneously, therefore the efficiency of the flow of critical supplies depends on the flow of low priority supplies.

There is no doubt that the study of the process of convergence during the disaster response process is of critical importance to an efficient and effective emergency logistic system. This thesis focuses specifically on the study of the flow of donations using Hurricane Katrina as a case study. As presented in Holguín-Veras, et al. (2007) and, as it was worldwide broadcasted, the Hurricane Katrina response was a humanitarian logistic debacle and one of the main issues was the lack of planning for the handling and distributing donations. For these reasons, a database of Katrina donations has been assembled based on post-processing of newspaper articles and web publications to be used for econometric modeling to quantify convergence. These data are used to investigate the donations' patterns with the objective of trying to figure out if donations can be explained in terms of the socioeconomic characteristics of the geographical locations of the donors. Regression analysis techniques have been used to develop such models. Developing such models is important because it might improve the efficiency of humanitarian relief agencies, giving them an idea of what to expect in the event of a disaster and thus helping the agencies to be ready for the management of donations in the response process.

1.1 Objectives

The main objectives of this thesis are to:

a) Identify the socioeconomic characteristics that may influence donations;

b) Develop models that enable emergency repose agencies to estimate material convergence so that humanitarian relief agencies may have an idea of what to expect in terms of donations and have an efficient plan for the management of donations.

1.2 Content and Organization

This thesis is organized in the following manner. *Literature Review* describes the findings from previous studies related to materiel convergence and more specifically the flow of unsolicited donations to the site of an extreme event. *Data Collection* describes the process of putting together the data as well as their limitations. *Descriptive Analysis* illustrates the basic characteristics of the data. *Modeling Methodology* provides the reader with a description of the modeling approach used in this thesis, as well as a brief description of regression analysis. *Results* focus on presenting and discussing the modeling results. *Analysis* consolidates the modeling results and compares them to results from previous research. *Conclusions* discuss the key findings of the study.

2. LITERATURE REVIEW

As part of this thesis an extensive research was conducted on the process of materiel convergence in humanitarian logistics and disaster response, specifically on the convergence of donations to the impacted area.

2.1 Humanitarian Logistics

One of the four main facets of the challenges of humanitarian logistics described by Sheu (2007) is that the definition of humanitarian logistics is still ambiguous. There is no clear definition that has been defined in previous literature of humanitarian logistics as it has been done with business logistics: Ballou (1999); Bowersox and Closs (1996); Johnson, et al. (1999). Sheu (2007) follows by adapting a definition for humanitarian logistics from that of business logistics from previous literature: humanitarian logistics is the "…process of planning, managing and controlling the efficient flows of relief, information, and services from the points of origin to the points of destinations to meet the urgent needs of the affected people under emergency conditions."

Predominantly, logistics research has focused on the commercial supply of goods and services, and rarely on humanitarian logistics. The social science disaster literature has examined institutional arrangements and multi-organizational responses to extreme events, but little attention has been given to the impact of such arrangements on logistics (Holguín-Veras et al., 2007). It is somewhat contradictory that both the logistics and the social science disaster research approaches have not paid the needed attention to such a significant subject as it is humanitarian logistics. The importance of this subject lies mainly in its unique characteristics which are simultaneously complex challenges to be overcome. As Bernard Chomilier, the head of logistics for the International Federation of Red Cross and Red Crescent Societies (IFRC), stated while describing the difficult job of emergency logisticians: "You do not know what you need, you do not know where you need it, but you have to get it there in a short amount of time under chaotic conditions or people will die…" (Fritz Institute, 2006). All of this suggests the need for a multidisciplinary approach in the humanitarian logistics research that could tackle these complex issues using both social science frameworks and transportation modeling techniques (Holguín-Veras et al., 2007).

2.2 Materiel Convergence

An extreme event usually leaves behind considerable physical damage to infrastructure; refugees without food, water, or shelter; a death toll; and, injured victims with limited or no medical assistance. In response to such devastation a convergence process is originated: a massive influx of personnel, information and material all directed to the impacted area. Fritz and Mathewson (1956) present the earliest comprehensive study on the subject, defining convergence as “movement or inclination and approach toward a particular point.” They outlined for the first time three basic components of convergence: personnel convergence, i.e., the movement of individuals; informational convergence, i.e., “the movement or transmission of symbols, imageries, and messages…”; and materiel convergence, i.e., “…the actual movement of supplies and equipment…” (Fritz and Mathewson, 1956).

Convergent behavior has been identified in almost all extreme events, being S.H Prince’s investigation of the Halifax munitions ship explosion in 1917 the first sociological study of a disaster that discussed this convergence process (Scanlon, 1991). In this very important subject—which deals with the flows of supplies, information and personnel in humanitarian logistics—the quantification, control and management of these flows would help with an efficient disaster response and ultimately preserving the human rights and saving lives. However, the amount of research in this topic has not been proportionate to its importance. Scanlon (1991) emphasized this highlighting the lack of research on convergence. Kendra and Wachtendorf (2003), Zakour and Gillespie (1998), Wenger and James (1994) are some of the few publications on this subject and have focused mostly on personnel convergence; and Neal (1994) is among the few publications that has focused exclusively on materiel convergence.

Regardless of the lack of research, materiel convergence is an extremely important subject as it deals with the interactions of the delivery of high priority supplies to the site of an extreme event. Experience stresses the need to formally take into account convergent behavior when defining ways to expedite the flow of high priority supplies. In particular the flow of donations is a major issue in disaster response and the materiel convergence process. Donations, specifically of non-priority items, can severely hamper the flow of critical supplies by distracting resources from critical tasks. The main problem is that the logistic system has a limited capacity and there is a high volume of low priority supplies and a low volume of high priority supplies trying to use the system simultaneously, therefore the efficiency of the flow of critical supplies depends on the flow of low priority supplies.

According to Kendra and Wachtendorf (2003), the convergence of people into an impacted area reflects the needs of legitimate claims of entry or reentry into the disaster zone and often brings with it much needed personnel support and expertise. Some convergers providing assistance meet needs and fill gaps not otherwise filled (Stallings and Quarantelli, 1985). At the same time, the convergence of people is often accompanied by many challenges, including volunteer management (Barton, 1969). As Drabek (1986) suggests, when so many people, representing so many organizations, are trying hard to be helpful, things do not always perform the way they should.

The same can be said of materiel convergence. The donations from charities and private citizens that converge to the impacted areas can fill tremendous needs. However this convergence can prove equally challenging to manage, particularly in terms of transportation, storage, preservation, inventory, sorting and distribution. Dynes (1970) for example, discusses the influx of supplies which "… (1) normally arrive in volumes far in excess of the actual needs; (2) in large proportion they are comprised of unneeded and unusable materials; (3) they require the services of large numbers of personnel and facilities which could be used for more essential tasks; (4) they often cause conflict relations among relief agencies or among various segments of the population; (5) they materially add to the problem of congestion in and near the disaster site; and (6) in some cases they may disrupt the local economy."

For illustration purposes in 1967 after the bushfires disaster in Southern Tasmania, Australia "… the 'convergence' phenomenon identified by American researchers (Fritz and Mathewson, 1956) was experienced in full measure, with messages, people, material and money pouring into the disaster area in such abundance that its organizational resources, caught completely unprepared, came near to collapsing under the strain" (Wettenhall, 1979). In 2001 after the World Trade Center disaster "[there] were examples of much needed materials, but we also saw donations of unnecessary goods… Examples include the five tractor-trailer loads of pumpkins donated to Ground Zero around Halloween that needed to be redirected to public schools as well as clothing donated in such amounts that distribution was challenging to an area where relatively few people actually lost their homes and personal processions" (Wachtendorf and Kendra, 2004). In 2005 in the Gulf Coast after Hurricanes Katrina, Rita and Wilma ""Donation management is the most difficult part of every disaster", he said of unsorted mountains of clothes. "We have a little bit of everything.""… (Corpus-Christi Caller-Times, 2005). Sometimes generosity can go awry."… In Katrina's immediate aftermath… collection sites along the Mississippi Gulf Coast became "nothing more than dump sites"…" (Purpura, 2005). In the case of Hurricane Katrina the government disaster response was widely discussed and criticized. Even official reports (U.S. House of Representatives, 2006; White House, 2006) recognized that there were many lessons to be learned from the response to this emergency. One of the key issues that led to the logistical debacle in the Katrina disaster response was the lack of planning for the handling and distribution of donations (Holguín-Veras et al., 2007).

Although donations can be helpful in certain circumstances, many commodities provided are inappropriate given emergent needs, donated at inappropriate times, or in excess of what is required. Consequently, the superfluous donations require the expenditure of considerable resources to manage or dispose it (Holguín-Veras et al., 2007). This insight was confirmed by a survey of logisticians from the largest international organizations active in the relief efforts to the areas affected by the 2004 Asian Tsunami (Fritz Institute, 2005). The survey concluded that the process of identifying, prioritizing, transporting and/or storing unsolicited donations that were delivered directly to disaster areas required valuable resources and had a detrimental effect on the recovery activities.

2.3 Likelihood of Donations

In this section a literature review has been conducted on the likelihood of donations. Questions like: what makes people and corporations donate, what makes them donate more or less, are interesting topics to research in the process of understanding material convergence and unsolicited donations.

It has been suggested (Schwartz, 1970) that individuals derive wellbeing from both giving and consuming, i.e. utility functions are defined over own consumption/saving and consumption by the recipient (Hood et al., 1977). In essence, depending on how much utility can be derived from giving or consuming, given a budget constraint every potential donor has the choice between own consumption/savings and donations.

Moreover, Bryant et al., (2003) suggest that people make choices about whether to give their time and money for the benefit of others in light of the resources at their disposal. Their resources include their "human," "cultural," and "social" capital (Wilson and Musick, 1997) as well as their time, income and wealth (Bryant et al., 2003). "[A person's] age, gender, and race/ethnicity all impact [its] human, social, and cultural capital. Age reflects the cultural environment and group into which an individual is born as well as being positively correlated with labor productivity increasing experience. Gender and race/ethnicity reflect the social and cultural capital encapsulated in the gendered and racial roles people play and are allowed to play" (Bryant et al., 2003).

The solicitation of donations and volunteering from charitable organizations puts social pressure on the individuals and increases the likelihood that they will agree to donate or volunteer. Bryant, et al. (2003) argue that some of the variables that influence the likelihood of individuals donating are: the extent to which employers exert subtle or direct pressure on employees to donate or to volunteer their time; the opportunity costs of individuals' time; individuals' net wealth; and, the extent to which donations are tax deductible. In accordance with the last variable, Hood, et al. (1977) found that individual charitable donations are responsive to their implicit 'price' as defined in the tax system.

Bryant, et al. (2003) explain the socioeconomic characteristics of individuals targeted by charitable agencies when soliciting donations: higher income individuals, wealthy, the more educated, those who are church-goers, those who have lived in the community longer which may have more geographic or social proximity to the issues of the community, those with wide networks in the community (assuming that single, separated and divorced individuals are less connected with societal networks than are married individuals). Furthermore, households with larger number of children are more likely to be solicited for donations or volunteering. In their study Bryant, et al. conclude that African American and Hispanic Americans are less likely to be solicited than whites; most likely because they are thought to have less social capital, or are less accessible than whites. And, because of the cultural roles that females and males have played in the past women more than men are expected to volunteer while men more than women are expected to donate money.

However, in their study about the probabilities that individuals will donate time or money given that they have been solicited or not, Bryant, et al. (2003) found that while there is some support for the hypothesis that argues that more social and human capital incline individuals to volunteer or donate, it is stronger with respect to volunteering than donating and it is also stronger with respect to volunteering and donating when the individual has not been asked to give.

Hood, et al. (1977) state that individual donations rise with income, although somewhat less than proportionately. This was reaffirmed by Bryant, et al. (2003) which also stated that higher income individuals except the very rich are more inclined to donate than individuals that are not. Furthermore, Bryant, et al. (2003) found that older individuals except the elderly, highly educated individuals, females, whites, individuals not living in standard metropolitan statistical areas and the suburbs, and married individuals all have higher probabilities of volunteering and donating than individuals who do not have these characteristics. Previous studies (Feldstein and Clotfelter, 1976; Feldstein and Taylor, 1976) that used micro-data on individuals from the United States to estimate the tax-responsiveness of individual charitable donations, found that giving rises substantially with age and donations of individuals do not appear to be responsive to others' donations.

Feldstein (1975), when discussing the preferences of charitable donations to religious institutions and to philanthropic and educational ones found that such religious donations are a much higher proportion of the donations of lower-income than of higher-income groups. This was reaffirmed by Bird and Bucovetsky (1975) who stated that lower-income groups give a higher proportion of their donations to religious organizations than do upper-income groups.

Schweitzer and Mach (2008) in their study of the statistical analysis of a data set of donations before and after the Asian Tsunami disaster of 2004, concluded that dissemination of the disaster event by the mass media triggered the first donations, which resulted in some global feedback dynamics which eventually slowed down because of a decreasing public interest and an exhausted resource (potential donors). They also found that even though the number and amount of donations changed tremendously there were statistical similarities in individual donations before and after the tsunami.

With respect to corporate donations, Muller and Whiteman (2008) argue that there is evidence of 'regionalization' in corporate philanthropic disaster response, meaning that organizational behavior in response to major disasters appears to vary systematically across regions. They also argue that there is a 'home regional effect' and a 'local presence effect' in corporate philanthropic disaster response, by which firms pay more attention to disasters that are closer to home, or in locations where they have a local presence, possibly out of a sense of responsibility or a greater degree of tangibility.

3. DATA COLLECTION

Hurricane Katrina was used as a case study to analyze the statistical relocation between donation flows and the socioeconomic characteristics of the donors. For this purpose, data were collected of donations made after Hurricane Katrina. However, some limitations should be acknowledged. Firstly, since newspaper articles and web publications were the source for the data collection, the data collected are not likely to represent the total donations made, as only donations that were reported in the media could be considered to be part of the data. Secondly, the amount of information that was available in these newspapers and web publications was not necessarily enough to include all donations found on the final data set.

The process started by reading newspaper articles and web publications containing information about Hurricane Katrina donations. The articles were found using Lexis Nexis, which is an online archive of content from newspaper, magazines, web publications and other printed sources. The search was done using the keywords "Hurricane Katrina donations" for articles that were published between August 2005 and December 2006. Around 3,080 articles were collected to be read and processed. Information about donations pertaining who, what, how, when, where, to whom, how much, among others, were captured in a form created for this purpose. The form was divided in five parts.

The first part was a universal header where an identification code was assigned to the article and general information about the source of the article such as title, author, publication name, date and type. The second part was the disaster information such as the name, type and location of the disaster; in this case this information was always the same, Hurricane Katrina that devastated the Gulf Coast region of Louisiana, Mississippi and Alabama. The third part captured information about actual donations: donor name, type, location and description of the donor, if the donation was made directly to the impacted area or indirectly through an organization (e.g., humanitarian relief organizations and government agencies), to whom was the donation made to (final recipients), location of the recipient, information about the logistics of the delivery, what was donated and how much. The fourth part was information about donation drives, essentially the information that was being captured was: who organized it, were there any partner organizations, where was it, when was it, who was the target audience, and what were the commodities accepted. The final part was a copy of the article where the information was extracted.

The next steps after the database was put together were to organize, clean, code, complete and filter the data. For the purpose of this research only the data about actual donations being made were included. Therefore, the overall data about donation drives, where there were no details about specific donations being made from specified donors, were excluded. In the cases where the articles were missing all the geographic information of the origin of the donation (country, state, city and ZIP code depending if it was a domestic or international donation), research was conducted using the Internet as to who the donor was to complete the location as best as possible. In the case of organizations (companies, associations, non-profit, non-governmental, charitable organizations) if the article did not specify the location of the organization, branch or division that made the donation the location was assumed to be the one of the main offices or headquarters. For famous individuals, the location of their residence was assumed to be the origin of the donation unless specified otherwise. For general individuals, the articles usually provided a specific or close enough location of where the donations were coming from.

As for the geographic information of where the donations were going to and who were the recipients, if the article did not specify this it was assumed that donations were going to Hurricane Katrina victims and hurricane relief in the Gulf Coast area of Louisiana, Mississippi and Alabama. The date of the donation, unless specified, was assumed to be one day before the article was published if the article talked about it in the past tense or one day after the publication date if it was talked about in the future tense. Another assumption was related to how the donations were made, usually it was specified if the donation was made through another organization such as the Red Cross or if the donation was made directly to the impacted area or in other words directly to the recipients of the donations. In the case where this was not specified in the article, it was assumed that the donation was made indirectly since this was usually the case, and it was not specified the organization through which the donation was made. In the observations where the quantities of the commodities donated where not expressly stated in the articles but could be inferred by the use of words such as “several truckloads” or “several thousand” a quantity of five was assumed.

The next step with the data was coding all the commodities donated. For this purpose the North American Industry Classification System (NAICS) was used (U.S. Census Bureau, 2007). Once the data was coded all the observations were sorted and filtered by the donor names to eliminate any repeated donations and to merge any donations from the same donor. In general donations or observations were taken out of the data if there was no information in the article or no way to assume the quantities of the commodities that were donated. Also, in the case of domestic donations, the observation were taken out if there was no reasonable way with the information provided to assign a ZIP code to the origin of the donation.

Once the commodity amounts have been estimated they were converted to U.S. dollars. For the conversion process the 2002 Commodity Flow Survey from the U.S. Department of Transportation and the U.S. Department of Commerce was used (Bureau of Transportation Statistics and U.S. Census Bureau, 2004), as well as research was conducted to find all the commodities’ prices. All prices were moved to the year 2005 or 2006 using the Consumer Price Index Tables (Bureau of Labor Statistics, 2009).

Unless it was specified some assumptions were made in order to convert all type of commodities to dollars. All technical and professional services (e.g., services of doctors, nurses, electric line workers and construction workers) were converted using the salary and an assumed amount of time of donated services. Also for donations of shelter or housing an amount of time was assumed. For donations of construction of houses and buildings the square footage was assumed.

For the purpose of the analysis, the data were divided into domestic and international data. The domestic data constitutes all donations that were made inside of the United States and the international data are all donations that came from other countries to the United States. The final domestic data represent 1,016 observations of donations made in the period from August 2005 to December 2006. Each observation represents a different donation and all donations are not necessarily made by different donors. For example, different donations can be made by the same donor but to different recipients or through different organizations. The 1,016 donations constitute 801 different donors and 1,267 commodities donated (including split donations) and around $1,069 million dollars worth of monetary and in-kind donations.

4. DESCRIPTIVE ANALYSIS

The data set was organized so that donations can be visualized as a flow. A flow of commodities (monetary or in-kind donations) from the origin which would be the donor's location, to the destination which in this case would be the Gulf Coast states impacted by Hurricane Katrina. The data captured if donations were made directly to the recipients or indirectly through an intermediary organization, e.g., the Red Cross, the Salvation Army, among others. Out of the 1,016 donations of the data 31.5% were made directly to the impacted area or to the final recipients, and 68.5% were made indirectly through another organization that would distribute the donations to the hurricane victims. Figure 1 represents the flow of the donations from each type of donor to the disaster site. It also shows what percentage of each donor type was donated directly to the disaster site and what percentage was donated through an intermediate agent like the Red Cross, or the Salvation Army. Most donors donated through another organization rather than directly to the hurricane victims. Only in the case of charitable organizations and government agencies did a larger percentage (no more than 56%) of donations go directly to the hurricane victims; which would be expected considering that these are usually the organizations that are responsible for distributing donations in the impacted areas to the victims. In the case of charitable organizations, these are typically the intermediate agents between the donors and the victims. As for the government this donor type refers to government agencies that have no official responsibility to help such as state governments, city governments and county governments that were not impacted by Hurricane Katrina.

Table 1 shows how the indirect donations were made. According to the data set the most popular organization was the Red Cross with 44% of the indirect donations being made through it. This is no surprise considering the fact that the American Red Cross raised donations in excess of $2 billion for Hurricane Katrina, or two-thirds of the total collection by charitable groups, and led the efforts of 220,000 staff and volunteers (U.S. House of Representatives, 2006). Other organizations that were used as well to make donations for Hurricane Katrina victims were the Salvation Army, Habitat for Humanity, the Bush-Clinton Katrina Fund, United Way, Feed the Children and America's Second Harvest. A smaller percentage of donations (3.3%) were made through individual people and through government agencies. Other donations (14%) were made through associations, schools, federations, clubs or hospitals and through other charitable organizations, foundations, companies or employee funds.

The purpose of a donation can be inferred in some cases by the selection of the organization through which the donor makes it, such as 0.7% of the indirect donations that were made through the Humane Society or the American Society for the Prevention of Cruelty to Animals (ASPCA); which were for animal shelters and to rescue pets that were left behind in the hurricane impacted areas. Some donations were made through unknown relief organizations either because it was stated like this in the articles: “a charitable organization” or “relief agencies”, or because it was not stated at all how the donation was made. As it has been explained before, for the cases were nothing was said about how the donation was made (directly or indirectly) it was assumed that donations were made indirectly as it is usually the case for formal donations. Therefore, 23% of the indirect donations were through unknown organizations.

Figure 1: Donations' flow

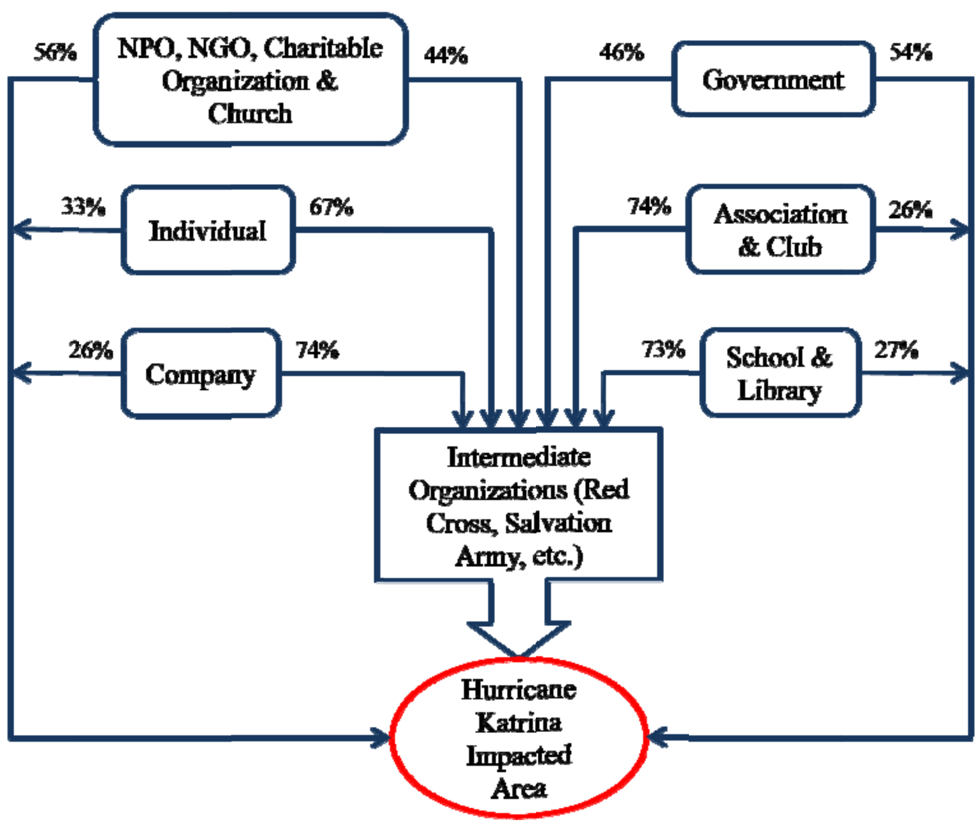


Table 1: Distribution of donations made through and organization

Indirectly Through:	Donation (%)
Red Cross	43.8%
Unknown organizations	22.8%
Others (e.g., Charitable Organizations, Companies, Company Employee Funds, Katrina Funds, Food Banks, Foundations)	11.9%
Mix (e.g., Salvation Army, Red Cross, America's Second Harvest)	5.2%
Salvation Army	4.3%
Association, School, Federation, Institute, Club, Hospital	2.0%
Individuals	1.7%
Government	1.6%
Habitat for Humanity	1.6%
Bush-Clinton Katrina Fund	1.4%
United Way	1.4%
Feed the Children	0.7%
Humane Society, American Society for the Prevention of Cruelty to Animals	0.7%
America's Second Harvest	0.7%
Total	100% (696)

Of the 1,016 donations around 48% were from companies; 20% from individuals; 10% from schools and libraries; 11% from non-profit organizations (NPOs), non-governmental organizations (NGOs), charitable organizations and churches; 8% from associations and clubs; and 3% from state, city or county government agencies that did not have official responsibilities to aid the hurricane struck region. In the case of the value of the donations 54% of the worth was donated by companies; 34% by charitable organizations, NPOs, NGOs and churches; 6% by individuals; 3% by associations and clubs; 1% by government agencies with no official responsibility to help, and 0.3% by schools and libraries. Table 2 shows the distribution of the donations by donor type and Figure 2 and Figure 3 show a visual representation of the amount and worth of the donations by donor type.

Table 2: Distribution of types of donors for all donations

Donor Type	Examples	No. of Donations (%)	Value in Dollars (%)
Company	Companies, corporations, newspapers, radio stations, private hospitals	48.3%	53.9%
Individual	Individuals and families	20.4%	5.9%
School and Library	Elementary schools, middle schools, high schools, universities, libraries	10.2%	0.3%
Charitable, Church and NPO	NPOs, NGOs, charitable organizations, fraternal organizations, foundations	10.6%	35.9%
Association and Club	Professional associations, business associations, clubs, sport teams, sport leagues	7.7%	2.5%
Government Agency	Government agencies, county councils, state/city/county governments, embassies	2.8%	1.4%
Total		100% (1,016)	100% ($1,069,256,178)

Figure 2: Amount of donations by types of donors

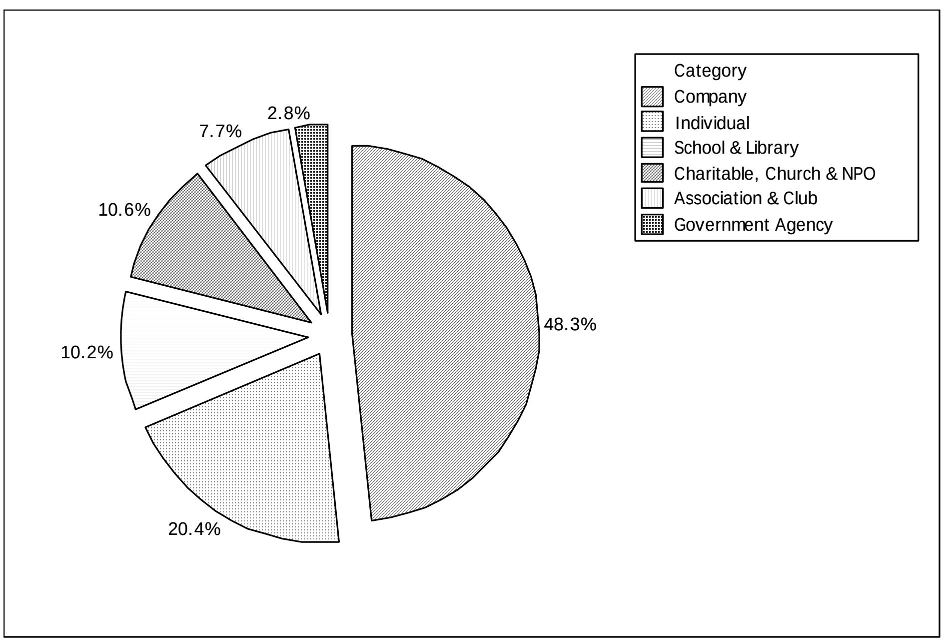


Figure 3: Monetary value of donations by types of donors

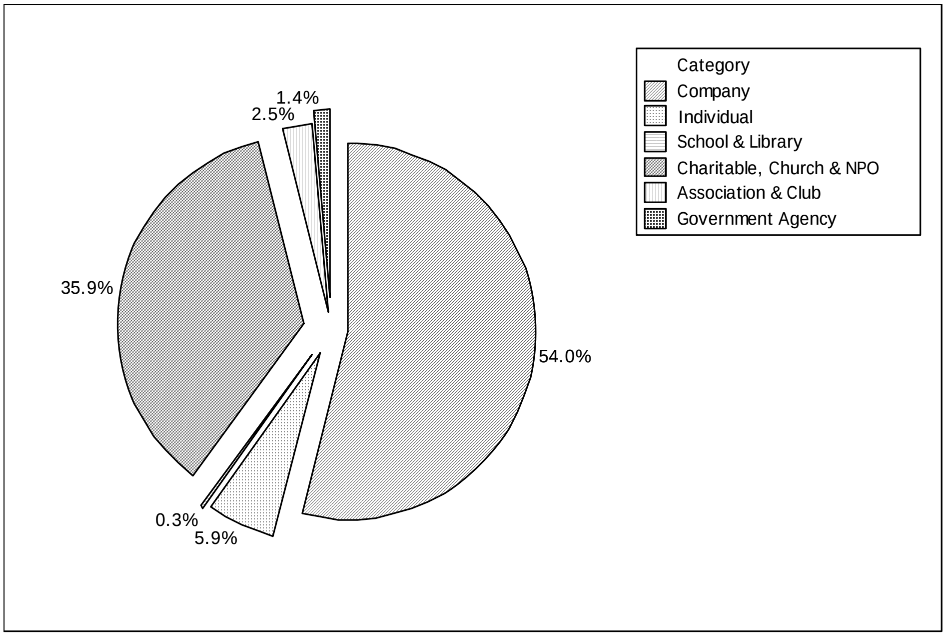


Table 3 shows the total dollar worth of each group of commodities donated. It should be noted that for the purpose of the analysis conducted in this thesis the monetary donations are treated as a commodity and were grouped in a "commodity group." It can be seen in Table 3 that the monetary donations constitute 58% of the value of all donations, followed "rebuilding efforts" which account for 15%, medical supplies which represent 8% of the total worth of donations, "telecommunications equipment and services" 4%, and food 3%. Other groups of commodities such as: transportation, "rescue and order"; critical supplies; "housing and shelter"; and "electric, electronic and mechanical equipment" represent roughly 2% of the total worth of donations. Groups such as advertisement, textiles, and water and ice constitute between 1.5% and 0.7%. Constituting less than 0.6% of the total worth of donations are the groups of school supplies, furniture, recreational items, temporary jobs and others. It should be noted that it is not known how the monetary donations were used, and that they could have been used in any of the other commodity groups.

These percentages of the worth of the commodity groups can be compared with the percentages of the amount of commodities that were donated in Table 3. It can be seen how high value commodities such as medical supplies and advertisement represent large percentages of the total worth of the donations and small percentages of the total amount of commodities. On the contrary cheaper commodities like food, water, textiles (e.g., clothing, shoes and blankets), toiletries, cleaning items, sanitary paper items, school supplies, books and recreational items (e.g., toys, bicycles and sporting goods) represent larger amounts of commodities than dollar worth. In the case of the rebuilding efforts, these were only a few donations (1.7%) but with huge monetary value (14.7%), this was because these donations represented the total amounts that specific charities would donate over long periods of time. The commodity groups of monetary donations, mixed critical supplies, furniture and jobs were fairly consistent in their percentages for both the value and the amount of commodities.

Table 4 shows the average value of the donations and the standard deviations for the different commodity groups (these donations are from all type of donors). In general for all groups the values of the donations are spread out around the mean, usually because of a few peak donations that tower over the rest or because the values range from really small donations to huge value donations. These peak values are usually from popular non-profit organizations that collected donations for a certain period and then donated the total collected donations. On average monetary donations were of 850 thousand dollars each (including all type of donors). As for the other groups each of the donations were worth on average: medical supplies donations were of 2 million dollar; food donations were of 300 thousand dollars; water and ice donations were of 250 thousand dollars; personal hygiene, cleaning and sanitary paper donations were of 190 thousand dollars; textile donations were of 167 thousand dollars; rebuilding donations were on average worth 7.5 million dollars each.

Table 3: Total amount and value of commodities donated by commodity group

Commodity Groups	Description/Examples	Value in Dollars ($)	Value in Dollars (%)	Donations (no.)	Donations (%)
Money	Monetary donations (cash, checks)	$620,262,769	58.01%	729	57.54%
Rebuilding efforts	Construction materials and services	$156,850,819	14.67%	21	1.66%
Medical supplies	Medicine, medical equipment, first aid kits, medical services including doctors and nurses, mobile exam rooms, and pet medical supplies	$85,687,973	8.01%	41	3.24%
Telecommu-nications	Telecommunications equipment and services, Internet service providers	$38,207,312	3.57%	30	2.37%
Food	Food (including animal food and mobile kitchens)	$27,009,083	2.53%	91	7.18%
Transportation, Rescue and Order	Transportation services and equip-ment, logistics services, fuel, and order forces and rescue teams (military, emergency personnel, policemen, firefighters)	$23,968,180	2.24%	46	3.63%
Supplies	Mixed critical commodities, emergency preparedness kits	$22,245,532	2.08%	24	1.89%
Housing	Housing and shelter	$18,021,065	1.69%	32	2.53%
Electric, electronic and mechanical equipment	Electrical, electronic and mechanical equipment and machinery (pumps, generators, computers, printers)	$17,434,029	1.63%	23	1.82%
Advertisement	Advertising time on TV to announce donation needs	$15,600,000	1.46%	4	0.32%
Textiles	Textiles (Clothing, shoes, blankets, quilts, tents, backpacks)	$12,014,236	1.12%	72	5.68%
Water and ice	Water, beverages and ice	$10,621,449	0.99%	43	3.39%
Personal hy-giene, cleaning and sanitary paper items	Toiletries, hygiene and cleaning items and diaper, paper towels, toilet paper and baby wipes	$7,508,993	0.70%	39	3.08%
School supplies	Books and school supplies	$6,105,396	0.57%	33	2.60%
Furniture	Cots, beds, mattresses, sofas, home furnishing	$3,695,098	0.35%	9	0.71%
Recreational items	Recreational items (toys, bicycles, sporting goods)	$2,109,295	0.20%	22	1.74%
Jobs	Jobs (temporary jobs)	$1,745,000	0.16%	3	0.24%
Others	Others (pet bowls, swipe cards)	$169,950	0.02%	5	0.39%
Total		$1,069,256,178	100%	1267	100%

Table 4: Average value of donations

Commodity Groups	Description/Examples	Number of Donations	Average Value of Donation	Standard Deviation
Money	Monetary donations (cash, checks)	729	$850,841	$3,352,960
Rebuilding efforts	Construction materials and services	21	$7,469,087	$22,277,576
Medical supplies	Medicine, medical equipment, first aid kits, medical services including doctors and nurses, mobile exam rooms, and pet medical supplies	41	$2,089,951	$7,121,285
Telecommu-nications	Telecommunications equipment and services, Internet service providers	30	$1,273,577	$3,681,704
Food	Food (including animal food and mobile kitchens)	91	$296,803	$705,363
Transportation, Rescue and Order	Transportation services and equipment, logistics services, fuel, and order forces and rescue teams (military, emergency personnel, policemen, firefighters)	46	$521,047	$1,068,823
Supplies	Mixed critical commodities, emergency preparedness kits	24	$926,897	$1,542,411
Housing	Housing and shelter	32	$563,158	$1,195,750
Electric, electronic and mechanical equipment	Electrical, electronic and mechanical equipment and machinery (pumps, generators, computers, printers)	23	$758,001	$1,185,492
Advertisement	Advertising time on TV to announce donation needs	4	$3,900,000	$4,631,055
Textiles	Textiles (Clothing, shoes, blankets, quilts, tents, backpacks)	72	$166,864	$580,169
Water and ice	Water, beverages and ice	43	$247,010	$599,234
Personal hygiene, cleaning and sanitary paper items	Toiletries, hygiene and cleaning items and diaper, paper towels, toilet paper and baby wipes	39	$192,538	$403,926
School supplies	Books and school supplies	33	$185,012	$693,071
Furniture	Cots, beds, mattresses, sofas, home furnishing	9	$410,566	$685,203
Recreational items	Recreational items (toys, bicycles, sporting goods)	22	$95,877	$278,504
Jobs	Jobs (temporary jobs)	3	$581,667	$552,728
Others	Others (pet bowls, pet beds, swipe cards)	5	$33,990	$70,517

The seven highest "commodity groups" in terms of value of donations were: money, construction, medical supplies, telecommunications, food, transportation, and mixed critical supplies. In terms of amount of commodities donated the seven highest donated groups were: monetary donations, food, textiles, transportation, water, medical supplies, and toiletries and sanitary paper items. Table 5 shows the distribution of the value of these commodity groups by donor type.

The companies and corporations donated the majority of the worth of mostly all commodity groups: monetary donations (53%); food (57%); textiles (84%); medical supplies (98%); water and ice (58%); personal hygiene, cleaning and sanitary paper items (81%); telecommunication equipment and services (97%); and, transportation, rescue and order related donations (73%). In the case of the mixed critical supplies the majority was donated by Non-Profit Organizations, charitable organizations and churches (53%) followed closely by companies, representing 43% of the total worth of the mixed critical supplies. As for donations related to rebuilding, 95% of the worth was donated by charitable organizations.

It is expected for individuals and schools typically to represent low percentages of the total worth in all the commodity groups of donations. This is because of their low capital power compared to large corporations, national business associations, or large international charitable organizations. It does not come as a surprise that government agencies donated 25% of donations related to transportation, rescue and order; considering police departments, fire departments and the military are usually responsible for rescuing and keeping the order.

Table 5: Distribution of commodity groups' value by donor type

Commodity Group / Donor Type	Money	Food	Textiles	Medical supplies	Water and ice	Supplies (mixed)	Personal hygiene, cleaning and sanitary paper items	Telecom-munication	Transportation, rescue and order	Rebuilding
Associations and Clubs	3.45%	3.91%	9.92%	0.02%	2.83%	0.00%	0.01%	2.62%	0.03%	0.00%
Companies	53.42%	57.42%	84.28%	97.59%	58.19%	43.46%	81.04%	97.24%	72.57%	5.27%
Government	0.13%	0.05%	0.11%	0.00%	36.45%	2.44%	0.50%	0.02%	24.89%	0.00%
Individuals	8.98%	0.63%	2.56%	0.83%	0.23%	2.38%	1.90%	0.01%	2.44%	0.01%
NPOs, charitable organizations and churches	33.77%	37.84%	0.52%	1.56%	2.18%	51.72%	16.40%	0.11%	0.08%	94.72%
Schools and Libraries	0.25%	0.14%	2.62%	0.00%	0.13%	0.00%	0.15%	0.00%	0.00%	0.00%
Total (10^6 USD)	**100% ($620.26)**	**100% ($27.01)**	**100% ($12.01)**	**100% ($85.69)**	**100% ($10.62)**	**100% ($16.36)**	**100% ($7.51)**	**100% ($38.21)**	**100% (23.97)**	**100% ($156.85)**

4.1 Temporal Distribution of Donations

Figure 4-7 are time series plots of the value of donations through August 2005 to December 2006. It is important to mention that the donation dates that were used for these analyses are estimates from what was stated in the news articles. Donation dates were usually not given in the articles so an approximate date usually had to be inferred. With this noted Figure 4 and Figure 5 show the flow of donations (all commodities) over time as well as the cumulative percentage over time. 82% of the value of all donations in the data was donated between August 2005 and December 2005, 15% between January 2006 and June 2006, and the remaining 3% from July to December 2006. There are some peaks in the data that range from $15 million to $79 million that are from funds or charities, such as Catholic Charities USA, the Bush-Clinton Katrina Fund and Habitat for Humanity, which represent the compilation of all donations collected by these organizations. The two highest peaks are in February 2006 corresponding to Catholic Charities USA and Habitat for Humanity, both of these peaks correspond to rebuilding housing units and represent an accumulation of all the money that both of these organizations have destined to rebuilding efforts in the affected areas. It is expected that the rebuilding projects are long term projects and are usually started after the critical needs (e.g., water, food, medicine and shelter) of the affected regions are satisfied; therefore it is likely that the news of how much was donated and spent for these means was announced in the months after the Hurricane struck the region.

Figure 4: Time plot of all commodities donated (in logarithmic scale)

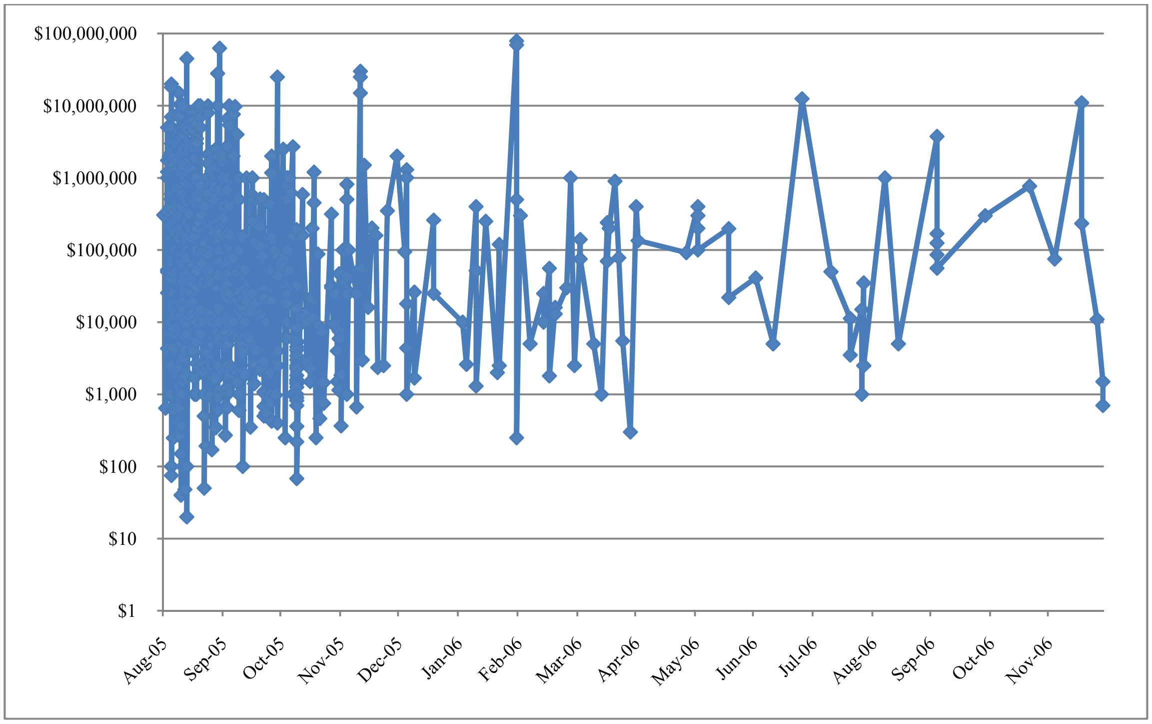


Figure 5: Cumulative percentage of all donations

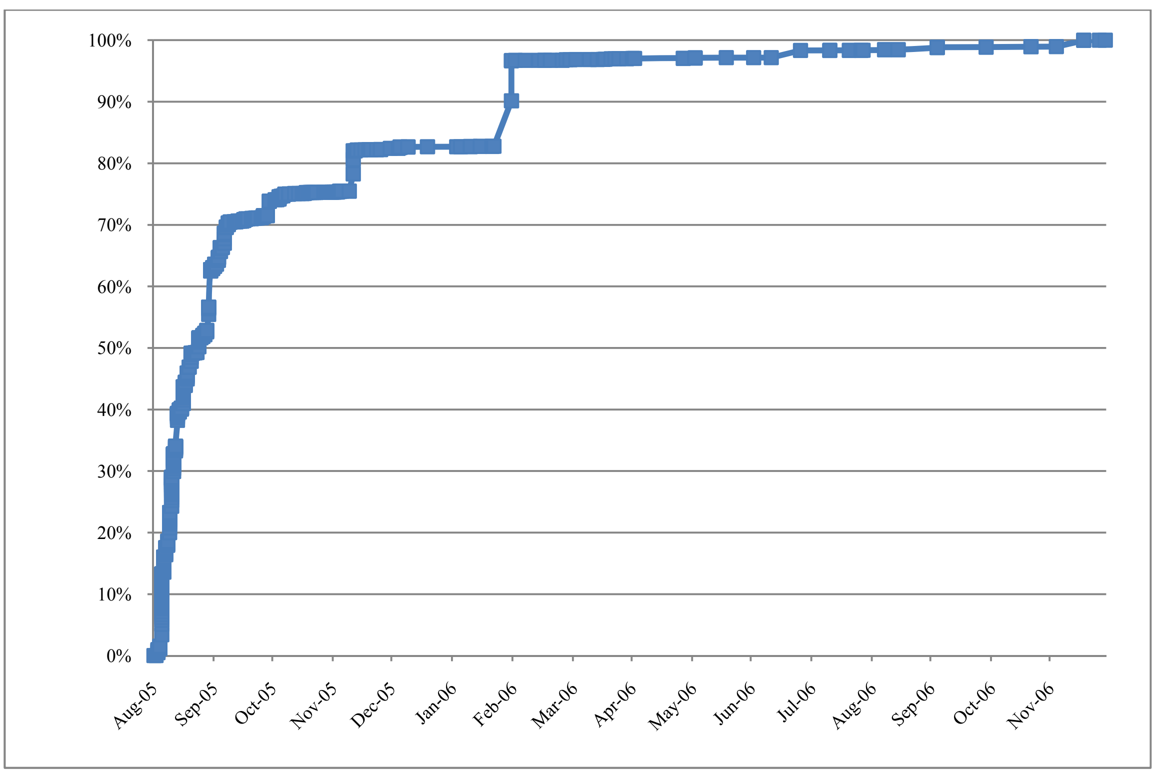


Figure 6 and Figure 7 represent the cumulative temporal distributions of the main commodity groups that were donated through the case study time period. Figure 6 shows the donations from August to October 2005 and Figure 7 from November 2005 to December 2006. The data show that 95% of the monetary donations were donated in the immediate months after Hurricane Katrina devastated the Gulf Coast region (August 2005 to December 2005). The remaining 5% was donated in 2006. All donations of the food, water, and, telecommunications groups were donated in the immediate months after Hurricane Katrina made landfall. More than 97% of the commodities in these groups: health; textiles; hygiene, cleaning and sanitary paper; transportation, rescue and order; and, mixed critical supplies; were donated in 2005. In the case of the donations related to rebuilding efforts the highest peak was in February 2006. As it was explained before, this is likely to be because rebuilding projects are usually long term and are also start once the refugees are relocated, their basic needs are satisfied, the consequences of the catastrophe have been contained and the situation has been "stabilized," the magnitude of the disaster is assessed, and estimates of the damages are quantified.

Figure 6: Cumulative temporal distribution of donations for the main commodity groups (August 2005 to October 2005)

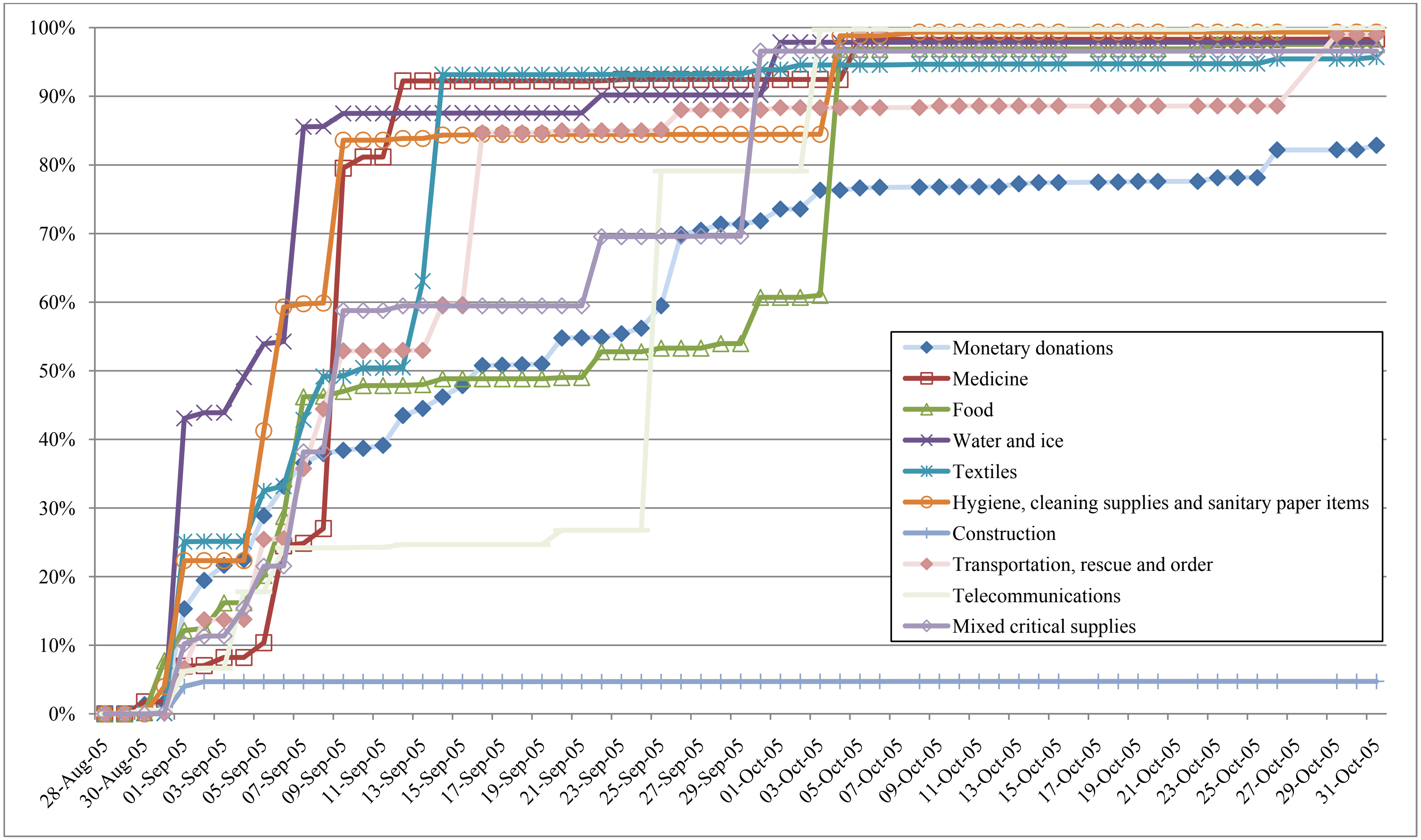
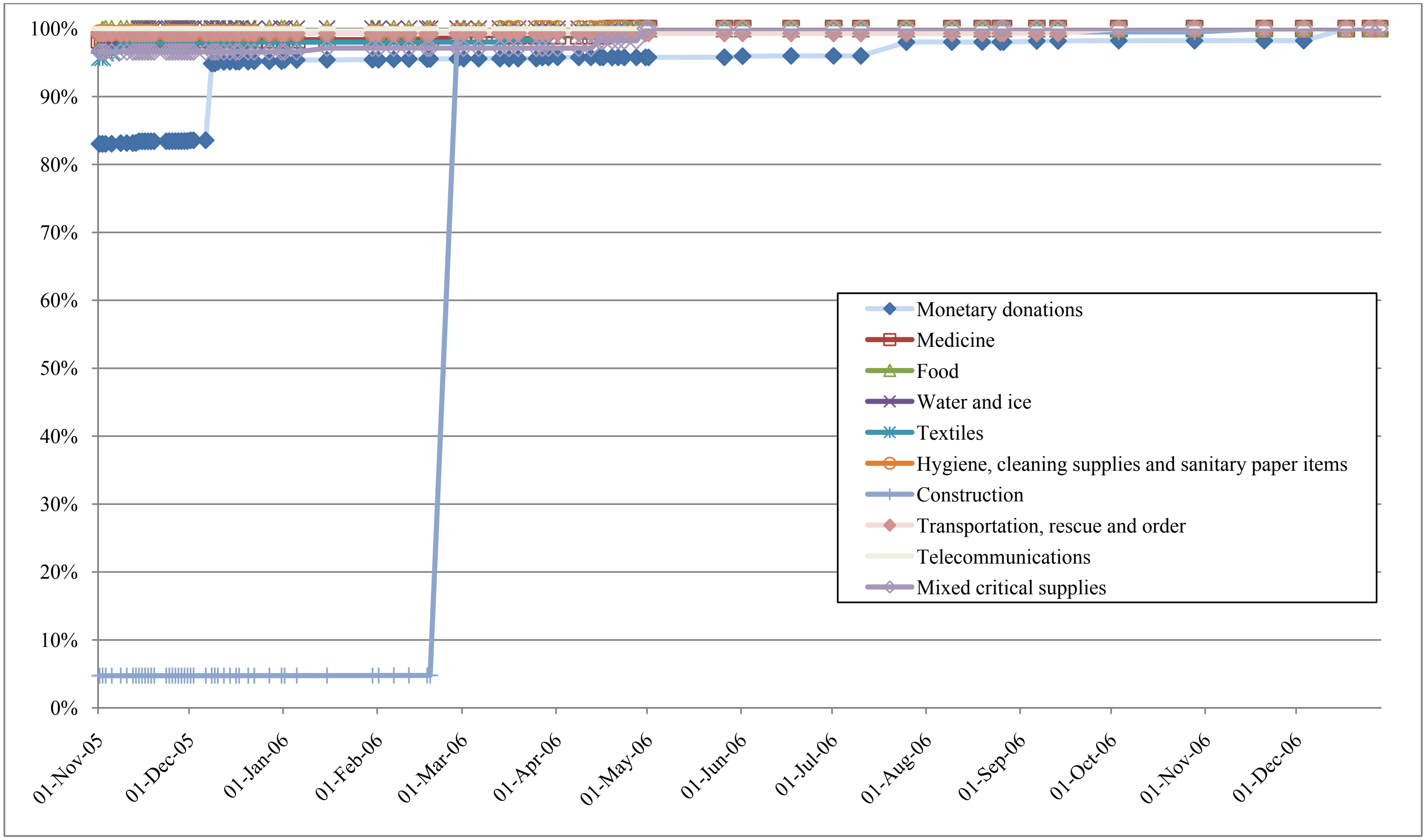


Figure 7: Cumulative temporal distribution of donations for the main commodity groups (November 2005 to December 2006)



4.2 Analysis of the Temporal Distribution of Donations versus the Temporal Distribution of Requests

In this section, a comparative analysis has been made of the requests of supplies (demand) made in the aftermath of Hurricane Katrina and the donations sent (supply) to the impacted population, assuming that all the donations that were made were received. This comparison has been done using the temporal distribution of donations (taken from the data collected) and the temporal distribution of requests made to the Federal Emergency Management Agency (FEMA) from August 28th to October 2005 used in Holguín-Veras et al. (Holguín-Veras et al., 2008).

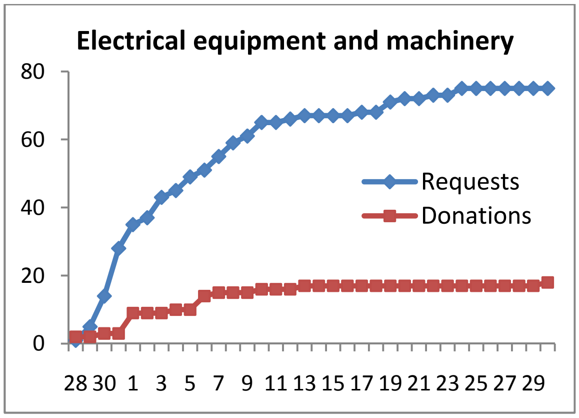
The data show that emergency responders requested critical supplies from the federal government when the needs exceeded what state and local agencies could have provided. In this study, the main commodity groups requested were, in this order: electrical equipment and machinery, transportation equipment, beverages, medical supplies, security and communication assessment personnel, plastic products, chemical products, food, and textiles. Of these, the common commodity groups that were both highly donated and highly requested are: transportation equipment, beverages, medical supplies, security and communication assessment personnel, chemical products, food, and textiles. Another important observation is that 58% of the total donations were monetary donations that could have been destined in the end to either one of the requested commodity groups.

However, the most requested group, which was the electrical equipment and machinery, was not part of the commodity groups highly donated as it accounted for only 1.6% of the total value of donations and 1.8% of the total amount of commodities donated. Although it should be noted that 99.9% of the donations from the electrical equipment and machinery group were donated in the time period of August to October 2005 which is when these commodities were most requested. In the case of the plastic products group, which mainly referred to plastic storage containers ('cambros') and portable showers, it did not appear at all in the donated commodity groups. And, in the case of the textile group, the requested textiles referred mostly to blankets, tents and sleeping bags, though, the donated textiles pertained mostly to clothing.

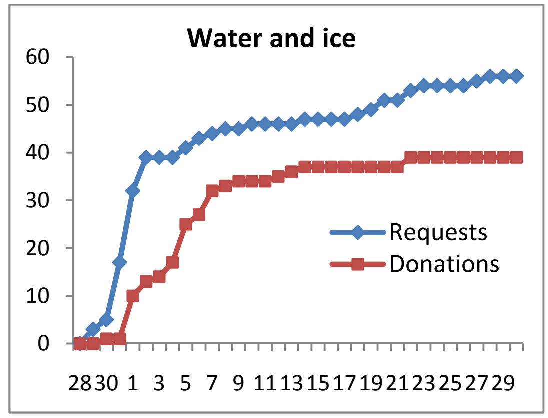
Figure 8 shows the time series plots of the number of requests and the number of donations between August 28, 2005 and September 30, 2005. The plots show the frequency by which the commodities were requested and donated. A more valid comparison would be between the value of these requests and the value of the donations; however, since the value of the requests was not available, this analysis was not possible. Consequently, we cannot know if the amounts of each donation could actually satisfy the requests. Nevertheless, the plots in Figure 8 give an idea of what were the most common commodities donated and requested. From the plots, food is the only group that was more commonly donated than it was requested. The rest were more commonly requested. The groups that presented the largest difference between the number of requests and donations are the electrical equipment and machinery, and transportation groups. These groups also have the largest marginal increment in the requests, thus it seems as if the requests keep increasing because they are being fulfilled.

Even though both, this investigation as well as Holguín-Veras, et al. (2008) research, have their limitations in quantifying the donation flows in the aftermath of Hurricane Katrina, and the needs of the hurricane victims, respectively. In reality these inconsistencies between what was donated and what was requested could be an indication of the lack of planning for the handling and distribution of donations in the Katrina response. Holguín-Veras, et al. (2007) mention the inefficient communication between the Voluntary Organizations Active in Disasters (VOAD) and the government: "…[The organization representatives] did not know what the priorities and urgent needs of the victims were…" (Holguín-Veras et al., 2007). It is also mentioned how "although the affected population did not need clothing as much as food, water and ice… large quantities of clothing continued to arrive at shelters and staging areas" (Holguín-Veras et al., 2007).

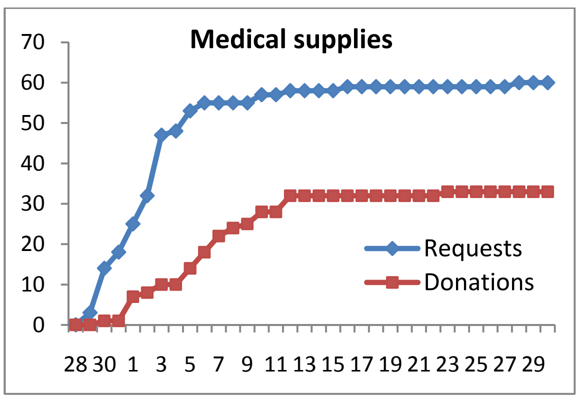
Figure 8: Time series plots of requests and donations for the key commodity groups



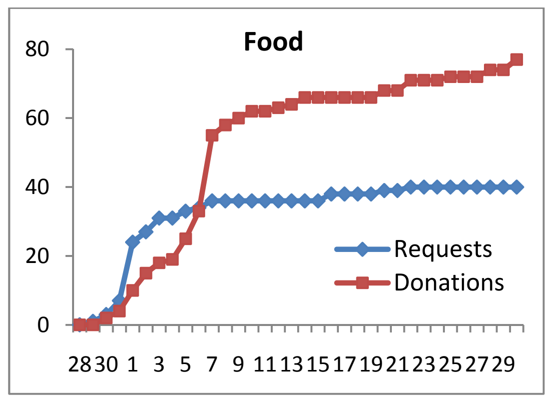
(a)



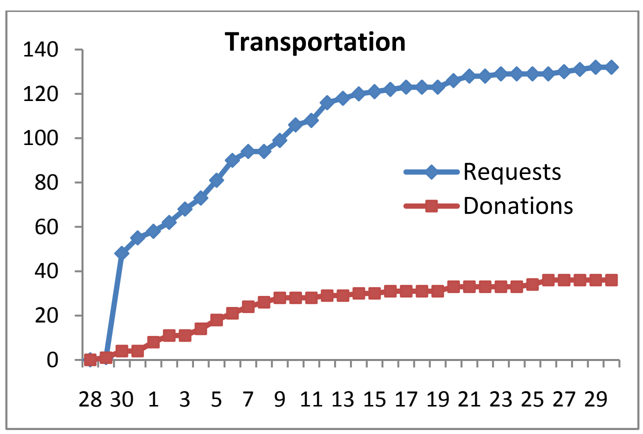
(b)



(c)



(d)



(e)

4.3 Donation Origins

In the event of Hurricane Katrina, monetary and in-kind donations from all over the country were sent to help out in the recovery of the affected region and the victims of the hurricane. All the donations that were collected for the data were localized by ZIP code using a Geographic Information System. Figure 9 shows a map of the United States where all the donation origins are marked with a blue star. There are 619 different ZIP codes representing the origins of the donations. The states where more donations originated are Florida with 122 donations (12%), New York with 118 donations (11.6%), California with 88 donations (8.7%), Maryland with 85 donations (8.4%) and Texas with 76 donations (7.5%). The ZIP codes where more donations originated are presented in Table 6.

Figure 9: Donation origins

Table 6: ZIP codes where the highest amount of donations originated

State	City	ZIP Code	Donations (No.)
NY	New York City	10022	12
NY	New York City	10036	12
AR	Bentonville	72712	11
NY	New York City	10017	10
NJ	East Rutherford	7073	9
DC	Washington	20036	8
MD	Mechanicsville	20659	8
TX	Houston	77002	8
FL	Inverness	34450	7
MD	Lexington Park	20653	7
NY	New York City	10001	7
NY	New York City	10007	7
NY	New York City	10019	7
VA	Fairfax	22030	7
LA	New Orleans	70130	6
NC	Charlotte	28202	6
TX	Irving	75039	6
TX	Dallas	75202	6
TX	Conroe	77385	6
DC	Washington	20001	5
FL	Saint Petersburg	33707	5
FL	Brooksville	34601	5
MD	Upper Marlboro	20772	5
NC	Salisbury	28144	5
PA	Philadelphia	19102	5

Figure 10 shows the total quantities donated per ZIP code. The map illustrates the locations where the most valuable flows of donations originated. Table 7 shows the twenty ZIP codes that donated more in terms of the monetary worth. The donations from these ZIP codes represent 60% of the total worth of the data and the values per ZIP code range from $143 million to $10 million dollars. The highest three ZIP codes correspond to the donations collected by Catholic Charities, Habitat for Humanity and the Bush-Clinton Katrina Fund and represent around $280 million dollars. If these peaks are removed the list would include the last three ZIP codes (30093, 10019 and 70130) and range from $45 million to $9 million dollars.

Excluding the three donors mentioned before, the donors located in the ZIP codes from Table 7 are corporate giants such as Wal-Mart, General Electric, Cisco Systems, Kellogg, Comcast, Verizon, Merck, Sony, and very wealthy celebrities or businesspersons such as Oprah Winfrey (talk show host), the Walton Family (who founded Wal-Mart), John Mortridge (chairman of Cisco), among others. In the case of New York City there were two main factors that caused these ZIP codes to be the origin of high value donations first of all there are a lot of headquarters and main offices of multinational and wealthy companies, national associations and philanthropic organizations, and secondly a lot of wealthy celebrities have residences in this city.

Figure 10: Total value of donations per ZIP code

Table 7: ZIP codes where the highest value of commodities were donated

Rank	State	City	ZIP Code	Total Quantity	Highlights
1	VA	Alexandria	22314	$143,675,000	All collected donations by Catholic Charities USA
2	DC	Washington	20036	$73,021,667	Bush-Clinton Katrina Fund
3	DC	Washington	20001	$69,562,330	Habitat for Humanity—Operation Home Delivery
4	MN	Eden Prairie	55344	$45,050,000	Starkey Laboratories (audiologist service and hearing aids)
5	AR	Bentonville	72712	$39,800,000	Wal-Mart and Walton Family Foundation
6	NY	New York City	10022	$32,050,000	Major company and national association headquarters (e.g., Sony Corp. of America, Omnicom, Bristol-Myers Squibb and National Basketball Association)
7	CA	San Jose	95134	$28,014,000	Cisco Systems
8	NC	Boone	28607	$25,043,800	Samaritan's Purse (Non-profit group)
9	NY	New York City	10007	$23,733,333	Celebrities and major company and philanthropic organizations headquarters (e.g., Verizon, Citigroup and Rosie O'Donnell's organization)
10	CT	Fairfield	06880	$18,050,000	General Electric
11	MI	Battle Creek	49016	$15,250,000	Kellogg
12	NY	New York City	10001	$14,975,000	E.g., National Basketball Player Association and Cablevision's Madison Square Garden
13	PA	Philadelphia	19103	$12,050,000	Comcast Corp (donated advertising time), Pew Foundation and Sunoco
14	NJ	Whitehouse Station	08889	$11,800,000	Merck & Co.
15	IL	Chicago	60607	$11,250,000	Oprah Winfrey and Oprah's Angel Network
16	VA	McLean	22102	$10,025,000	Freddie Mac
17	IN	Indianapolis	46208	$10,000,000	Lilly Endowment Inc. (private foundation)
18	MN	Minnetonka	55343	$10,000,000	UnitedHealth Group (health insurer)
19	ID	Boise	83706	$10,000,000	Albertson's, Inc.
20	CA	Portola Valley	94028	$10,000,000	John Morgridge (Cisco Chairman)
21	GA	Atlanta	30093	$9,763,099	Salvation Army
22	NY	New York City	10019	$9,353,417	E.g., Toyota, Time Warner, ING Group and UBS
23	LA	New Orleans	70130	$9,060,744	Office Depot, celebrities affected

5. MODELING METHODOLOGY

The final cleaned data set to be used for modeling consists of 1,009 donations with both monetary and in-kind donations. The original data set consisted of 1,016 observations; however, this data set had to be reduced to 1,009 observations because there were seven observations that constituted about 29% (over $300 million) of the value of all donations. These outliers were mainly compilations over time of all donations collected by non-profit organizations and charities, such as Habitat for Humanity, Bush-Clinton Katrina Fund and Catholic Charities. The process of data cleaning can be reviewed in detail on chapter three of this thesis.

Since many of the reported donations corresponded to aggregations of individual contributions, the socio-economic indicators for the originating ZIP codes were assumed as the characteristics for the actual donors. Although far from complete because it only includes the donations that were reported in the media, the data provide a unique look into the statistical patterns of material convergence.

For the model estimation there were over 170 predictor variables to be taken into consideration. The dependent variable is the total worth of donations in U.S. dollars and the independent variables are the socioeconomic characteristics of the donation origin ZIP code, the distance from the origin to the impacted area, and interaction terms between binary variables and the socioeconomic variables. The socioeconomic variables corresponding to the ZIP codes were taken from the U.S. Census Bureau ZIP Code Tabulation Areas data. The Census data has general demographic characteristics (e.g., population, age, sex, race, household by type, housing occupancy and housing tenure), selected social characteristics (e.g., school enrollment, educational attainment, marital status, and nativity and place of birth), selected economic characteristics (e.g., employment status, occupation, industry, and income), and selected housing characteristics (e.g., housing units in structure, vehicles available, house heating fuel, value, mortgage status, owner costs and gross rent as a percentage of household income). All of these variables were joined with the donations data using Geographic Information System (GIS). The binary variables correspond to qualitative data that had to be transformed into binary variables to be able to model it. Information such as the state from where the donations came from, were grouped into six categories: the Gulf Coast

(Texas, Oklahoma, Alabama, Louisiana, Arkansas, Mississippi, Georgia, Florida, Tennessee, South Carolina and North Carolina); Northeast (Virginia, Maryland, District of Columbia, New Jersey, Philadelphia, West Virginia, New York, Massachusetts, New Hampshire, Connecticut, Delaware and Rhode Island); Mideast (Kentucky, Ohio, Indiana, Illinois, Michigan, Wisconsin, Minnesota and Montana); Midwest (Kansas, Nebraska, Colorado, Utah, Idaho, Arizona and Nevada); West Coast (California, Oregon and Washington); and non-continental United States (Hawaii and Puerto Rico). The donor type was categorized as: company; individual; school and library; charitable organization, church, NPO and NGO; association and club; and, government agency. In addition, the type of organization (e.g., company, association, club, charitable organization, school and NPO) was further categorized as either local or headquarters. "Local" refers to a branch or an independent local organization or company; and "headquarters" refers to an organization main office or headquarters (e.g., company headquarters, charitable organization main offices and national professional association).

Ordinary Least Squares (OLS) was the technique used to estimate regression models that could present the significant socioeconomic characteristics of the donors that donated more or less monetary or in-kind donations in the aftermath of Hurricane Katrina. The objective was to observe and analyze which demographic and socioeconomic characteristics of the donors were significant in the models. The most disaggregate level of geographic information was at the ZIP code level and so the census information of each ZIP code where a donation was made was assigned to the donation and therefore to the donor responsible for the donation.

A linear (Equation 1) and a nonlinear model were used (Equations 2-5) to represent the relation between the donations value and the independent variables previously described. In the case of the nonlinear model, in order to be able to estimate the parameters with OLS this model was transformed into the linear form applying natural logs (Equations 4-5).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 \delta_1 x_2 + \ldots + \beta_p x_n \qquad (1)$$

$$y = \beta_0 x_1^{\beta_1} x_2^{\beta_2} x_2^{\beta_3 \delta_1} e^{\beta_4 \delta_2} \ldots x_n^{\beta_p} \qquad (2)$$

$$y = \beta_0 x_1^{\beta_1} x_2^{\beta_2 + \beta_3 \delta_1} e^{\beta_4 \delta_2} \ldots x_n^{\beta_p} \qquad (3)$$

Applying natural logs:

$$\ln y = \ln \beta_0 + \beta_1 \ln x_1 + (\beta_2 + \beta_3 \delta_1) \ln x_2 + \beta_4 \delta_2 + ... + \beta_p \ln x_n \tag{4}$$

$$\ln y = \ln \beta_0 + \beta_1 \ln x_1 + \beta_2 \ln x_2 + \beta_3 \delta_1 \ln x_2 + \beta_4 \delta_2 + ... + \beta_p \ln x_n \tag{5}$$

5.1 Review of Regression Analysis

Regression analysis was first developed by Sir Francis Galton in the late 19th century. Galton had studied the relation between heights of parents and children and noted that the heights of children of both tall and short parents appeared to "regress" to the mean of the group (Kutner et al., 2004). He developed the mathematical description of this regression tendency, which would be the precursor of today's regression models.

The simple linear regression model is:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \tag{6}$$

where:

Y_i is the value of the response variable in the ith trial

β_0 and β_1 are parameters

X_i is a known constant, namely, the value of the predictor variable in the ith trial

ε_i is a random error term with mean $E\{\varepsilon_i\}=0$ and variance $\sigma^2\{\varepsilon_i\}=\sigma^2$; ε_i and ε_j are uncorrelated so that their covariance is zero

$i = 1, \ldots, n$

The regression model implies that the responses Y_i come from probability distribution whose means are $E\{Y_i\}=\beta_0 + \beta_1 X_i$ and whose variances are σ^2, the same for all levels of X; and, any two responses Y_i and Y_j are uncorrelated (Kutner et al., 2004).

To estimate the regression parameters the least squares minimization is employed. According to the method of least squares, the estimators of β_0 and β_1 are those values b_0 and b_1 that minimize (7) for the given sample observations. Q measures the sum of the squared errors.

$$Q = \sum_{i=1}^{n} \left(Y_i - \beta_0 - \beta_1 X_i\right)^2 \tag{7}$$

To minimize Q, the optimality conditions are:

$$\frac{\partial Q}{\partial \beta_0} = 0 \tag{8}$$

$$\frac{\partial Q}{\partial \beta_1} = 0 \tag{9}$$

Solving (8) and (9), it can be shown for (6) that the values b_0 and b_1 that minimize Q for any particular set of sample data are given by the simultaneous equations, which are called normal equations:

$$\sum Y_i = nb_0 + b_1 \sum X_i \tag{10}$$

$$\sum X_i Y_i = b_0 \sum X_i + b_1 \sum X_i^2 \tag{11}$$

The normal equations (Equations 10-11) can be solved simultaneously for b_0 and b_1:

$$b_1 = \frac{\sum \left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{\sum \left(X_i - \overline{X}\right)^2} \tag{12}$$

$$b_0 = \frac{1}{n}\left(\sum Y_i - b_1 \sum X_i\right) = \overline{Y} - b_1 \overline{X} \tag{13}$$

where $\overline{X}$ and $\overline{Y}$ are the means of the X_i and the Y_i observations respectively.

In the more general case, there are multiple parameters to be estimated:

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_{p-1} X_{i,p-1} + \varepsilon_i \tag{14}$$

where:

β_0, β_1, …, β_{p-1} are parameters

$X_{i\,1}$, …, $X_{i\,p-1}$ are known constants

ε_i are independent $N(0, \sigma^2)$

$i = 1, \ldots, n$

The estimation of the regression coefficients in multiple regression analysis with the least squares criterion (7) for the general regression model (14) can be found in Kutner et al., (2004). Nonlinear models can also be estimated using regression analysis if the model can be 'linearized' using transformations. For the estimation of the donations' models a nonlinear model was used and the transformations were presented in Equations 2-5. Once a model has been estimated in order to measure the degree of linear fit, the correlation coefficient (r) is computed. The correlation coefficient (r):

$$0 \leq |r| \leq 1 \tag{15}$$

The closest r is to zero the lower the fit and the closer to one the higher the fit. The correlation coefficient r measures the degree of association between the output of the model and the input data; it estimates the quality of the model. However, r has some limitations; it can only capture the degree of a linear correlation between X_i and Y_i, though this does not mean that there may not be a nonlinear relation between X_i and Y_i. In addition, r depends on the number of independent observations or the degrees of freedom, thus the less number of observations the higher the correlation coefficient.

The Student's t-test is another key statistic. It it used to assess the statistical level of significance of individual parameters. It can be proved that the parameters of an OLS follow a t distribution with a t-statistic equal to:

$$t = \frac{\hat{\beta} - \beta}{SE_{(\hat{\beta})}} \tag{16}$$

where:

$\hat{\beta}$ = OLS parameter

β = Population parameter

$SE_{(\beta)}$ = Standard error

To assess the significance of individual variables the test of hypothesis is used:

H_0: $\hat{\beta} = 0$ → Null hypothesis

H_1: $\hat{\beta} \neq 0$ → Alternative hypothesis

To have a large t-statistic implies that the coefficient was able to be estimated with a fair amount of accuracy. If the t-statistic is more than two, the coefficient is at least twice as large as the standard error, it is generally concluded that the variable has a significant impact on the dependent variable.

In order to assess the statistical significance of the model as a whole, the F-test is used to test the hypothesis that all parameters simultaneously are equal to zero:

$$F = \frac{ESS/(k-1)}{RSS/(n-k)} \tag{17}$$

where:

ESS = error due to the regression

RSS = Error due to residuals

k = parameters

It can be proven that the joints distribution of all parameters equal to zero follows an F distribution.

H_0: $\beta_1 = \beta_2 = ... = \beta_k = 0$ → Null hypothesis

H_1: $\beta_i \neq 0$ → Alternative hypothesis

After briefly reviewing Ordinary Least Squares, the next sections will describe the estimation process for disaggregate and aggregate donation models.

5.2 Disaggregate Model Estimation Process

These models were estimated for the individual flow of donations. In the disaggregate data used for this estimation, each observation is a donation. Two data sets were put together for this type of models. In the first data set each observation is a donation as it was made by the donor (according to the source where the data was retrieved from); this means that an observation or a donation could consist of one or more different types of commodities. In the case where a donation had two or more different types of commodities, the value of the donation was the summation of the value of all the commodities donated.

In the second data set each observation is a donation with only one commodity type. Therefore, if a donation in the first data set consisted of two or more commodity types, this observation was divided into two or more observations in the second data set, one for each commodity type. The purpose of putting together the second data set was so that the data could be divided into monetary donations and in-kind donations, and models could be estimated for both.

As it was previously mentioned the response variable is the value of the donations and the independent variables are mainly the demographic and socioeconomic characteristics of the ZIP codes were the donors made donations. Due to very high multicollinearity new variables were created. Densities and ratios were created using the area and total populations. Both linear and nonlinear models were estimated, however the most significant models were nonlinear. For the estimation of nonlinear models all variables were transformed as shown in Equations 2-5.

Afterward, using a statistics software the parameters for each model with all uncorrelated predictor variables were estimated. Once the parameters were obtained the statistical significance and the conceptual validity of the models were assessed. If the models had any predictor variables that were statistically insignificant they were taken out, and the parameters of a new model were estimated again, this procedure was repeated until a statistically significant and conceptually valid model was found. For this, the t-values aided to identify when a variable should be kept or dropped from the model. The R^2-adjusted values were also considered when selecting the best models.

5.3 Aggregate Model Estimation Process

The aggregate models constitute models that are estimated for the total flows of donations by ZIP code or county. In the aggregated data each observation corresponds to a ZIP code or a county, depending on the level of aggregation, and all the donations that were made in that ZIP code or county are aggregated into that observation. The aggregated data consolidates the flows of donations per ZIP code or per county. Aggregated models were estimated for all donations, as well as for monetary donations and in-kind donations individually. Two modeling alternatives were studied to estimate for the total flows of donations: (1) the direct alternative, where the dependent variable is the total value of donations per ZIP code or per county; (2) a combined alternative where the number of donations per ZIP code or county, and the average value of donations per ZIP code or per county are both estimated in two different models. In the combined approach, the total flow of donations would be the product of these two models. The same process described above for the estimation of disaggregate models was used for aggregate models. Both linear and nonlinear models were estimated and the results are shown in the next chapter.

6. RESULTS

This chapter focuses on the results obtained for the econometric modeling of the donations. The data were modeled from both disaggregate and aggregate perspectives for monetary donations, in-kind donations and all donations. The disaggregate modeling approach estimates the individual flows of donations, and the aggregate approach estimates the total flows of donations at the aggregation level (e.g., county level). For the aggregated models two modeling approaches are presented:

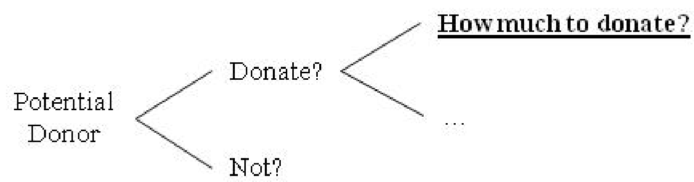
- The direct approach: The dependent variable is the total value of the donations made in the county;
- The combined approach, where two set of models were estimated: (1) the number of donations made in the county; and, (2) the average value of donations made in the county. The product of these two models is the total flow of donations.

The following sections present the results for the best models estimated. The relative low coefficient of correlation (R^2-adj) in all models found suggests that there are other important factors that have not been captured by the models, which is something to be expected in complex problems like this one. Nevertheless, considering the "informality" or lack of homogeneity of the data collection process and all the assumptions that were made in the data cleaning and modeling process the results found were very satisfying and in accordance with the "expected" behavior of the donations/donors.

6.1 Disaggregate Models

In any individual donation process the first question that a potential donor tries to answer is whether to donate or not. Once the decision to donate has been made, the next question at hand would be how much to donate (see Figure 11). Since the data collected for this analysis had no information on individuals or organizations not making donations the decision process of whether to donate or not could not be modeled; however, the question of how much to donate was. This section will discuss the findings for the disaggregate models for the value of all donations, monetary donations and in-kind donations.

Figure 11: Approach for disaggregate modeling



6.1.1 Value of All Donations

The first models estimated with the disaggregate data were for all donations (monetary and in-kind). Table 8 shows the best model found. The results suggest that the value of the donations has a direct relation with a number of socio-demographic characteristics. In essence, the value of the donations increases with:

- Family income per capita. This makes sense as donors that are better off have a larger capacity to donate.
- The population density of the area in which company headquarters are located. This indicates that company with headquarters located in denser areas donated more than those in less denser ZIP codes.
- Donor type (Individuals and Companies). Donors identified as 'individuals' or 'companies' tended to donate more compared to government agencies, used as the base group for the estimation process. It should be noted that individual's donations that made it to the news did so because of the high profile of the donor or the relatively large amount of the donation. In this context, it should be of no surprise that the other donor types donated in lower amounts. Also, government agencies' donations were only included when they were voluntary donations from agencies that had no mandate to provide support.

In contrast, the value of donations decreases with:

- Distance from the donor ZIP code to the impacted site. This suggests that the geographic proximity, and maybe cultural affinity, plays a role. In accordance with what Muller and Whiteman (2008) discuss about corporate philanthropic disaster response, firms pay more attention to disasters that are closer possibly out of a sense of responsibility or a greater degree of tangibility.

- Ratio of unemployed population, and population with only high school diploma, with respect to total population. These results indicate the role played by the education level and unemployment. The lower the educational attainment, the lower the value of the donations; and increases in unemployment, decreases the value of the donations.

Table 8: Best disaggregate model for all donations (nonlinear model)

Variable	Name	Coefficient	t-value
Population Density for donors that are organization headquarters	HQ*Pdens	0.391	17.26
Ratio of Population 16 years and over in labor force that are unemployed and Total population	16+_In LF_Civ_Unempl pp	-0.189	-2.81
Distance in miles from donation origin to impacted area	DIST	-0.381	-4.35
Ratio of Population 25 years and over educational attainment (high school graduates) and Total population	25+_High school grad pp	-0.773	-6.07
Family income per capita	Fam_Per capita income	0.092	1.81
Donors that are individuals	I	0.612	3.03
Donors that are companies	C	0.420	2.32
Constant	Constant	8.490	10.26
F	95.68		
R^2	40.10%		
R^2-adj	39.70%		
n	1,009		

6.1.2 Value of Monetary Donations

The next models were estimated specifically for the monetary donations. Table 9 and Table 10 show the best models found. The first model (Table 9) suggests that the value of monetary donations increases with:

- Distance. These results indicate that donors that are closer to the disaster site would prefer to send goods rather than monetary donations; and in contrast, donors located farther from the impacted area are more inclined to send larger monetary donations.

- Family income per capita for organizations that are headquarters. This implies that donors that are organization headquarters located in ZIP codes where the population is well off are more inclined to make larger monetary donations.

In contrast, the value of monetary donations decreases with:

- Ratio of population with only high school diploma, with respect to total population. Which makes sense since the population with lower levels of education would be less inclined to make larger monetary donations possibly due to their income level.
- Ratio of unemployed population, with respect to total population for donors from the 'Midwest' region. As previously mentioned unemployment is usually related to lower income levels and therefore less ability to donate larger quantities of money.

Table 9: Best disaggregate model 1 for monetary donations (nonlinear model)

Variable	Name	Coefficient	t-value
Distance in miles from donation origins to the impacted area	DIST	9.917	12.61
Ratio of Population 25 years and over educational attainment (high school graduates) and Population 25 years and over	25+_High school grad %p25	-0.832	-7.20
Family income per capita for donors that are organization headquarters	HQ*Fam_Per capita inc	0.333	21.72
Percentage of civilian unemployed population in labor force that are 16 years and over located in the Midwest region	MW*16+_Civ_ Unempl_%	-0.317	-2.13
Constant	Constant	9.917	12.61
F	144.75		
R^2	44.60%		
R^2-adj	44.30%		
n	724		

The second model found to be statistically significant and conceptually valid is presented in Table 10. The results for this model were more specific to donor types and donor locations as there were more interaction terms present in the model; though, in essence the results were very similar to the results found in the previous model. As shown in Table 10, the value of monetary donations increased with:

- Distance, for donors that are 'individuals'. Monetary donations made by donors identified as individuals tended to be higher when the donor was further away from the impacted area. This makes sense as individuals that are closer to the disaster site would prefer to donate goods rather than money and individuals that are farther away would prefer to send more money rather than goods.

- Distance, for donations originating in the 'Northeast' and the 'Gulf Coast' regions. Donors from the 'Northeast' and the 'Gulf Coast' regions tended to donate more money if they were located farther away from the impacted area, compared to donors from Hawaii and Puerto Rico, which were used as the base group for the estimation process.
- Family income per capita of the area in which company headquarters are located. This indicates that organizations with headquarters located in areas where the population has higher income would have a larger capacity to donate money.
- Family income per capita of donors that are 'individuals'. Which makes sense as donors that make more money would be more inclined to donate more money.
- The population density of the areas in the 'Northeast region'. This indicates that donors from the Northeast region located in denser areas donated more than those in less denser ZIP codes (compared to donors from Hawaii and Puerto Rico, which were used as the base group for the estimation process).
- The population density of the areas in which 'companies' are located. Which means that companies located in denser areas donated more money than companies located in less denser areas (compared to government agencies, which were used as the base group for the binary variable).
- Ratio of population with a bachelor's degree or higher, with respect to total population for donor located in the 'Mideast' and 'West Coast' regions. These results indicate the role played by the education level at having better jobs which can increase people's capacity to donate more money.

On the contrary, the value of monetary donations decreases with:

- Average family size. This makes sense as larger families usually have fewer resources to spare for donations. Also, families with less means and lower levels of education are usually above the average family size.
- Ratio of population with only high school diploma, with respect to total population. This shows the negative relation between lower educational attainment and high value monetary donations.

- Ratio of population with only high school diploma with respect to total population, for donors that are 'individuals'. In the case of individuals the education level is significant to the amount of the monetary donation.
- Ratio of unemployed population with respect to total population, located in the 'Midwest' region. For donations made in the Midwest region employment plays a significant role.

Table 10: Best disaggregate model 2 for monetary donations (nonlinear model)

Variable	**Name**	**Coefficient**	**t-value**
Average family size	Average Family Size	-0.196	-2.11
Distance in miles from donation origins in the Northeast region to the impacted area	NE*DIST	0.403	4.26
Distance in miles from donation origins in the Gulf Coast region to the impacted area	GC*DIST	0.171	3.36
Distance in miles from donation origins to the impacted area for donors that are individuals	I*DIST	0.487	3.23
Ratio of Population 25 years and over educational attainment (high school graduates) and Population 25 years and over	25+_High school grad %p25	-0.542	-3.62
Ratio of Population 25 years and over educational attainment (high school graduates) and Population 25 years and over for donors that are individuals	I*25+_HS grad %p25	-0.500	-2.01
Ratio of Population 25 years and over educational attainment (bachelor's degree or higher) and Population 25 years and over for donors that are in the Mideast region	ME*25+ Bach OR + %p25	0.387	1.43
Ratio of Population 25 years and over educational attainment (bachelor's degree or higher) and Population 25 years and over for donors that are in the West Coast region	WC*25+ Bach OR + %p25	0.807	3.08
Family income per capita for donors that are organization headquarters	HQ*Fam_Per capita inc	0.317	14.05
Family income per capita for donors that are individuals	I*Fam_Per capita inc	0.316	3.68
Population density for donors that are companies	C*Pop Density	0.039	1.48
Population density for donors that are located in the Northeast region	NE*Pop Density	0.188	2.74
Percentage of civilian unemployed population in labor force that are 16 years and over located in the Midwest region	MW*16+_Civ_Unempl_%	-0.272	-1.88
Constant	Constant	9.271	19.95
F	52.91		
R^2	49.20%		
R^2-adj	48.30%		
n	724		

6.1.3 Value of In-Kind Donations

As for the in-kind donations Table 11 presents the best model found. In this case, the value of the donations increases with:

- Donor Type (Organization Headquarters). Donors identified as ‘headquarters’ tended to donate more compared to non-organizations or ‘individuals’, who were used as the base group for the estimation process.
- Median rent. This suggests that donors that are located in areas where the rent is high tend to send more goods than in areas where the rent is low. It is expected that expensive areas are populated by people that can afford it; which makes sense since there is some degree of correlation between median rent and median income.
- Population density in the Midwest region. The denser ZIP codes in the Midwest region donated more goods than the less dense ones.

On the contrary, the value of the in-kind donations decreases with:

- Distance. This implies that donors which are closer to the impacted area send more in-kind donations than donors located farther away. It appears that in-kind donations have the opposite relation with distance than monetary donations. This makes sense as donors that are farther away from the impacted area prefer to send money rather than goods; and conversely, donors located closer to the impacted area send more goods.
- Ratio of population younger than twenty years old with respect to total population. This makes sense since teenagers and children are not likely to make significant in-kind donations.
- Percentage of unemployed civilian population in labor force over sixteen years old.

Table 11: Best disaggregate model for in-kind donations (nonlinear model)

Variable	Name	Coefficient	t-value
Distance in miles from donation origins to the impacted area	DIST	-0.433	-3.76
Donor Type: Organization Headquarters	HQ	3.181	16.28
Ratio of Population younger than 20 years old and Total Population	Age 0 to 19 %pp	-0.525	-2.39
Median rent	Median rent	0.298	4.75
Percentage of civilian unemployed population in labor force that are 16 years and over	16+_In LF_Civilian_Unempl_%	-0.278	-3.32
Population density of the Midwest region	MW*Pop Density	0.201	2.17
Constant	Constant	9.511	11.17
F	57.93		
R^2	39.60%		
R^2-adj	38.90%		
n	537		

6.2 Aggregate Models at the ZIP Code Level

The first attempt to estimate the aggregate models was done by aggregating the data by ZIP code. However, it was found that the data did not support estimation at the ZIP code level, as the majority of the ZIP codes had only one or two donations. The predictor variables were all the demographic and socioeconomic characteristics of the ZIP code, as well as the distance from the ZIP code to the disaster site. The dependent variable was either: the sum of the value of all the donations made in the ZIP code, or the number of donations made in the ZIP code.

Table 12 and Table 13 show the best models found aggregated by ZIP code. Both models' R^2 are fairly low which is another reason why the aggregation was further done by county. Table 12 presents a nonlinear model such as the one presented in Equation (2) which estimated the total value of donations made at the ZIP code level. In this model the aggregated value of donations per ZIP code increases with: population density (denser ZIP codes are inclined to donate more than less dense ZIP codes); and, family income per capita. Conversely, the aggregated value of donations per ZIP code decreases with: average household size; ratio of population younger than twenty years old with respect to total population (teenagers and children are the least productive members of society, usually having zero income and zero capital); distance, for the Northeast region; ratio of population with only high school diploma, with respect to total population; and, specifically ratio of population with only high school diploma, with respect to total population for ZIP codes located in the Midwest and Mideast regions.

Table 12: Best ZIP code aggregated model for value of donations (nonlinear)

Variable	Name	Coefficient	t-value
Population density	Pop Density	0.179	2.38
Ratio of Population of less than 20 yeas of age and Total population	Age <20 pp	-0.336	-2.02
Average household size	Average HH Size	-0.980	-3.44
Distance in miles from donation origins in the Northeast Region to impacted area	NE*Dist	-0.094	-2.91
Ratio of Population 25 years and over educational attainment (high school graduates) and Total population	25+_High school grad pp	-1.313	-6.35
Ratio of Population 25 years and over educational attainment (high school graduates) and Total population of Donations from the Midwest Region	MW*25+HSpp	-0.669	-1.82
Ratio of Population 25 years and over educational attainment (high school graduates) and Total population of Donations from the Mideast Region	ME*25+HSpp	-0.627	-3.50
Family income per capita	Fam_Per capita income	0.167	1.92
Constant	Constant	6.051	5.61
F	15.18		
R^2	16.60%		
R^2-adj	15.50%		
n	619		

The model shown in Table 13 estimates the number of donations per ZIP code. This model is a linear model so no transformations of variables were necessary. In essence it implies that the number of donations per ZIP code increases with: population density; and, median earnings of female full-time year-round workers (which implies that females that are better off make more donations). In contrast, the number of donations decreases with: family size; distance (the areas that are closer to the impacted areas donated more frequently); distance specifically for donations in the Mideast region (compared to donations from Hawaii or Puerto Rico which was the base group for the 'region' location); and, total population younger than twenty five years old.

Table 13: Best ZIP code aggregated model for number of donations (linear)

Variable	Name	Coefficient	t-value
Average family size	Average Family Size	-0.219	-1.41
Distance in miles from donation origins to impacted area	DIST	-3.643E-04	-3.41
Distance in miles from donation origins in the Mideast Region to impacted area	ME*Dist	-4.611E-04	-2.67
Population density	Pop Density	1.242E-05	2.96
Median earnings: Female full-time, year-round workers	Fam_Median earnings_Female FT	1.834E-05	3.29
Total population of age 24 or less	Age <25	-1.778E-05	-1.65
Constant	Constant	2.204	4.76
F	9.27		
R^2	8.30%		
R^2-adj	7.40%		
n	619		

6.3 Aggregate Models at the County Level with Direct Approach

Since the ZIP code aggregation did not lead to statistically solid models, the donations were further aggregated by county; and, the process for model estimation was repeated with the demographic and socioeconomic characteristics of the counties, the distance, and the binary variables for donation location (states grouped in regions). Models for monetary, in-kind and all donations were estimated. In this section the aggregated models estimated for the total flow of donations with the direct approach will be presented.

6.3.1 Total Flow of All Donations

Table 14 show the best model found for the total value of all donations aggregated by county. It is a linear model as presented in Equation (1) since it was found to be more significant than the nonlinear models. In essence, the value or flow of donations per county increases with:

- Total population between the ages of twenty and sixty four years. People between these ages are the most productive; therefore the more people between these ages the larger the donations.
- Household density. The more households per square mile the larger the donations.

- Family income per capita. As previously described in this chapter, income has a positive relation with the value of donations.

  And, the value of donations per county decreases with:

- Average family size for counties located in the 'Northeast' region. This suggests that in the 'Northeast' region the average family size plays a significant role, as families that are larger donate less than smaller families.

Table 14: Best county aggregated model for value of donations (linear)

Variable	Name	Coefficient	t-value
Total population between 20 years and 64 years of age	Age 20 to 64	3.779	4.16
Household density	Households DENS	1,571.6	8.27
Family income per capita	Fam_Per capita income	312.78	3.74
Average family size for donors located in the Northeast region	NE*Avg Family Size	-884,980	-2.67
Constant	Constant	-5,003,905	-2.70
F	35.93		
R^2	41.00%		
R^2-adj	39.80%		
n	212		

6.3.2 Total Flow of Monetary Donations

The best model for the total flow of monetary donations aggregated by county is shown in Table 15. Results show that the total value of these donations increases with:

- Total population between the ages of twenty and sixty four years.
- Household density.
- Percentage of population with fifteen years and over that is now married. As it was previously described married individuals tend to donate more because they usually have wider networks in the communities.

On the contrary, the value of monetary donations per county decreases with:

- Ratio of population with only high school diploma, with respect to total population for counties in the 'Northeast' region.

Table 15: Best county aggregated model for value of monetary donations (linear)

Variable	Name	Coefficient	t-value
Population between 20 years and 64 years of age	Age 20 to 64	2.911	5.07
Household density	Households DENS	2,003.3	15.75
Percentage of population of 15 years or older that is now married	15+_Now married %p15	18,641,737	3.90
Ratio of Population 25 years and over educational attainment (high school graduates) and Total population of Donations from the Northeast Region	NE*25+_HS grad %p25	-5,631,825	-2.70
Constant	Constant	-9,526,204	-3.59
F	80.86		
R^2	65.30%		
R^2-adj	64.50%		
n	177		

6.3.3 Total Flow of In-Kind Donations

Finally, the aggregated model for in-kind donations was estimated. Table 16 shows the best model for the total value of in-kind donations. This model is nonlinear and indicates that the value of in-kind donations per county increases with:

- Total population.
- Family income per capita.

Table 16: Best county aggregated model for value of in-kind donations (nonlinear)

Variable	Name	Coefficient	t-value
Total population	Population	0.567	3.63
Family income per capita	Fam_Per capita income	2.456	3.08
Constant	Constant	-19.018	-2.54
F	17.67		
R^2	21.60%		
R^2-adj	20.40%		
n	131		

6.4 Aggregate Models at the County Level with Combined Approach

In this section the aggregated models estimated for the total flow of donations with the combined approach will be presented.

6.4.1 Total Flow of All Donations

For the combined modeling approach, the first model estimated is for the number of donations per county. A linear model was estimated with a regression through the origin. Table 17 shows that the number of donations per county increases with:

- Population density (eighteen years and over). This suggests that the more people over seventeen years of age per square mile, the greater the number of donations per county.
- Total households.
- Family income per capita.

In contrast, the number of donations per county decrease with:

- Distance.
- Percentage of population with fifteen years and over that has never married. This may be because married individuals are assumed have more social capital than individuals that are not married. Individuals that are not married tend to be less connected with societal networks than married individuals and therefore less likely to donate than not married individuals (Bryant et al., 2003).

Table 17: Best county aggregated model for number of donations (linear)

Variable	Name	Coefficient	t-value
Population density (older than 18 years old)	Age 18+ DENS	6.48E-04	8.07
Distance in miles from county origins to impacted area	DIST	-1.54E-03	-2.18
Total households	Households	8.992E-06	7.23
Family income per capita	Fam_Per capita income	2.559E-04	4.85
Percentage of population of 15 years or older that has never married	15+_Never married %p15	-8.781	-2.07
Constant	Constant	0	NA
F	70.85		
R^2	63.12%		
R^2-adj	61.92%		
n	212		

The second model estimated is for the average value of donations per county. In this case a nonlinear model was found best for the estimation. Table 18 shows that the average value of donations per county increases with:

- Population density (between twenty and sixty four years old). This suggests that the more people between twenty and sixty four years of age per square mile, the greater the average value of donations per county.

On the other hand the average value decreases with:

- Ratio of population older than twenty five with only high school diploma, with respect to total population over twenty five. Continues to show the negative relation between lower educational attainment and high value monetary donations.
- Distance, for donations originating in counties of the 'Northeast' region.

Table 18: Best county aggregated model for average value of donations (nonlinear)

Variable	Name	Coefficient	t-value
Population density (between 20 years and 64 years)	Age 20 to 64 density	0.381	2.9
Ratio of Population 25 years and over educational attainment (high school graduates) and Population 25 years and over	25+_High school grad %p25	-2.488	-3.36
Distance in miles from donation origins in the Northeast region to impacted area	NE*DIST	-0.180	-3.54
Constant	Constant	6.717	8.07
F	18.75		
R^2	21.30%		
R^2-adj	20.20%		
n	212		

6.4.2 Total Flow of Monetary Donations

For the combined model, the best model found for number of monetary donations per county is shown in Table 19. A linear model was estimated with a regression through the origin. This model shows that the number of monetary donations per county increases with:

- Total population over 21 years.
- Household density.
- Family income per capita.

Table 19: Best county aggregated model for number of monetary donations (linear)

Variable	Name	Coefficient	t-value
Total population over 21 years	Age 21+	2.92E-06	5.95
Household density	Households DENS	1.35E-03	11.31
Family income per capita	Fam_Per capita income	7.14E-05	4.37
Constant	Constant	0	NA
F	128.80		
R^2	68.95%		
R^2-adj	68.02%		
n	177		

For the second part, Table 20 shows the best model found for the average value of monetary donations per county. This shows that the average value of monetary donations increases with:

- Population density (between twenty and sixty four years old).
- Family income per capita for donations made in the 'Mideast' region

On the other hand the average value of monetary donations decreases with:

- Ratio of population older than twenty five with only high school diploma, with respect to total population over twenty five.
- Average family size for donations made in the 'Northeast' region.

Table 20: Best county aggregated model for average value of monetary donations (nonlinear)

Variable	**Name**	**Coefficient**	**t-value**
Population density (between 20 years and 64 years)	Age 20 to 64 density	0.440	2.74
Ratio of Population 25 years and over educational attainment (high school graduates) and Total population 25 years and over	25+_High school grad %p25	-1.865	-2.2
Family income per capita in the Mideast region	ME*Fam_Per capita inc	0.091	1.65
Average family size in the Northeast region	NE*Avg Family Size	-1.243	-3.21
Constant	Constant	6.763	6.52
F	11.48		
R^2	21.10%		
R^2-adj	19.20%		
n	177		

6.4.3 Total Flow of In-Kind Donations

Table 21 shows the best model found for the number of in-kind donations per county. This model was estimated with a linear regression through the origin and it shows that the number of donations increases with:

- Population density (between twenty and sixty four years).
- Total households.
- Family income per capita.

In contrast the number of in-kind donations per county decreases with:

- Percentage of population with fifteen years and over that has never married.

Table 21: Best county aggregated model for number of in-kind donations (linear)

Variable	Name	Coefficient	t-value
Population density (between 20 and 64 years)	Age 20 to 64 density	1.91E-04	2.57
Total households	Households	3.44E-06	3.59
Family income per capita	Fam_Per capita income	2.22E-04	5.10
Percentage of population of 15 years or older that has never married	15+_Never married %p15	-8.107	-2.16
Constant	Constant	0	NA
F	46.62		
R^2	59.49%		
R^2-adj	57.74%		
n	131		

Table 22 shows the best model found for the average value of in-kind donations per county. This model is nonlinear and it shows that the number of donations decreases with:

- Ratio of population older than twenty five with only high school diploma, with respect to total population over twenty five.

Table 22: Best county aggregated model for average value of in-kind donations (nonlinear)

Variable	Name	Coefficient	t-value
Ratio of Population 25 years and over educational attainment (high school graduates) and Population 25 years and over	25+_High school grad %p25	-2.631	-3.68
Constant	Constant	8.338	8.66
F	13.57		
R^2	9.50%		
R^2-adj	8.80%		
n	131		

7. ANALYSIS

This chapter summarizes and analyzes the modeling results, making comparisons with results from previous research.

The disaggregate models it was found that, in accordance with Bryant, et al (2003), as income and education levels increase, the value of donations increases as well. In contrast, as unemployment levels increase the value of donations decreases. Donor type was also found to be significant, as companies and ‘organization headquarters’ make larger donations. ‘Individuals’ were also found to make larger donations; however, these individual’s donations refer to donations that made it to the news and did so because of the high profile of the donor or the relatively large amount of the donation. Another important finding is that organizations located in highly populated places tend to donate more than the ones located in less populated places. The donors located in the denser areas of the ‘Northeast’ region donated more money that the ones located in the less dense areas; and the donors located in the denser areas of the ‘Midwest’ region donated larger in-kind donations than the ones located in the less dense areas. In essence, big donations come from highly populated areas. In addition, this population should be composed in its majority from productive and working individuals; hence the more children and teenagers there are, the less in-kind donations, which agrees with Bryant, et al (2003) that stated that older individuals except the very rich have higher probabilities of donating.

Distance was used as a measure of the geographical proximity of the donor to the disaster site, and very interesting results were found in the disaggregate models. The geographic proximity of the donor to the disaster site has two opposite effects on the value of the donations. Donors that are farther away from the disaster site tend to donate larger monetary donations than the ones closer to the disaster site; conversely, donors closer to the disaster site tend to donate larger in-kind donations than the ones far away. This shows that donors that have a geographic proximity to the impacted area are more likely to make larger in-kind donations, and donors that are farther away prefer to make larger monetary donations. The behavior of the in-kind donations agrees with what Muller and Whiteman (2008) discuss, specifically for corporate donations.

In the aggregate models, used to estimate the total flows, the county aggregation was found to be superior to the ZIP code aggregation due to the fact that there were not enough observations per ZIP code. Two modeling approaches were used to estimate the total flows: (1) models for the total value of donations per county, and (2) a combined approach where two models are estimated, the number of donations per county and the average value of donations per county. From these models, a very significant finding is that, the more the areas are populated, in the majority of cases specifically with individuals between 20 and 64 years of age, the higher the value of the donations; and this was the case for all donation types (monetary, in-kind and both). Also the total number of households or the household density in the county was found to have a positive relation with the value of donations and the number of donations. Income and education levels were also found to be significant as in the disaggregate models; and for the 'Northeast' region, family size was also found to be significant. Counties with more married individuals were found to donate more money and counties with more individuals that have never married were found to make fewer donations. Bryant, et al (2003) suggest that married individuals are more inclined to donate because they are more connected and have more societal network than individuals that are not married.

8. CONCLUSIONS

The amount of analytical research on material convergence and its determinants is very small, as only a handful of studies have worked on this subject (Fritz and Mathewson, 1956; Neal, 1994). In order to contribute to the understanding of this complex problem, this thesis analyzes donations made in the aftermath of Hurricane Katrina, as documented in Lexis Nexis. The information was processed as needed to estimate the monetary value of these donations. Since many of the reported donations corresponded to aggregations of individual contributions, the socio-economic indicators for the originating ZIP codes were assumed as the characteristics for the actual donors. Although far from complete because it only includes the donations that were reported in the media, the data provide a unique look into the statistical patterns of material convergence.

The data were modeled from both disaggregate and aggregate perspectives for monetary donations, in-kind donations and all donations. The disaggregate modeling approach was used to estimate econometric models for the individual flows of donations as a function of the donors' attributes. The data was further aggregated at the county level to estimate models for the total flows of donations as a function of the county's attributes (assumed as the attributes of the aggregated donors). For the aggregated models two modeling approaches were presented: (1) the direct approach, in which the dependent variable is the total value of donations made in the county; and (2) a combined approach, where two set of models were estimated: (a) the number of donations made in the county; and, (b) the average value of donations made in the county. In the combined approach, the total flow of donations is the product of these two models.

All the best disaggregate models fit the nonlinear model shown in Equation (2). However this was not the case for the models for total value of donations and total number of donations, which were in the majority of cases linear models. In addition, in these models 'totals' (e.g., total population) seem to estimate the value and number of donations very well; however, this was not the case for the disaggregate models. In the case of the models for the average value of donations, all were nonlinear and 'ratios' and 'densities' seemed to estimate them better. The relative low coefficient of correlation in all models (R^2-adj usually between 20-60%) suggests that there are other important factors that have not been captured by the models, which is something to be expected in complex problems like this one.

This thesis shows that donations have a systematic relation with the donors' socioeconomic characteristics. In general, donations have a positive relation with income, education, married individuals, total population or population density, and total households or household density; and a negative relation with unemployment, unmarried individuals and family size. Distance was used as a measure of the geographical proximity of the donor to the disaster site, and very interesting results were found in the disaggregate models: donors that have a geographic proximity to the impacted area are more likely to make larger in-kind donations, and donors that are farther away prefer to make larger monetary donations.

This thesis represents a step forward in the estimation of material convergence. From the disaggregate perspective, very important factors such as geographical proximity, income, education, unemployment, type of donor (e.g., organization headquarters, company and individual) have been shown to be fundamental to donors making larger or smaller monetary and in-kind donations. From an aggregate point of view, highly populated areas of working, educated, wealthy, married individuals make larger donations. These results have important implications for large emergency management because they suggest that the magnitude of the material convergence and its impacts on humanitarian logistics depends on variables such as the distance to large population centers. The model suggests that should an event like Katrina had happened in the vicinity of a large population center, e.g., it would have generated a significantly larger volume of in-kind donations than if it had happened in a remote area. Therefore, the impacts on the humanitarian logistics would be greater and e.g., the resources to control and reduce the flows of low priority goods and to expedite the flow of high priority supplies.

The ultimate objective of this thesis is to improve the efficiency of humanitarian relief agencies, giving them an idea of what to expect in the event of a disaster and thus helping the agencies be prepared for the management of material convergence in the response process. Since the flows of high and low priority goods compete for the same resources once they reach the impacted area, analytical models for humanitarian logistics should explicitly consider them. This would certainly lead to better models, and more efficient deliveries of high priority goods.

Further analytical research is needed to understand this complex subject. This includes but is not limited to: the estimation of models with more accurate and complete data in which the particular attributes of the donors are known and the data is preferably obtained directly from the charitable and humanitarian organizations and not from the media which represent only the publicized donations. Another important aspect for further research is the analysis and comparison of the Katrina donations to donations made in other disasters; as well as the estimation of the mathematical function that can best describe the behavior of donations.

9. REFERENCES

Ballou, R. H. E. (1999). Business Logistics Management, Prentice-Hall International Inc.

Barton, A. H. (1969). Communities in Disaster: A Sociological Analysis of Collective Stress Situtation. Garden City, NY, Doubleday and Company, Inc.

Bird, R. and M. Bucovetsky (1975). Canadian Tax Reform and Private Philanthropy. Canadian Tax Foundation.

Bowersox, D. J. and D. J. E. Closs (1996). Logistics Management: The Integrated Supply Chain Process. Singapore, McGraw-Hill.

Bryant, W. K., H. Jeon-Slaughter, H. Kang and A. Tax (2003). "Participation in Philanthropic Activities: Donating Money and Time." Journal of Consumer Policy **26**: 43-73.

Bureau of Labor Statistics. (2009). "Archived Consumer Price Index Detailed Report Information." Retrieved December 18, 2008, from http://www.bls.gov/cpi/cpi_dr.htm.

Bureau of Transportation Statistics and U.S. Census Bureau. (2004). "Transportation: 2002 Commodity Flow Survey." Retrieved November 10, 2008, from http://www.census.gov/prod/ec02/ec02tcf-us.pdf.

Corpus-Christi Caller-Times (2005). Officials sort out leftover Katrina donations. Corpus-Christi Caller-Times. Corpus-Christi, Texas.

Drabek, T. E. (1986). Human System Responses to Disaster: An Inventory of Sociological Findings. New York, Springer-Verlag.

Dynes, R. R. (1970). Organized Behavior in Disaster. Lexington, Massachusetts, Heath Lexington Books.

Feldstein, M. (1975). "The IncomeTax and Charitable Contributions. Part II, Impact on Religious Educational and Other Organizations." National Tax Journal **28**: 209-227.

Feldstein, M. and C. Clotfelter (1976). "Tax Incentives and Charitable Contributions in the United States: Microeconomic Analysis." Journal of Public Economics **5**: 1-26.

Feldstein, M. and A. Taylor (1976). "The Income Tax and Charitable Contributions." Econometrica **44**: 1201-1222.

Fritz, C. and J. H. Mathewson (1956). Convergent Behavior: A Disaster Control Problem. Special Report for the Committee on Disaster Studies. Washington D.C., National Academy of Sciences.

Fritz Institute (2005). Logistics and Effective Delivery of Humanitarian Relief. San Francisco.

Fritz Institute (2006). Humanitarian Logistics: Enabling Disaster Response. San Francisco.

Holguín-Veras, J., M. Jaller, S. Ukkusuri, M. Brom, C. Torres, T. Wachtendorf and B. Brown (2008). "An Analysis of the Immediate Resource Requirements After Hurricane Katrina: Policy Implications for Disaster Response." TRB 87th Annual Meeting.

Holguín-Veras, J., N. Pérez, S. Ukkusuri, T. Wachtendorf and B. Brown (2007). "Emergency Logistics Issues Affecting the Response to Katrina: A Synthesis and Preliminary Suggestions for Improvement." Transport Research Record **2022**: 76-82.

Hood, R. D., S. A. Martin and L. S. Osberg (1977). "Economic Determinants of Individual Charitable Donations in Canada." The Canadian Journal of Economics **10**(4): 653-669.

Johnson, J. C., D. F. Wood, D. L. Wardlow and P. R. J. E. Murphy (1999). Contemporary Logistics. Upper Saddle River, NJ, Prentice Hall.

Kendra, J. and T. Wachtendorf (2003). "Reconsidering Convergence and Converger Legitimacy in Response to the World Trade Center Disaster." Terrorism and Disaster: New Threats, New Ideas.: Elsevier, New York, 97-122.

Kutner, M. H., C. J. Nachtsheim and J. Neter (2004). Applied Linear Regression Models. New York, McGraw-Hill/Irwin.

Muller, A. and G. Whiteman (2008). "Exploring the Geography of Corporate Philanthropic Disaster Response: A Study of Fortune Global 500 Firms." Journal of Business Ethics **84**(4): 589-603.

Neal, D. M. (1994). "The Consequences of Excessive Unrequested Donations: The Case of Hurricane Andrew." Disaster Management **6**(1): 23-28.

Purpura, P. (2005). Overloaded. The Times-Picayune. New Orleans, LA, The Times-Picayune Publishing Company.

Scanlon, J. (1991). Convergence Revisited: A New Perspective on a Little Studied Topic, Institute of Behavioral Sciences, University of Colorado, Boulder.

Schwartz, R. A. (1970). "Personal Philanthropic Contributions." Journal of Political Economy **78**: 1264-1291.

Schweitzer, F. and R. Mach (2008). "The Epidemics of Donations: Logistic Growth and Power-Laws." PLoS ONE **3**(1).

Sheu, J. B. (2007). "Challenges of Emergency Logistics Management." Transportation Research Part E **43**: 655-659.

Stallings, R. A. and E. L. Quarantelli (1985). "Emergent Citizen Groups and Emergency Management." Public Administration Review **45**(January): 93-100.

U.S. Census Bureau. (2007). "North American Industry Classification System (NAICS)." Retrieved September 20, 2008, from http://www.census.gov/eos/www/naics/2007NAICS/2007_Definition_File.pdf.

U.S. House of Representatives. (2006). "A Failure of Initiative: Final Report of the Select Bipartisan Committee to Investigate the Preparation for and Response to

Hurricane Katrina." Retrieved April 11, 2006, from http://www.gpoaccess.gov/congress/index.html.

Wachtendorf, T. and J. M. Kendra (2004). "Considering Convergence, Coordination, and Social Capital in Disasters." Disaster Research Center Preliminary Paper: University of Delaware.

Wenger, D. E. and T. F. James (1994). The Convergence of Volunteers in a Consensus Crisis: the Case of the 1985 Mexico City Earthquake. Disasters, Collective Behaviour and Social Organization. Associated University Presses, Cranbury, NJ.

Wettenhall, R. L. (1979). Organisation and Disaster: The 1967 Bushfires in Southern Tasmania. Natural Hazards in Australia. R.L. Heathcote and B. G. Thom (eds.). Canberra, Australian Academy of Science**:** 431-435.

White House. (2006). "The Federal Response to Hurricane Katrina: Lessons Learned." Retrieved March 13, 2006, from www.whitehouse.gov/reports/katrina-lessons-learned.pdf.

Wilson, J. and M. Musick (1997). "Who Cares? Toward an Integrated Theory of Volunteer Work." American Sociological Review **62**: 694-713.

Zakour, M. and D. F. Gillespie (1998). "Effects of Organizational Type and Localism on Volunteerism and Resource Sharing During Disasters." Nonprofit and Voluntary Sector Quarterly **27**(1).