Towards the Identification of Predictor Variables for Highway Safety

by

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Abstract

Highway safety remains one the most critical issues in the United States. In recent years, new safety programs and policies have been adopted to save more lives, prevent tragedies, and reduce economic loss. Unfortunately, there are a limited number of surveillance methods for collecting, measuring and analyzing highway safety data. The correlation between research outcomes and stakeholder expectations must be strengthened. The objective of this dissertation is to help decision makers gain a better understanding of the impact of traffic policies, so that they can optimize their use of resources. Specifically, this work: 1) provides a visual data-mining toolkit for policy makers to uncover hidden information, monitor spatiotemporal issues, and determine the impact of policy changes; 2) investigates the complex relationships among socioeconomic factors, the public policies adopted, and fatality rates; and 3) provides information to assist decision makers in monitoring safety performance trends while reducing waste of resources. Overall, the research goal is to identify important factors that can facilitate the generation of a new vision for safety surveillance.

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Preface

This dissertation is submitted to the Graduate Faculty of Auburn University in partial fulfillment of the requirements for the Degree of Doctor of Philosophy in Industrial and Systems Engineering. The completion of this dissertation involved many steps. It all began with an idea. More specifically, in the summer semester of 2012, I devised a concept for a performance evaluation using Data Envelopment Analysis. My concept was well received by Dr. Megahed, my advisor, and he suggested working with Dr. Swartz in the area of transportation safety. After several meetings with Dr. Megahed and Dr. Swartz, a stream of research ideas involving data analytics and transportation safety was established.

The first paper in the stream used visual data mining to enhance traffic safety. Dr. Megahed guided me to use appropriate traffic safety analyses; he also recommended several writing style and structure changes for better understanding of the paper idea. He then suggested that I develop a toolkit for practitioners with limited budgets, rather than expensive software. One of his students, Huw Smith, helped me develop the visual data mining toolkit in Visual Basic Application (VBA). When I wrote my visual data mining paper, Dr. Swartz provided his expertise to further develop the paper. I presented this work at the *INFORMS 2013 Annual Meeting* in Minneapolis, Minnesota. It was then written up as a journal article and submitted to the Journal of Transportation Management; not long afterwards, it was accepted for publication in the journal. The paper is presented in Chapter 2.

After finishing the first paper, I was reminded of another idea that I had in one of my previous class projects: to measure the relationship between demographic factors and traffic accidents. Consequently, I talked to Dr. Megahed and Dr. Swartz about my idea; they thought that I should identify the impacts of socioeconomic factors and public policies on traffic safety. I then talked about my idea with Theyab Alhwiti, another PhD student working with Dr. Fadel. He was willing to help me with the data collection process. I chose a panel data analysis in this study to analyze the cross-sectional time-series data. Dr. Megahed and Dr. Swartz provided feedback for improving my paper. This paper is presented in Chapter 3; it has also been published in the Journal of Transportation, Law, Logistics and Policy.

Dr. Megahed, Dr. Swartz, and I had several meetings to discuss the variables related to commercial motor carriers and government investments during the spring semester of 2015. I selected variables from state government agencies, reviewed the literature, designed the analysis, interpreted the results, and wrote the paper. With their feedback, I revised my draft and submitted my paper to the Transportation Journal for consideration.

I have learned a great deal about the field of data analytics and transportation safety while I was writing this dissertation. The focus of my work has addressed the lack of a comprehensive surveillance system in current traffic safety research, which has made the dissertation more valuable.

1 Introduction

1.1 Problem Description and Significance

The goal of this dissertation was to develop a set of tools for examining the factors that can be used to evaluate the effectiveness of how state governments commit their limited resources to the adoption of safety methods to reduce vehicle crashes on highways in the United States. In addition, the research findings are expected to assist decision-making with respect to public policy legislation. Determining the effectiveness of various public policy choices is critical for improving occupational environments and safety programs. Yet many successful regulatory and supervisory approaches currently being applied to industry workplace safety settings are not achieving the same results for modern commercial motor vehicle (CMV) operators. The difficulties in studying these types of safety programs has led to gaps in our understanding of how public policy choices shape individual decisions and outcomes. Specifically, there is currently a serious problem regarding heavy-duty truck-related crashes, which, according to the Department of Transportation (DoT), cause 4,808 deaths annually (Transport Topics, 2008), according to the Department of Transportation (DoT), and cost nearly $2 billion dollars annually in healthcare, property damage, and other related social costs (Center for Disease Control, 2012). In fact, heavy-duty truck-related crashes increased slightly from 2013 to 2014. Passenger vehicle crashes are also a problem that requires continuous monitoring. A variety of CMV issues are addressed in this study and extended the topic to private passenger vehicles. Despite a decreasing annual number of highway accidents, a more effective and comprehensive strategy is required to analyze related data and examine the underlying causes of crashes. In this dissertation, analytical tools are proposed that can provide: 1) a visualization toolkit for transforming results, 2) a means to investigate the impacts of public and safety policies on the number of fatal crashes, and 3) state governmental safety performance data. In addition, these tools can be integrated into a diagnostic system for monitoring changes in traffic safety levels.

1.2 Significance

For the purposes of this study, highway safety is divided into two main categories: commercial motor vehicles and private passenger vehicles. The trucking industry is considered to be "the driving force behind the U.S. economy" (American Trucking Association, 2008), with over 3.5 million truck drivers (American Trucking Association, 2008) that deliver just about everything the nation consumes or uses. Not only does a fatal accident involving a truck involve the loss of life, it also impacts the supply chain of goods. However, most fatal accidents involve private passenger vehicles. The importance of providing a comprehensive study of these two vehicle types, and the reasons for studying commercial motor vehicles separately are as follows.

First, truck operations directly affect the public interest. Truck accidents have a tremendous impact on society and truck drivers must avoid any operations that may pose a risk to the motoring public (Mejza, 1999). Second, a truck driver's operating environment is complex. Drivers encounter different routes, weather, traffic conditions, and locations (among other things) each time they take a trip. These conditions increase their risk of accident. Third, truck drivers experience little direct physical supervision or contact with other company drivers. Some drivers are alone on the road for weeks or months at a time. In many cases, the only contact a driver's managers (supervisors) have with their on-the-road truck drivers is electronic (i.e., phone, e-mail, etc.). The combination of low levels of supervision and high levels of responsibility with potentially devastating consequences makes for a unique and particularly hazardous occupational environment.

Highway safety has been monitored for several decades, and the number of fatalities and injuries has a decreasing trend over time. Nevertheless, in 2013, more than 20,000 people were involved in passenger-related fatal crashes and two million people were injured in accidents (National Highway Traffic Safety Association, 2014). Based on the limited resources available and current state and federal regulations, improved evidence-based decision-making processes are needed to address safety enforcement procedures and regulations.

1.3 Research Objectives

The research objectives are as follows:

1) Transform the low-level traffic related data into high-content information. This is especially important because it allows policy makers and stakeholders to understand the results effectively. Therefore, they can respond more rapidly and optimally.

2) Study the importance of demographic and socioeconomic factors and safety policies. Despite the analysis of driver behavioral factors through safety datasets collected from the Department of Transportation (DoT), other demographic factors and effectiveness of safety policies also influence the occurrences of highway fatal accidents.

3) Develop an evaluation system to measure the effectiveness of how limited inputs transform to outcomes and monitor a long term trends. This can help the decision makers consider their potential investments and policies.

This work will facilitate the development of more accurate and meaningful decision-making measures for evaluating the effectiveness of public policies and intervention techniques in reducing fatal highway accidents. With the increasing amount of data collected by the Federal Motor Carrier Safety Administration (FMCSA) and the National Highway Traffic Safety Administration (NHTSA), and by the application of data analytics techniques, better-decision making is possible regarding policy development, interventions, and research activities. This research focused on a wide range of policies and results among 12 states in the Southeastern United States, including: Alabama, Kentucky, Mississippi, South Carolina, North Carolina, Georgia, Florida, West Virginia, Virginia, Tennessee, Arkansas, and Louisiana.

1.4 Dissertation Layout

This dissertation is organized as follows: Chapter 2 describes the proposed easily operated visual data-mining toolkit that can increase the current understanding of the effect of traffic safety measures. It should be noted that Chapter 2 is comprised of a paper that was accepted in 2015 for publication in the Journal of Transportation Management. Chapter 3 provides a macro prospective method for determining other factors that may also affect highway accident fatality rates. The pre-crash analysis was based on socioeconomic factors and public policies that have received little attention in previous research efforts. Chapter 3 is a paper that was published in 2015 in the Journal of Transportation Laws, Logistics & Policy. Chapter 4 discusses how government funding, safety program priorities, and inspection forces affect current traffic safety performance. A data envelopment analysis (DEA)-based Malmquist productivity index was used to benchmark the efficiency of state governments. This chapter is a paper that was submitted to the Transportation Journal. Chapter 5 is the concluding chapter, which summarizes the contributions of this dissertation and makes recommendations for the direction of future studies.

2 Using Visual Data Mining to Enhance the Understanding of Traffic Safety

2.1 Abstract

Much research has been done on accident data to identify the causal factors for crashes and communicate these factors to policy-makers and vehicle manufacturers. An ongoing, two-fold challenge involves extracting useful information from the massive amounts of collected safety data and explaining complicated statistical models to inform the public. One method to analyze complex data is through the application of visual data mining tools. In this paper, we address the following three questions: 1) what existing data visualization tools can assist with theory development and in policy-making?; 2) can visual data mining uncover unknown constructs/relationships to inform the development of theory or practice?; and 3) can a data visualization toolkit be developed to assist the stakeholders in understanding the impact of public-policy on transportation safety? To address these questions, we developed a visual data mining toolkit that allows for understanding safety datasets and evaluating the effectiveness of safety policies.

2.2 Introduction

Transportation accidents represent a global epidemic. Road traffic injuries are the eighth leading cause of death, and the leading cause of death for individuals aged 15-29 ("Global Burden of Disease," 2008; Lozano et al., 2012). In 2010, transportation injuries resulted in 1.24 million fatalities worldwide according to the World Health Organization (WHO), "Global status report on road safety 2013: supporting a decade of action" 2013), p. v. In addition to the lost lives, the costs associated with road traffic accidents runs to billions of dollars (Jacobs et al., 2000). These numbers are unacceptably high, especially since most, if not all, of these fatalities may have been avoided with evidence-driven road safety interventions.

Road safety interventions can be effective in reducing the number of accidents and/or mitigating their effects. The WHO states that “adopting and enforcing legislation relating to important risk factors – speed, drunk–driving, motorcycle helmets, seat-belts and child restraints – has been shown to lead to reductions in road traffic injuries” ("Global status report on road safety 2013: supporting a decade of action," 2013, p. v). These five risk factors are a sample of a larger pool of behavioral factors that lead to accidents. There is an increasing number of regulations worldwide that have been passed to cover these behavioral factors. However, “in many countries these laws are either not comprehensive in scope or lacking altogether. Governments must do more to ensure that their national road safety laws meet best practice, as well as do more to enforce these laws” ("Global status report on road safety 2013: supporting a decade of action," 2013, p. v) The problem is more complex in the U.S., since highway safety policies can be different in neighboring states and the identification of best practices is often unclear ("Highway Safety law Charts," 2013).

One approach to identifying best practices is to investigate the causes of vehicle crashes, assess the factors that are correlated with high severity/frequency accidents, and propose interventions that can prevent/mitigate these accidents. Examples include the works of Shibata and Fukuda (1994), Massie et al. (1995), Shankar et al. (1995), Al-Ghamdi (2002), K. K. W. Yau (2004), and Aarts and Van Schagen (2006). These papers followed a common framework that started with identifying (or using previously identified) causal factors and then validating how these factors contribute to traffic crashes. While these approaches are built on a solid statistical foundation, they are often difficult for stakeholders to understand due, in a large part, to the number/complexity of variables and relationships in the data. Additionally, it is difficult to evaluate whether differences among locations affect the generalizability of their conclusions across geographical regions with different environmental and behavioral conditions.

Another approach to identify the best practices is to retrospectively evaluate whether safety regulations have been effective in reducing accident, injury and/or fatality rates. It should be noted that such studies may not only capture the differences pre and post regulation changes, but they may also assess the enforcement levels (especially if they compare across states and/or counties). Thus, these studies can be seen to measure whether the policies are *comprehensive* (or effective), an important consideration highlighted above in the WHO report. These studies investigated several behavior-related regulations, including: a) the impact of hand-held cell phone bans on reducing fatalities (Nikolaev et al., 2010; Sampaio, 2012); b) the impact of legislation of medical marijuana on reducing fatal crashes involving alcohol through substitution effects (Anderson & Rees, 2011); and c) the effectiveness of seatbelt laws in reducing the number of teenage traffic fatalities (Carpenter & Stehr, 2008). The results of these research works are usually explained by statistical summaries and p-value tables, which are singularly unconvincing to non-scientist public policy decision makers (and the general public, for that matter, who must sometimes be convinced politically about the rationale behind changes to existing laws).

Based on the above discussion, there is a need for developing new or innovative data-driven traffic safety models that can be understood by the different stakeholders (general public, policy-makers, researchers, etc.). Many researchers have discovered that new or innovative methodological approaches to traditional problems can reveal unique insight (see for example Ahmady et al., 2013; Cheon, 2009; Percin & Min, 2013). In this paper, a new way of showing how visualization tools can address this gap is presented, with a focus on their use in detecting trends in highway safety and affecting safety policy making. In Section 2, the field of *visual data mining* and how it can be helpful in generating insights from spatiotemporal datasets is introduced. Section 3 presents a brief description of our methodology and the datasets used in our paper. Section 4 then presents how existing data visualization tools can assist with traffic safety theory development and policy-making. Section 5 provides several examples of how data visualization tools can uncover relationships that may not be captured by traditional modeling methods. In Section 6, a demonstration of how the developed visualization toolkit can assist in evaluating the impact of safety policy changes on fatal and nonfatal accidents is provided. Concluding remarks are provided in Section 7.

2.3 Visual Data Mining

Visual data mining is an approach to data mining that is based on the integration of concepts from computer science, psychology and data analysis to assist in uncovering trends/patterns that may be missed with other non-visual methods. Visual data mining also helps overcome one of the main limitations in data mining approaches, where the "data are analyzed in a hypothesis testing mode in which one have a priori notions about what the important results will be before the analysis actually begins" (Simoff et al., 2008, p. i). The use of visualization methods has been found to be a simple, effective, and assumption-free approach to discover trends in the data in several instances and contexts (Greitzer et al., 2011; Han & Kamber, 2011; Keim et al., 2002; Simoff et al., 2008). In addition, visualizing the associations among the data can provide a solid foundation for statistical modeling in the cases when additional analysis is warranted.

The use of "visualizations" (visualization applications) to uncover patterns is not a new phenomenon in public safety. An early example can be seen in the work of John Snow, whose plots of the Cholera outbreak on a London Map in the 1850s allowed him to discover the cause of Cholera (Rajaraman et al., 2012, p. 3-4). Wickham (2013) briefly discusses some of the historical foundations of statistical graphics. Well-done graphical displays can help us to solve complex problems without making any assumptions or the need to understand complicated mathematical algorithms. The visual exploration of data can also be used to supplement mathematical models, and can lead to better results, especially in situations when automated data mining tools fail (Keim et al., 2002).

It is important to mention that not all graphical representations of data are useful, and some can be misleading. Wickham (2013), p. 39-40 includes a list of some of the formal instructions on the effective use of visualizations that was written in 1901 by the *International Institute of Statistics*. Below, we repeat these oft-forgotten recommendations.

(1) "We must keep symbols to a minimum, so as not to overload the reader's memory. Some ancient authors, by covering their cartograms with hieroglyphics, made them indecipherable."

(2) "One of us recommends adopting scales for ordinate and abscissa so the average slope of the phenomenon corresponds to the tangent of the curve at an angle of 45 degrees."

(3) "Areas are often used in graphical representations. However, they have the disadvantage of often misleading the reader even though they were designed according to indisputable geometric principles. Indeed, the eye has a hard time appreciating areas."

(4) "We should not, as it is sometimes done, cut the bottom of the diagram under the pretext that it is useless. This arbitrary suppression distorts the chart by making us think that the variations of the function are more important than they really are."

(5) *"To increase the means of expression without straining the reader's memory, we often build cartograms with two colors. And, indeed, the reader can easily remember this simple formula: 'The more the shade is red, the more the phenomenon studied surpasses the average; the more the shade is blue, the more phenomenon studied is below average."*

While there are no universal visuals that will work for every application domain and problem, there are several factors/guidelines that can help in choosing/developing informative statistical graphics. For example, Tufte (1983), p. 13-15 introduced the term graphical excellence to reflect on graphics that communicate complex ideas with clarity, precision and efficiency. Keim et al. (2002) provided some general rules for expressive and effective visualizations. The expressiveness of a visual relates to the constraint that all relevant attributes, without any others, must be expressed by the visualization (Mackinlay, 1986). Effective graphics are the ones that allow the viewer to interpret the information hidden within the data correctly and quickly. These guidelines were used in developing the graphics for traffic safety presented in this paper.

2.4 Methods and Description of Datasets

2.4.1 Methodology

The purpose of this investigation is to develop and apply a small subset of data visualization tools to a large, complex dataset of transportation safety data for the purposes of addressing three research questions:

RQ1. What existing data visualization tools could be appropriate to inform researchers in theory development and decision makers in setting transportation safety policy?

RQ2. Can a data visualization tool be developed to assist in uncovering previously unknown constructs/relationships to inform the development of theory or practice?

RQ3. Can a data visualization tool be developed to assist decision makers in applying and evaluating public policy choices in order to improve transportation safety in practice?

RQ1 will be answered through a focused literature review on data visualization tools used in the context of transportation and safety, as well as a consideration of tools applied successfully in other contexts. A small number of tools will be developed based on this review. RQ2 and RQ3 will be answered by applying the tools developed to “real world” transportation data in an effort to demonstrate efficacy and at least minimal utility of the general approach.

Transforming accident related data into graphical information for better facilitating further analysis is our basic principle. Three common types of data in the transportation safety area of interest in this effort are temporal, spatiotemporal, and the effectiveness of policymaking (before-after comparison). The temporal data was analyzed using a calendar-based clustering application, and the graphical results show the characteristic of the clusters; thereby aiding researcher insight and theory development. Next, the mapping tool combines the geographic data with accident related information and statistical reports displaying on a map as an example of the treatment of spatiotemporal data. It consists of a VBA-based dataset and Microsoft MapPoint. The constraint for the mapping tool is the limitation of VBA functions. The speed of executing the tool relies on the quality and quantity of the VBA codes and dataset. While the current application is scalable, additional refinement will be needed as the volume of the dataset increases. The current application can handle up to 1,048,576 rows by 16,384 columns of data with execution speed, a function of computing resources.

2.4.2 Datasets

In this paper, we have used two datasets to depict the effectiveness of the proposed/developed visual data mining tools in enhancing our understanding of emerging patterns and trends that are related to traffic safety. Both datasets were collected on U.S. traffic by state and/or governmental agencies. The first dataset consists of traffic flow counts per hour data collected by the Alabama Department of Transportation (ADoT) using a traffic camera between January 2005 and December 2010 ("Directional Monthly Volume Report," 2011). We do not use the 2011 and 2012 data in our dataset since they were missing a significant amount of data. We provide a sample of the directional traffic flows captured hourly by the sensors on a busy interstate highway (I-85, sensors located 6.0 miles South of Macon Co. Line) in Figure 2.1. The sensor captures whenever a motor vehicle passes the location and counts for a record. It is important to note that traffic volume is one of the measures traditionally used to normalize accident data (Gregoriades et al., 2011; Ivan, 2004; Laessig & Waterworth, 1970; Stamatiadis et al., 1997). However, the estimation of the target variable may contain misleading information because the traffic volumes vary by location and time. Thus, we investigate how visual data mining tools can be used to disaggregate traffic flows to account for seasonal variations and emerging patterns.

Station : 000044 RI I-85 | Alabama Department Of Transportation | Run Date: 3/30/2011 1:58:52 PM
6.0 Miles South of Macon Co. Line | Transportation Planning Bureau - Traffic Division | Direction Of Travel: North
Mt. Meigs Co: MONTGOMERY | Directional Monthly Volume Report | **April 2010**

DAY	1 AM	2 AM	3 AM	4 AM	5 AM	6 AM	7 AM	8 AM	9 AM	10 AM	11 AM	12 PM	1 PM	2 PM	3 PM	4 PM	5 PM	6 PM	7 PM	8 PM	9 PM	10 PM	11 PM	12 AM	TOTAL
1 T	296	199	173	167	299	425	728	1012	1003	1023	1150	1253	1353	1418	1533	1681	1881	1971	1446	1221	995	888	611	425	23151
2 F	268	207	192	201	254	356	589	837	1006	1146	1106	1216	1277	1412	1655	2088	2035	1776	1489	1217	1038	889	707	472	23433
3 S	**366**	**204**	**191**	**182**	**169**	**233**	**369**	**587**	**743**	**856**	**1104**	**1143**	**1225**	**1141**	**1201**	**1217**	**1081**	**1064**	**1012**	**905**	**793**	**677**	**607**	**385**	**17455**
4 S	**255**	**168**	**121**	**109**	**111**	**174**	**223**	**380**	**552**	**712**	**965**	**1078**	**1258**	**1393**	**1507**	**1652**	**1788**	**1820**	**1758**	**1785**	**1272**	**841**	**609**	**400**	**20931**
5 M	228	161	155	177	265	460	708	945	1082	1075	1207	1391	1316	1564	1473	1541	1829	1757	1152	994	743	647	410	292	21572
6 T	188	156	133	174	257	416	728	1060	1009	952	1085	1083	1275	1258	1317	1524	1569	1603	1266	911	798	682	445	287	20176
7 W	202	168	160	178	253	463	720	975	999	977	1085	1164	1344	1345	1539	1584	1830	1746	1236	901	735	638	434	324	21000
8 T	209	148	159	185	263	441	740	945	938	930	1075	1174	1359	1329	1560	1679	1844	1686	1272	1027	809	719	466	340	21297
9 F	218	186	153	193	269	437	785	1059	1015	1143	1222	1433	1623	1753	1850	2013	2139	2089	1736	1316	1201	1014	720	500	26067
10 S	**311**	**206**	**159**	**172**	**208**	**355**	**466**	**754**	**901**	**1047**	**1283**	**1430**	**1593**	**1844**	**2040**	**1888**	**1627**	**1357**	**1199**	**1023**	**869**	**810**	**704**	**476**	**22722**
11 S	**333**	**186**	**157**	**139**	**153**	**188**	**304**	**496**	**769**	**1008**	**1250**	**1347**	**1764**	**1712**	**1658**	**2056**	**2054**	**1929**	**1434**	**1136**	**860**	**630**	**543**	**334**	**22440**
12 M	223	162	122	165	249	421	730	911	953	946	998	1084	1138	1133	1213	1385	1591	1548	958	812	642	574	421	247	18626
13 T	161	124	118	166	242	429	763	978	902	864	953	927	1052	1102	1180	1298	1656	1572	1049	812	685	611	371	274	18289
14 W	209	131	149	154	248	439	749	1019	913	923	1011	1012	1133	1136	1313	1371	1614	1579	1103	821	722	584	401	287	19021
15 T	202	171	143	148	243	461	775	1064	916	1010	1167	1157	1208	1247	1314	1517	1759	1680	1212	971	799	750	432	291	20637
16 F	221	183	147	177	253	440	723	1041	1033	1045	1176	1418	1462	1558	1638	1760	2049	1864	1550	1266	1064	911	740	470	24189
17 S	**268**	**202**	**177**	**195**	**226**	**316**	**477**	**787**	**1067**	**1608**	**1889**	**1591**	**1328**	**1136**	**1115**	**1235**	**1107**	**1095**	**1053**	**865**	**785**	**611**	**516**	**352**	**20001**
18 S	**264**	**174**	**184**	**157**	**124**	**164**	**263**	**418**	**586**	**757**	**982**	**1104**	**1262**	**1503**	**1448**	**1520**	**1466**	**1517**	**1146**	**1071**	**863**	**619**	**399**	**301**	**18292**
19 M	196	143	128	138	254	448	727	950	894	879	955	1088	1097	1129	1149	1345	1597	1553	968	801	624	521	312	247	18143
20 T	158	127	134	158	249	442	754	946	933	873	864	874	1043	1102	1185	1305	1648	1543	956	808	664	587	367	267	17987
21 W	169	125	142	177	234	478	809	981	914	933	961	941	1140	1148	1260	1324	1540	1570	1042	863	684	573	393	316	18717
22 T	206	154	146	166	276	466	762	967	907	901	986	1035	1175	1184	1359	1422	1668	1677	1236	935	773	673	454	315	19843
23 F	221	164	145	189	271	415	769	995	990	1009	1083	1264	1369	1461	1619	1630	1859	1814	1441	1113	983	740	604	382	22530
24 S	**252**	**193**	**144**	**162**	**171**	**278**	**371**	**529**	**645**	**757**	**965**	**912**	**993**	**953**	**947**	**952**	**865**	**813**	**701**	**619**	**487**	**469**	**416**	**309**	**13903**
25 S	**193**	**150**	**132**	**101**	**105**	**114**	**216**	**387**	**577**	**824**	**993**	**1164**	**1395**	**1463**	**1548**	**1639**	**1530**	**1536**	**1296**	**1133**	**863**	**611**	**489**	**325**	**18784**
26 M	195	152	139	143	237	397	766	978	865	946	979	1044	1201	1174	1240	1340	1398	1465	987	798	644	546	327	273	18234
27 T	156	115	137	143	240	400	768	933	918	826	920	921	1115	1135	1169	1362	1559	1533	968	770	654	587	378	235	17942
28 W	203	139	125	170	250	441	810	986	950	937	852	938	1095	1132	1206	1240	1720	1578	1020	818	719	613	384	289	18615
29 T	167	154	159	148	248	436	790	982	958	913	1011	1102	1086	1238	1276	1482	1667	1638	1193	913	817	641	449	320	19788
30 F	223	160	170	183	318	445	805	1022	1034	1028	1160	1223	1370	1537	1587	1801	1919	1859	1525	1199	1008	877	623	434	23510

Figure 2.1 Directional (North) Monthly Traffic Volume Report for Station 44 on I-85

The second dataset was gathered using the *Fatality Analysis Reporting System (FARS)* from the *National Highway Traffic Safety Administration (NHTSA)* ("Fatality Analysis Reporting System (FARS) Encyclopedia," 2012). For the purpose of our analysis, the captured data frame is for *commercial vehicles* (trucks and buses) involved in fatal accidents from 2002 to 2011 within 12 southeastern U.S. states. Commercial vehicles are trucks with gross vehicle weight greater than 10,000 lb. or buses that can hold more than 10 passengers. The 12 southeastern states studied were: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, and West Virginia. These states have similar demographic factors and weather conditions, which allows us to make a “fair comparison” (i.e. the exogenous effects of weather, demographics and urban/rural effects can be mitigated). We have used this dataset to demonstrate the utility of visualized spatiotemporal safety data and the potential impact of policy-making on commercial vehicle safety.

2.5 Review of Relevant Data Visualization Tools Subset

Visualization tools can be implemented in research to observe the occurrence of traffic events and explore the information from the events. One of the concerns for practitioners is to provide more efficient and understandable results to stakeholders by improving the current approaches or other useful emerging techniques. The key is to determine the best way of integrating the data and the optimal presentation of results. We introduce the highlights in recent transportation safety research and emphasize some of the appropriate data visualization tools from the current practice related to these common types of transportation research.

For a large dataset, it is difficult to move forward without understanding the basis of the contents. The histogram, one of the basic visualization tools, can indicate the distribution of information. The daily pattern and seasonal trends of the fatal crash data from 2001 to 2011 can be explored using histograms, according to N. Yau (2013). From the results, he stated that most of the crashes occur in the evening in terms of time of day, and trends can also be found regarding the day of the week and month. Instead of looking at the meaning of each individual data point, the aggregate values of the data sometimes extract more hidden information.

Another example can be found in traffic volumes, which began to be studied in the mid 1960's (Roddick & Spiliopoulou, 2002). Cluster analysis was initially adopted to analyze traffic volumes in the 1990's (Black, 1991; Flaherty, 1993). Weijermars and van Berkum (2005) classified highway flow patterns by the daily flow profile chart and defined the characteristic of clusters by a summary table. Based on the data selected, only 118 days were included in their analysis. In addition, the summary table and the presentation of the daily pattern charts from the dataset do not interpret the results clearly. Van Wijk and Van Selow (1999) developed a calendar-based clustering application to present daily patterns and seasonal changes in employee and power demand, which displays the results on a calendar. This was the approach adopted for this research used to analyze traffic flows. The details are interpreted in the following section.

Some researchers have used the Geographic Information System (GIS) to transform data into a map to analyze traffic accidents (Erdogan et al., 2008; Liang et al., 2005; Yi et al., 2001). Besides using a GIS, a large number of practitioners constructed internet-based mapping tools to monitor different safety related incidents such as the Global Incident Map and the National Incident Map. They used graphics to display where the incidents occurred. A text box with detailed information is also shown with the selected incident. The text box may contain useful information, but the detailed information sometimes causes difficulty in interpretation and communication. In addition, the information could not be extracted or synthesized among multiple points. Some advanced mapping tools are designed and displayed on the websites such as Baton Rouge Traffic Incident Map, CrashMap, and English Road Safety Comparison to show the incidents with selected variables.

The behavioral factor determination includes finding important factors in the accident analyses and evaluating the effectiveness of safety policymaking. A histogram and bar chart showing the data exploration are usually embraced in these analyses. Nevertheless, none of the transportation safety research has used visualized statistical results such as a heat map. The heat map can show the significance of testing results transforming from the statistical reports.

2.6 Developing a Data Visualization Toolkit to Inform Theory and Practice

In Section 5, some of the visualization tools that are relevant to transportation safety were presented. Here, two tools are used to demonstrate the power of visualization in uncovering unknown contrasts, which can be used in informing the relevant stakeholders. First, we present how the approach of Van Wijk and Van Selow (1999) can be used to detect seasonal trends in the Alabama traffic flows. Animation is then used to highlight how spatiotemporal traffic accidents can be depicted on a map.

2.6.1 Uncovering Seasonal Patterns in Traffic Flows

Using the ADoT dataset and the approach of (1999), we examined the traffic flows for 2005. Since the approach is based on *k-means* clustering, we also explore the effect of the number of clusters (*k*) on the observed patterns. One can think of the choice of the value for *k* as the degree of granularity required for the data analysis. This method partite n data points into *k* sets, and typical values of *k* can range from 2-12 depending on the application and *a priori* theoretical framework. The result for k=2 is portrayed in Figure 2.2. The *y*-axis represents the average traffic volume per cluster, the *x*-axis represents the time of the day, and the color corresponds to the different clusters. Prior to the analysis, one could hypothesize that using $k=2$ should result in distinguishing between weekdays and holidays. However, the two clusters depicted in Figure 2.2 show that in general Fridays have a different pattern than weekdays with larger counts of vehicles on the road starting from around 9 am until midnight. This pattern is also observed on spring/summer Sundays as well as days around holidays (Martin Luther King, Jr. Day, Fourth of July, Thanksgiving, Christmas, etc.)

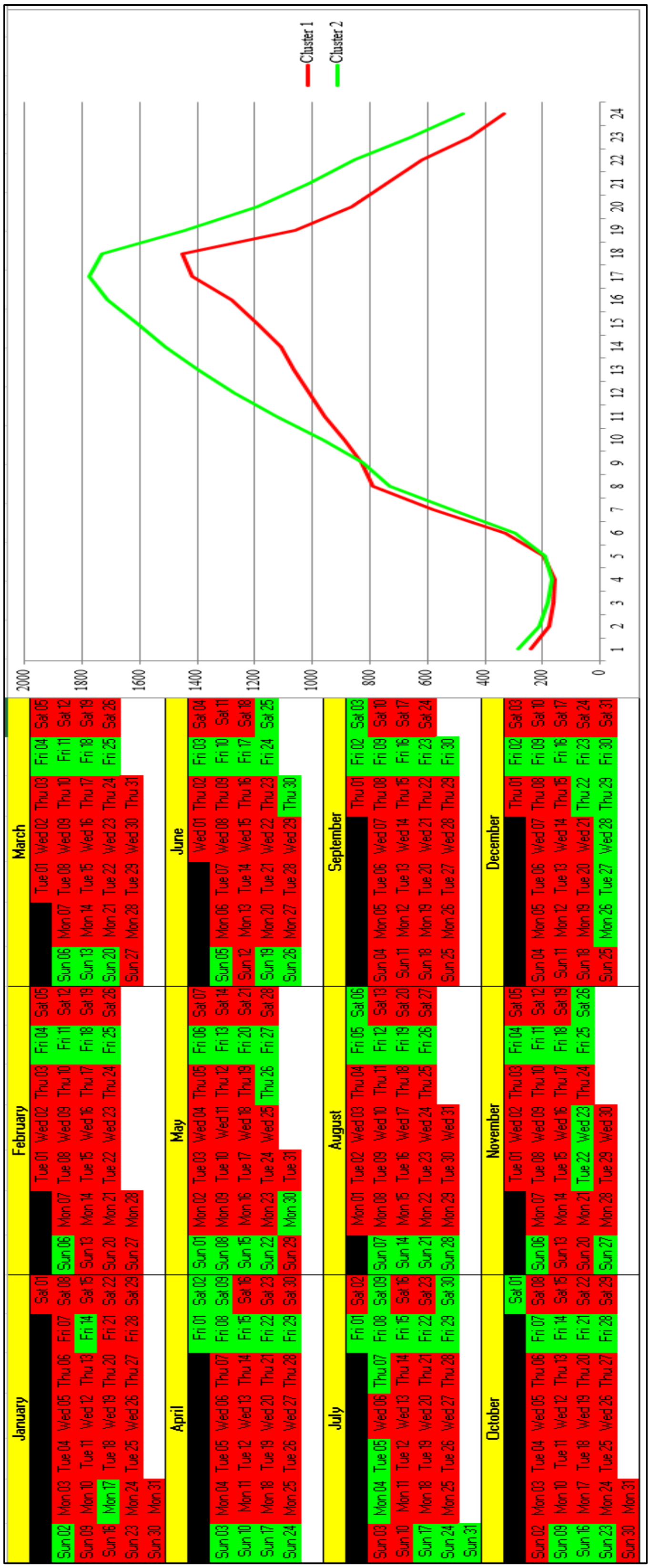

Figure 2.2 Traffic Flow Analysis Using 2-Clusters for the Year 2005

If more detail is needed, our VBA-tool allows the user to pick the value of *k* and see the corresponding effect. Figure 2.3 provides the results for k=5 clusters. Here, one can see that the patterns become different (i.e. not only magnified, but having different shapes) for the different clusters. For example, the blue cluster corresponding to Saturdays shows a uniform traffic flow peak between 9 am and 5 pm. Such a pattern is quite distinct from the regular weekday patterns (the two shades of yellow) where the peak is around 5 pm where most employees leave. The light yellow cluster representing Fridays indicates that employees leave work earlier (and in greater numbers) on Fridays, which is an expected outcome. Thus, the use of clustering can provide evidence for daily and seasonal effects, which can inform hypotheses and research regarding traffic volumes. The calendar view allows the viewer to capture all the information in one screen (which presents the addition on the work of Weijermars and van Berkum (2005)).

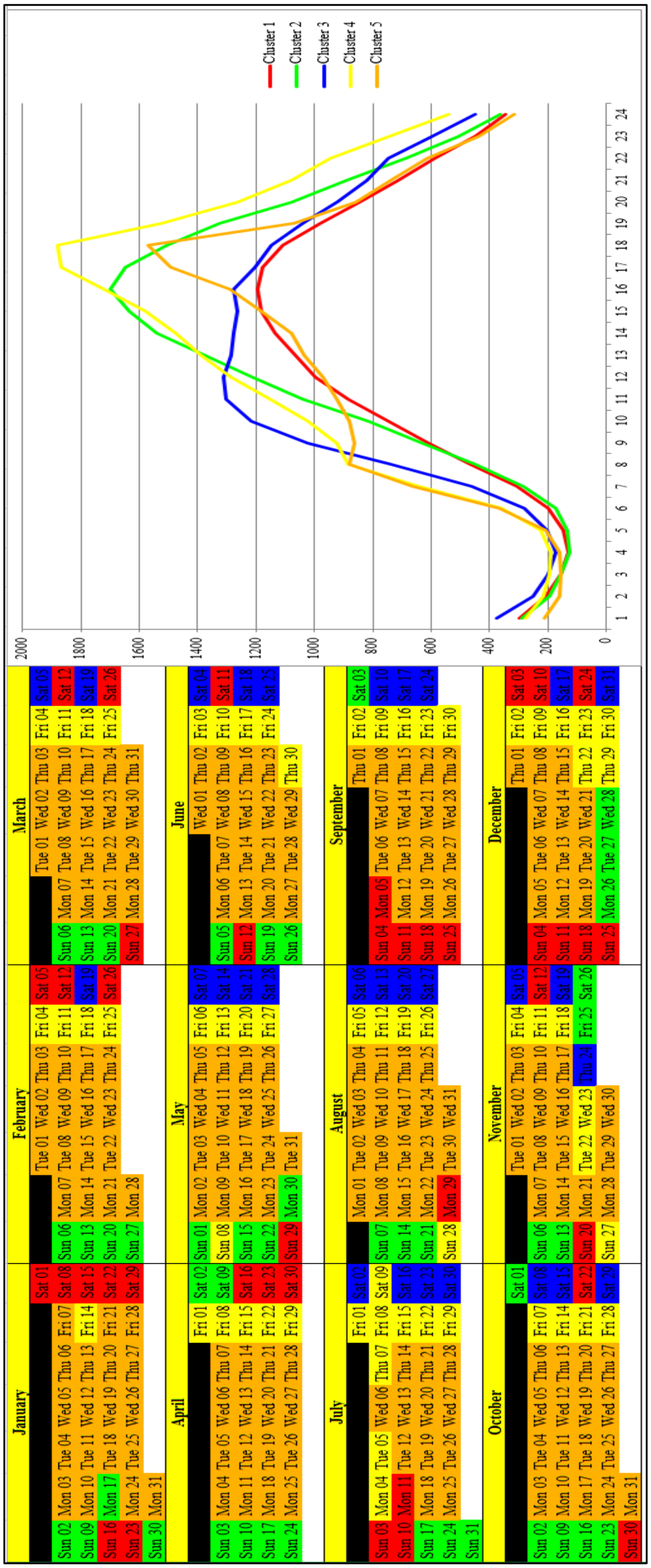

Figure 2.3. Traffic Flow Analysis Using 5-Clusters for the Year 2005

We present the very interesting case of *k*=8 in Figure 2.4. While the increase in number of clusters resulted in clusters that are almost identical (i.e. clusters 5 and 6), we were able to capture a significant departure from the patterns described above in cluster 3. Cluster 3 is significant even though it captures only five Saturdays in the fall. This unanticipated result suggests an underlying phenomenon not previously anticipated. Upon further investigation, the researchers uncovered a local cultural phenomenon driving increased traffic volumes. These days correspond to five out of eight Saturdays when the Auburn University College Football team played home games. With a stadium capacity over 87,000, these football games result in heavy commuter traffic on I-85 which passes through the city of Auburn. It is interesting to mention that all these five games were morning/early-afternoon games with a latest start of 2:30 PM local time. On the other hand, the remaining three games (Sept. 3rd, Oct 1st and Nov. 12th) were all evening games with an earliest start of 6 PM local time. Therefore, cluster 3 captured a coherent set of events that have a tremendous impact on the local community and has a unique traffic pattern consistent with alumni driving to Auburn from Mobile and Montgomery (two of the largest cities in the state) to watch the game. Note that Station 44 is approximately 40 miles away from Auburn and I-85 is the only interstate which can be used to drive to Auburn University. While this may seem like an “obvious” factor to consider for those familiar with the popularity of American college football, two points need to be made. First, not all transportation safety researchers are familiar with all characteristics of human behavior that may drive traffic patterns. The tool can discover factors the researchers may be unaware of *a priori*. Second, this visualization can also be used to uncover a previously unaccounted for phenomenon, and explain or highlight its impact on traffic patterns. For example, the tool can then be used to drive policy decisions for government (increased policing on game days, re-routing of commercial traffic, postponement of lane closures, etc.) and industry (alternative routing during congestion, timing of travel through congested lanes, etc.). The tool can be used for both discovering and alleviating the impact of “predictable” event-driven safety and efficiency factors.

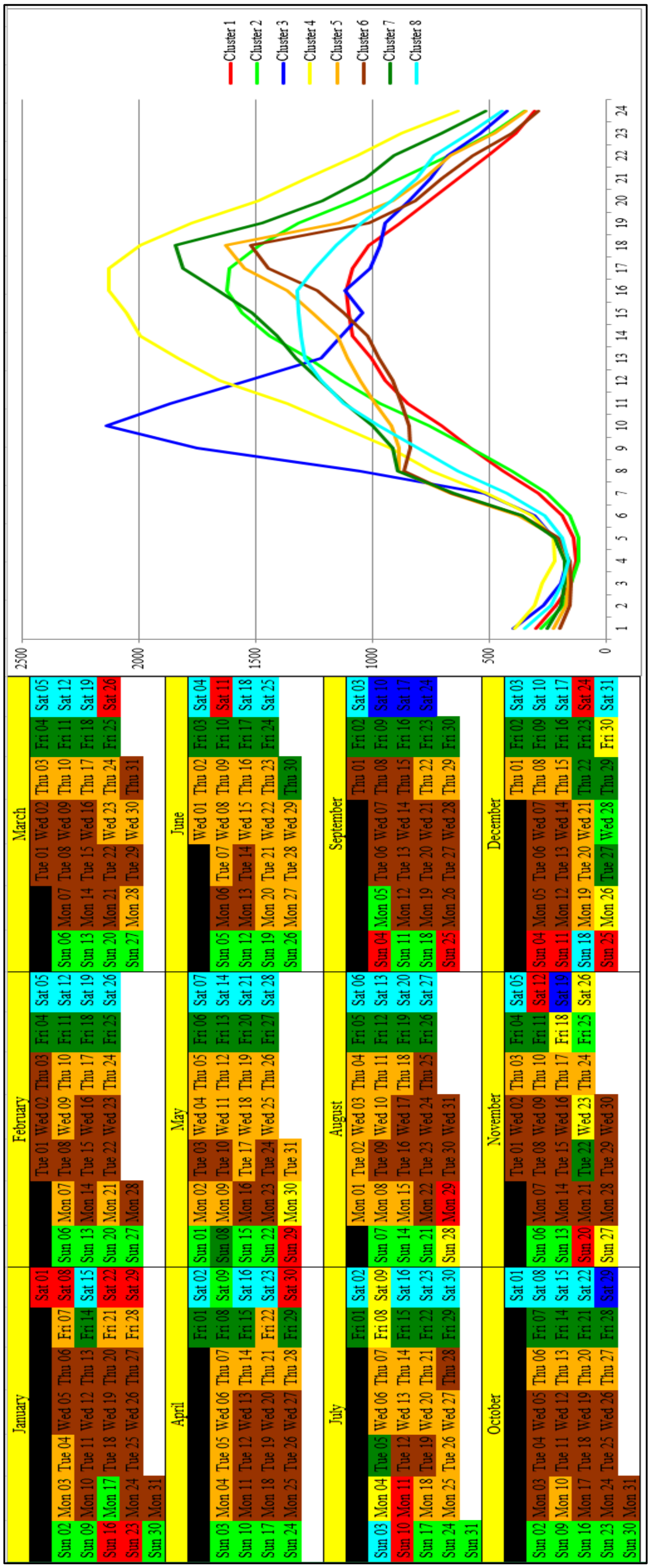

Figure 2.4. Traffic Flow Analysis Using 8-Clusters for the Year 2005

This calendar-based clustering tool is also useful for exploratory disconfirmation. In recent years, there has been a strong geographical shift in the location of manufacturing plants in the U.S. Specifically, major assembly plants (and their suppliers) have been located in the Southeast due to the availability of trained, efficient and lower cost (non-union) workforce, proximity to major logistics hubs, as well as state support and financial incentives in the form of lower taxes. From a research standpoint, one would anticipate greatly increased volumes of commercial traffic along the major corridors linking vendors and manufacturers. One would expect that this might lead to increased accident rates and reduced transportation efficiencies. Because the ADoT provided traffic volume reports since 2005, the comparison of traffic volumes between before and after automotive plants shifting was possible. However, this has not been shown to be the case with traditional analytical methods. The use of the calendar-based clustering tool by the investigators revealed a potential explanation for the lack of evidence. The economic crisis also hit the automotive industry hard in 2008, and this moderating factor could have suppressed any expectation of increased activity. While it is quite possible that other tools could have been used to uncover and explore the influence of counter-balanced factors (economic activities), we found it particularly useful in guiding our investigation to this hypothesis.

2.6.2 Visualizing/Understanding Spatiotemporal Transportation Safety Data

Referring to the existing relatively expensive commercial software, we developed a low cost VBA-based interactive visualization tool that can transform accident data into a map with animation. In addition to displaying location (longitude and latitude) and time on the map, our new tool is able to show three other variables dynamically denoted by symbols, shapes, and colors selected by the user. Also, built-in functions of software, such as population per state, can be acquired from the map. This six dimensional visualization tool is proposed as a new, potential informative way to provide an effective overview and a set of flexible selection for users to analyze the data.

In Figure 2.5, the map layer is shaped by population size for each state. The darkest color of the states represents a state with a population size greater than 30 million. The colors for the symbols show the accidents that have occurred on the different days of the week; red, green, blue, yellow, and black represent accidents occurring Monday through Friday. It should be noted that the user can select the number of days that will be shown on the map, which allows for visualizing different hypotheses and research questions. The symbol (on the right side of Figure 2.5) indicates the number of fatalities per traffic accident. Additional relevant information can be depicted with the histogram, line chart, bar chart and/or pie chart, which we provide as a part of our toolkit. In Figure 2.5, we summarize the counts of types of route where fatal accidents occurred in 2011. The state highway system shows the highest occurrences of accidents. We believe that this snapshot view of the data can be very informative, especially with the ability of the user to query and select specific ranges (or values) for the variables he/she would want to depict.

This visualization tool provides a complete accident monitoring system, seeing different accident-related variables associated with the location and time in the same graph. The users can now know the frequency of accidents based on of location, time, weather conditions, type of vehicle or any other variable of interest they select. Researchers or public policy decision makers could get precise information of how to interpret the data in the data preparation stage and then move forward to analyze the data.

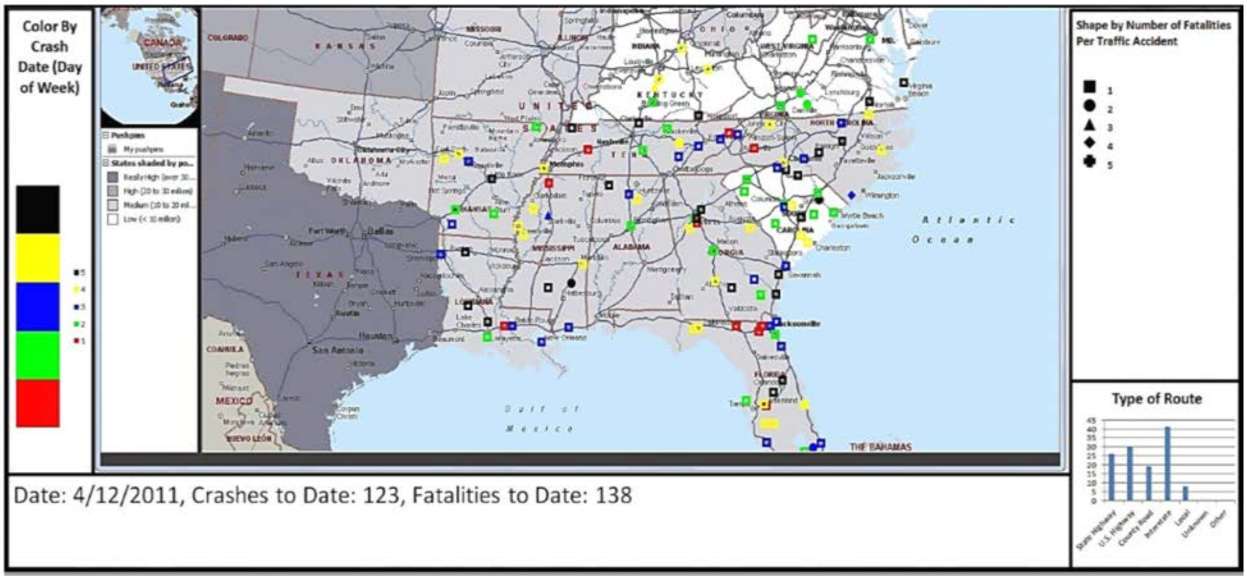

Figure 2.5. Spatiotemporal Data Mapping Tool Interface

2.7 Developing a Data Visualization Toolkit to Evaluate the Safety Policy Changes

In Section 6, we use the developed data visualization toolkit to demonstrate the hidden patterns from the traffic flows and examine the animated transformation from spatiotemporal traffic accidents onto a map. In this section, a new data visualization toolkit form is introduced. A statistical analysis is performed initially to catch the potential impact of policy changes. The conclusions are displayed on a heat map where different colors shade the significance of policy adoption and symbols simply represent the results of interest.

2.7.1 Examining the Potential Impact of the Safety Policy on Fatal/Non-fatal Crashes

The example in this study focused on the “Distracted Driving Laws,” which have been enacted in recent years. Within the 12 southeastern states, seven have banned texting while driving including Arkansas, Georgia, Kentucky, Louisiana, North Carolina, Tennessee, and Virginia before January 2012. The laws apply to all vehicle drivers including CMV drivers. There are two accident measures within southeastern states for the time periods before and after text messaging ban laws were enacted. These two measures are fatal injury rate and non-fatal injury rate standardized by 100 million vehicle miles traveled by all vehicles as a measure of overall highway safety. Based on the state size, there are four different indicators: 100 million vehicle miles traveled, 100,000 population, 100,000 registered vehicles, and 100,000 licensed drivers, for calculating the fatality rate as well as injury rate. Nevertheless, 100 million vehicle miles traveled is more accurate for measurement. The main target is to test the efficacy of laws of those states, which have adopted the distracted driving law, and to transform the results into a graphical pattern. In other words, better efficacy means there is significant evidence to show a decreased fatality rate after embracing the distracted driving law.

The first step of the analysis is conducted at a 5% significance level by testing the hypothesis that the text messaging ban law had a positive influence on reducing fatal and non-fatal injury rates (Table 2.1 and Table 2.2). The F-test is applied first to determine if equal variances are used to compare two populations in the given time frame from 2002 to 2011, which are pre-law periods and post-law periods. Five out of seven states have a p-value lower than 0.05 in the one tailed t-test. Considering compound effects such as other policies deployed, the result can only provide relatively sufficient evidence that the distracted driving law may reduce the fatal injury rate in these five states. The hypothesis to test the impact of policy change for the non-fatal injury rates led to different results. Georgia did not have significant results for reducing non-fatal injury rates while Arkansas joined the group with a low p-value. Meanwhile, North Carolina and Tennessee are the only two states to have high p-values demonstrating the influence of the distracted driving law.

Table 2.1 Pre-Law and Post-Law Comparison for Fatal Injury Rates

State	Mean (pre-law)	Mean (post-law)	F test	Test type	T test
Alabama	0.08				
Arkansas	0.19	0.14	0.064299	Pooled	0.070650
Florida	0.07				
Georgia	0.09	0.06	0.085005	Pooled	0.015296
Kentucky	0.1	0.07	0.305648	Pooled	0.036469
Louisiana	0.11	0.08	0.799955	Pooled	0.039319
Mississippi	0.12				
North Carolina	0.16	0.1	0.105840	Pooled	0.000002
South Carolina	0.14				
Tennessee	0.1	0.07	0.061262	Pooled	0.001466
Virginia	0.06	0.06	0.732827	Pooled	0.377121
West Virginia	0.15				

Table 2.2 Pre-Law and Post-Law Comparison for Non-Fatal Injury Rates

State	Mean (pre-law)	Mean (post-law)	F test	Test type	T test
Alabama	0.11				
Arkansas	0.26	0.11	0.000001	NotPooled	0.000034
Florida	0.11				
Georgia	0.14	0.1	0.072980	Pooled	0.074797
Kentucky	0.12	0.11	0.170566	Pooled	0.379479
Louisiana	0.17	0.12	0.194961	Pooled	0.178359
Mississippi	0.14				
North Carolina	0.24	0.14	0.025124	NotPooled	0.000001
South Carolina	0.19				
Tennessee	0.16	0.07	0.000118	NotPooled	0.000016
Virginia	0.07	0.09	0.000000	NotPooled	0.312040
West Virginia	0.21				

2.7.2 Visualizing the Statistical Results of Policy Changes

In order to improve the understanding of the impact of policy changes, we visualized the outcomes by plotting the results on a U.S. map according to the p-values (Figure 2.6 and Figure 2.7). Three categories are classified for the potential impact of policy making by symbols: the smiley face, sad face, and prohibition sign. A ”smiley face” indicates where the policy has had significant impact in reducing fatality and injury rates, the “sad face” shows the non-significant result, and the “prohibition sign” means the state has not adopted the selected policy. In addition, the gradient of the color from red to blue specifies the significance of each state’s results. In this case, North Carolina, which is painted dark blue, is affected most positively by the policy. Virginia, which shows “mad face” and darkest red, indicates significant evidence that there was no reduction after adopting the distracted law in both fatal and non-fatal accidents.

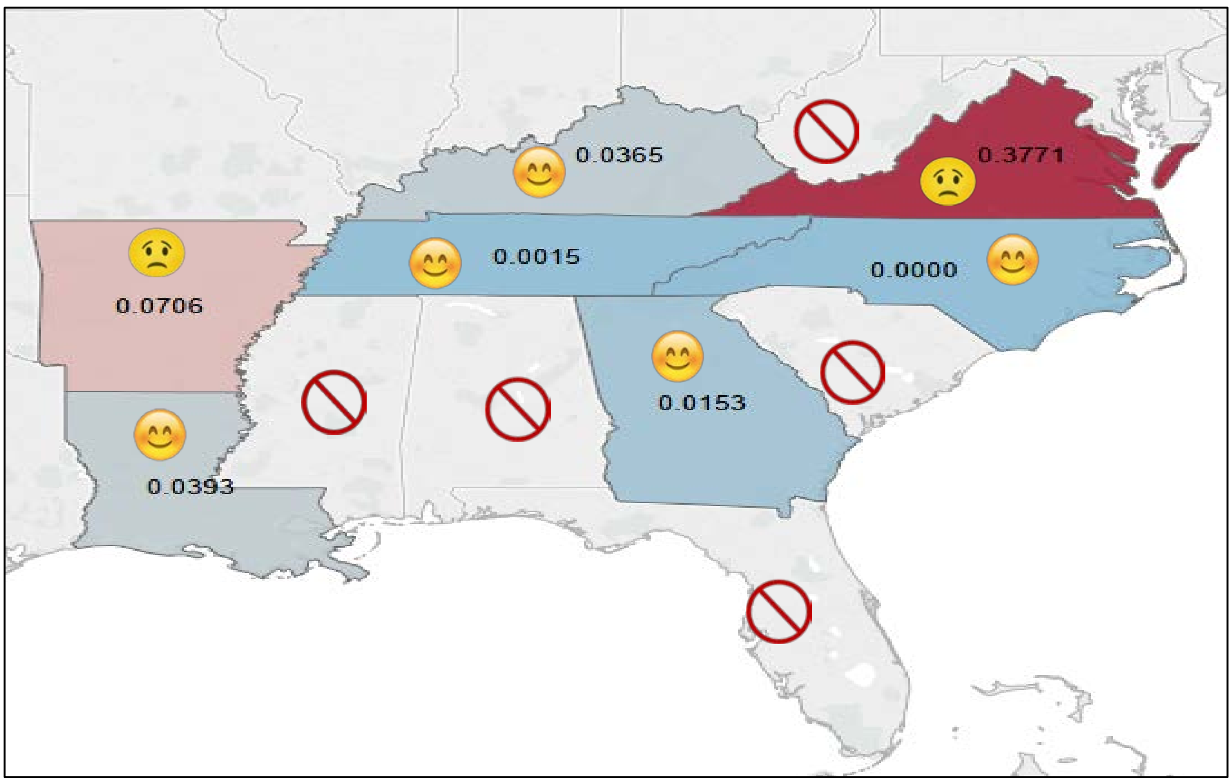

Figure 2.6. Fatal Injury P-Value Map

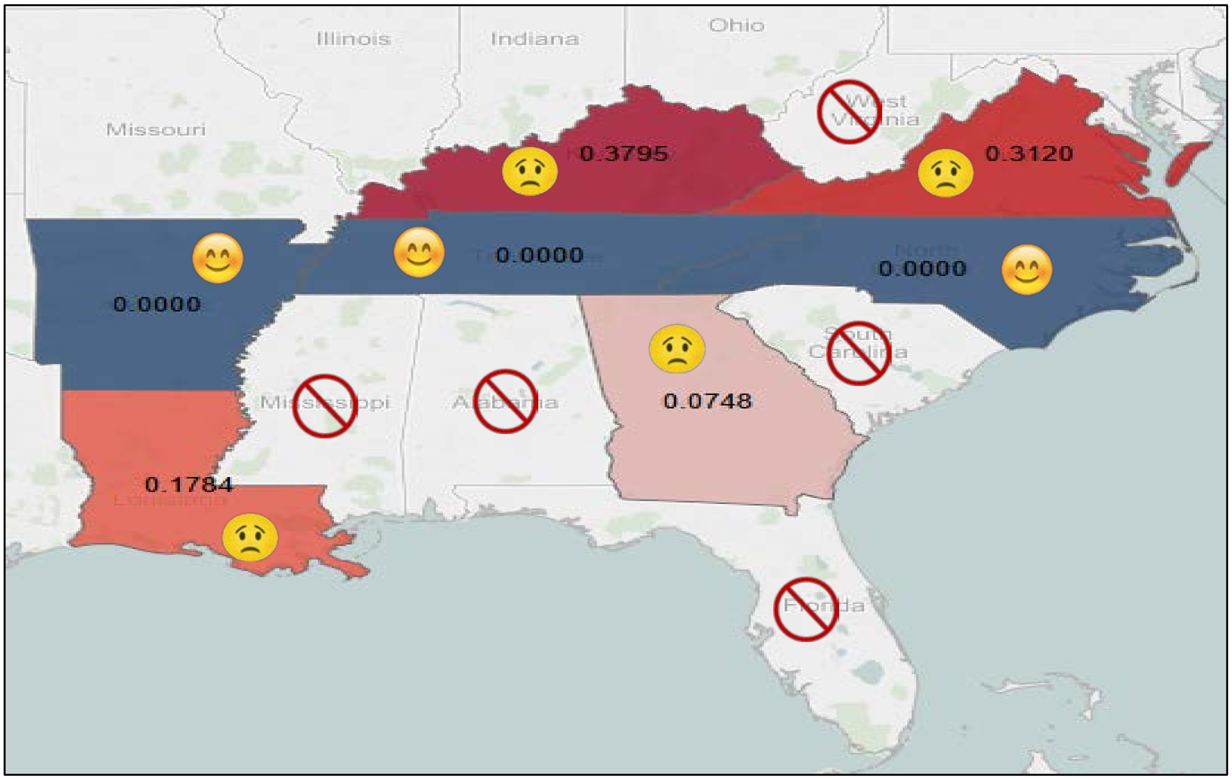

Figure 2.7. Non-Fatal Injury P-Value Map

For policy makers who do not have a statistical background, graphical information would attract their attention and provide clearer results. Therefore, they are able to have quick responses for the effectiveness of traffic policies and are able to ultimately make better decisions. For those audiences who know how to read statistical reports, they may be not willing to focus on understanding the complicated tables due to busy work or other issues; the graphical results can provide clear directions in less time. The example is only to provide one single policy evaluation with 12 southeastern states; however, once the results correspond to the multiple policy evaluation in the entire U.S., the complexity of reading and interpreting the reports increase. It is suggested that transforming p-values into a colored map could improve clarity and understanding.

This easy-to-use and straightforward visualization tool can also show the impact of any policy making after gaining the results from statistical analysis. Although discussing a single traffic policy may ignore the compound effects with other policies, this tool shows a potential way to present how policies impact the drivers' behavior in easy to understand visual form.

2.8 Concluding Remarks

To effectively learn from the ever-increasing volume and complexity of traffic data collected, this research effort explored how visualization techniques can be used to extract trends and to gain further understanding about factors of interest affecting transportation safety. First, we examined how existing visual data mining tools can assist in theory development and policy making. The focus was on presenting some of the tools that have not been heavily used in the exploratory data analysis of transportation datasets. Some of these tools have been used for exploring similar traffic datasets (e.g., the work of N. Yau (2013)), while others have been applied outside the transportation field. Using the insights from these methods and some fundamentals of visual data mining, we developed a new and potentially useful "visualization toolkit" that can be used to uncover unknown relationships in traffic volume; primarily in the clustering of traffic flows and visualizing the patterns associated with each cluster. We also provided a spatiotemporal multi-characteristic plot that allows practitioners and researchers to simultaneously visualize up to five variables of interest on a map; the model used included time and space variables. Such a tool can be useful when studying a dataset for the first time and in evaluating the validity of modeling assumptions. Our third completed contribution is based on the development and use of a "p-value heat map" that assists policy-makers, researchers and the general public to succinctly see the potential impact of public policy on the reduction of nonfatal and fatal crashes. This tool helps policy-makers who may not have a strong statistical background to understand statistical outputs of policy-analysis models.

The results from this paper demonstrate the power of visualization and how it can assist with both theory development and explaining the results of statistical models. There remains significant work to be done in this area, including integrating visualization methods with traffic databases for real-time visualization of emerging trends, better understanding of the limitations of these approaches, and ensuring that these tools can be generalized to multiple application domains.

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3 The Effects of Socio-Economic and Public Policy Factors on U.S. Highway Safety

3.1 Abstract

Transportation accidents continue to be one of the leading causes of death in the U.S, with an annual death toll of ~33,000 lives and an estimated annual economic cost of $300 billion. Driver behavior and traffic related variables are commonly used to analyze accidents for determining the root causes. This paper suggests that it is also important to look at the influence of socioeconomic factors and safety policies on highway safety. In this paper, we focus on three research questions: what are the most influential socioeconomic and demographic factors involved in highway safety research; what have been the significant factors that impact highway fatality rates over time in the United States from a macro perspective; and what are the implications for U.S. public policy with respect to highway safety policy? To address these questions, a "panel data" analysis was performed to examine the effects of five socioeconomic factors and two safety policies during the years 2005 to 2011. Our findings suggest that some socioeconomic and demographic factors do influence highway safety, and public policy decision makers should consider these factors.

3.2 Introduction

More than 30,000 people involved in motor vehicle accidents are killed annually in the United States, which is the top cause of death and injuries in US transportation (Research and Innovative Technology Administration, 2014). Moreover, the costs for treating the injured related to car crashes were estimated at 41 billion dollars, and the total social costs of crashes were estimated to be 300 billion dollars(Center for Disease Control, 2012; Larry Copeland, 2011) . A key goal of safety improvement for policy makers, especially related to highway safety, has been to reduce motor vehicle fatality rates. For example, the goal made in 2002 by the U.S. Department of Transportation was to reduce the highway fatality rate to no more than 1.0 per million vehicle miles traveled by 2008 (National Highway Transportation Safety Administration, 2007). Although the goal was not achieved, the decreasing trend from the year 2002 to 2008 showed that motor vehicle accidents could be avoided. At the same time, a series of accident-related research has been produced to explore the root causes of motor vehicle accidents in order to provide suggestions for policy making.

Although highway fatalities have been decreasing since 2005, policy makers still lament the difficulties of revising the existing safety regulations to reduce the loss of life. In fact, the newest data released by the National Highway Transportation Safety Association (NHTSA) states that highway fatalities increased slightly in 2012 (National Highway Transportation Safety Administration, 2012). The increasing number of fatalities was attributed to noncompliance with seatbelt, drunk driving, and motorcycle helmet laws. These laws are considered three of the important risk factors for legislation and enforcement (World Health Organization, 2013). The effectiveness of safety policies should be studied and monitored for improvement; since different government entities make and enforce their own regulations, there may be opportunities for shared “best practices” between and among organizations and levels of government.

Making policies for reducing fatalities and injuries is directly related to three main categories of causes of highway accidents: mechanical, environmental, and behavioral (National Highway Traffic Safety Administration, 2008). Due to the role of the vehicle operator in performing high risk driving behavior, many previous studies focused on the investigation of drivers’ behaviors imputed from crash datasets collected by government agencies. According to the speech by the chairman of the International Organization for Road Accident Prevention, “More than 90 percent of road accidents are caused by human error” (Olivia Olarte, 2011). As technological and infrastructural engineering improvements have been extensively studied and implemented for decades, it would seem that a promising way to further reduce vehicle crashes is to prevent drivers from making the wrong decisions. Inappropriate drivers’ behaviors while they are driving include things like speeding, driving under the influence, and decision errors (improper lane changes, improper merge timing, etc.).

Previous studies have analyzed the relationships between these factors and highway accidents (Aarts & Van Schagen, 2006; Al-Ghamdi, 2002; Fowles et al., 2013; Lueck & Murray, 2011; Massie et al., 1995; McKnight & McKnight, 1993; Oster & Strong, 2013; Parker et al., 1995; Peck et al., 2008; Shibata & Fukuda, 1994; Stamatiadis & Deacon, 1995; Wang et al., 2013). However, a traffic accident is ultimately the result of a sequence of events that may be influenced by other issues that affect the driver, such as his or her education, culture, personal ethics or values, or socioeconomic status. It is noted that only a few studies have addressed socioeconomic factors in road safety analysis in the United States (O'Neill & Kyrychenko, 2006; Oster & Strong, 2013). Furthermore, these studies are also limited in that they generally only considered after-crash data; there is no readily available database of safe driving events and associated factors. It is proposed that it may be helpful to study the impacts of the socioeconomic status factors as additional causal factors for better policy making (Pawlovich et al., 1998).

Based on the discussion above, the authors propose that there is a need for considering the effects of socioeconomic factors and safety regulation/law as risk factors associated with highway accidents. For the purposes of contrast, the state level (state-wise comparison) is considered as the unit of analysis for contrasting regulations (policy) and socioeconomic differences. This paper focuses on analyzing these two categories. A description of the investigation and results are presented in the following order: the next section includes a comprehensive literature review; then a brief description of methodology and the data; followed by the empirical results. Concluding remarks are provided in the last section.

3.3 Literature Review

Our target is to study the impact of some selected socioeconomic factors and public policy (regulation) to fatal crashes. It is noted that research on the socioeconomic factors of road safety have received more emphasis in other countries outside the US. For example, the Europe Transport Safety Council has confirmed that traffic injury is associated with social status in Europe (Elvik et al., 2007). In addition, there are more traffic accidents associated with lower socioeconomic status (Grimm & Treibich, 2010). In this section we introduce the factors that were found to be significant in earlier research, and we will define a new series of factors to study the relationship between these predictors and the dependent variable (fatal crashes) at the state level in the United States.

3.3.1 Review of Socioeconomic Factors

Previous studies have found that driving behaviors are the most critical issues to cause road accidents. The studies usually determined behavioral factors from crash datasets to be the causes in these accidents. Some analyses including socioeconomic factors from previous studies were performed. We will review several main socioeconomic factors below.

Income

Income per person or household represents economic growth and industrialization in a country. A country with higher incomes may indicate a more comprehensive traffic system and better driver behavior. There are several studies that explored the relationship between income and road traffic fatalities at a cross-country level, as well as some other factors such as population density or road density (Anbarci et al., 2006; Bishai et al., 2006; Paulozzi et al., 2007). In these studies, lower income countries have higher traffic-related crashes. A relationship between fatalities and mean incomes should also be inspected within the state level. States with higher levels of income may also be expected to have lower fatality rates.

Education

According to the definition from Census Bureau, education attainment refers to the highest education one individual has completed (United States Census Bureau). This factor has been found to be a significant factor in traffic fatalities (Kirk et al., 2005). Higher education attainment also leads to higher income. Thus, a high correlation between income and education is expected. In this study, we chose education level to be the independent variable of interest.

Unemployment

Unemployment rates can tell the status of a country's economy. Higher unemployment rates indicate a weak economy, and it also affects road safety. For example, a person who is unemployed may have mental stress that leads to bad or inattentive driving behavior (Leigh & Waldon, 1991). However, unemployed people would drive fewer miles, which may reduce the risk of traffic accidents (Wagenaar, 1983). As previous research has found the unemployment rate to have a significant influence on fatal crash rates (Wagenaar, 1984), we have included it in the current study.

3.3.2 Review of Safety Policies

Previous researchers have attempted to evaluate the effectiveness of different safety policies expressed as regulations or laws (specific examples to follow). Accident datasets have been reviewed and analyzed to determine if these policies help reduce the occurrence of fatalities and avoid bad driving behaviors. Usually, a time series analysis is performed to analyze crash data from single state or regions associated with regulations over time. The laws that seemed to show the most impact were those dealing with distracted driving, drunk driving, seatbelts, and speeding, which account for a large number of traffic citations ("moving violations") or got involved in an accident. We reference this previous research in the examples of relevant safety policies below.

Distracted Driving

Distracted driving refers to a situation where the driver is unable to focus on their primary task of driving, due to any activity that diverts their attention (Officeal US Gevernment Website for Distracted Driving). Most recently, "distracted driving laws" are defined as prohibiting handheld cell phone use- including texting, emailing and chatting on a cellphone. Because the use of cell phones has become a growing safety problem in the last decade, state and local governments started adopting distracted driving laws in 2007 (Wilson & Stimpson, 2010). These laws have been evaluated by several researchers in a short time, and the results identified that these laws have improved highway safety (Jacobson et al., 2012; Nikolaev et al., 2010; Sampaio, 2014). The effects of these policies will be included in this study.

Seat Belt Use

Except in New Hampshire, seat belt laws have been adopted in all states in the United States. The problem of seat belt use is important because more than half of people involved in fatal crashes did not wear a seatbelt (Centers for Disease Control and Prevention). State governments have tried to reduce the fatalities and injuries due to unworn seat belt by raising the fines for violations and improving the strength of enforcement. In recent years, the percentage of seat belt use has significantly increased. Also, the effectiveness of this law has been demonstrated in several studies (Cohen & Einav, 2003; Dinh-Zarr et al., 2001; Rivara et al., 1999). We will include seat belt usage as an independent variable in this study.

Drunk Driving

All states have adopted laws prohibiting impaired driving, usually focusing on alcohol use. While “Drunk Driving” has been defined and enforced differently over the years, there is now a high degree of standardization among political entities. Currently, a blood alcohol concentration at or above 0.08 while driving is considered de facto “impairment” and therefore a crime. There have been studies to analyze the effectiveness of drunk driving laws (Eisenberg, 2003; Freeman, 2007). The evidence shows that the current regulation is presumed effective, because the alcohol-impaired fatality rate decreased 48% between 1991 and 2012 (Foundation for Advancing Alcohol Resposibility). In addition, there has been no major improvement in recent years. Based on the lack of contrast between political divisions, and the nature of this current study discussed in the next section, these laws were not considered in our model.

Speeding

Speeding- driving faster than the posted legal maximum speed- is one of the most common factors investigated in fatal crashes, and found to be a contributing factor in one third of traffic accidents (National Highway Traffic Safety Administration, 2011). Around 55 percent of speeding-related vehicle accidents were associated with “exceeding posted speed limits,” and 45 percent of those were attributed to “driving too fast for conditions.”(Liu & Chen, 2009) According to a study conducted by the Federal Highway Administration in 1997, changing the speed limit does not have a significant effect on the number of crashes (Federal Highway Administration, 1997). Indeed, the effects of “differential speed” vs. “average speed” issues as they relate to safety have not been extensively studied, and more work needs to be done in this area. As a result of these mixed findings, many states raised their speed limits to increase traffic flow and reduce the load on constrained road capacity. Still, many people continue to drive over the newer, increased posted speed limits in order to shorten traveling time. Some states use speed detection devices to improve enforcement, and the speeding-related injuries decreased by at least 20% (Decina et al., 2007). Several states have enacted an aggressive driving laws and increased fines for speeders; however, further investigation is still needed because the progress of reducing speeding-related fatalities is slow (Governors Highway Safety Association). The complex nature of this factor requires focused study outside the scope of the current effort.

3.4 Data and Methodology

Previous studies have demonstrated a variety of analytical methods used to analyze crash and safety data in accident research (Mannering & Bhat, 2014). Panel data analysis is one type of time-series analysis. Unlike normal time-series analysis, which examines one or multiple subjects over time ("subject" being an individual person or entity), panel data analysis involves comparisons between groups of individuals (like residents of a state) inspected repeatedly over time (Frees, 2004). Hsiao listed several benefits of using panel data analysis: 1) using panel data can control for individual heterogeneity; 2) Panel data gives lower collinearity and higher efficiency of estimates; 3) Panel data can provide better inferences about the dynamic of change from cross-sectional study (Hsiao, 2014). Because we wanted to determine the effects of factors between states within a time period, which satisfies the theoretical requirements for panel data, we decided to use panel data analysis as our method.

The data used in this study were collected from the Census Bureau and the crash database of the United States Federal Highway Administration. The dataset covers the lower 48 states over 2005-2011 in the United States. To test the influence of socioeconomic factors and safety policy on fatality rates, we collected data for seven principal variables and four control variables, including several factors used in the existing literature and a few newly introduced factors (shown in Table 3.1). The factors education, noinsurace, new, and unemployment were from the American Community Surveys. The rest of the variables were collected from Federal Highway Administration. A description with details will be listed in the next section.

Table 3.1: Variable Description

Variable	Definition
Fatality	Fatalities per 100 million vehicle miles traveled (%).
Edu	Percentage of people who have at least bachelor's degree (%).
NoIn	Percentage of people who are not covered by health insurance policy (%).
NewV	Percentage of new vehicle registration out of all vehicle registrations (%).
MCost	Average highway maintenance costs per highway length (Thousand $/mile).
Unem	Unemployment rate (%).
DisD	"1" if distracted driving law is adopted; "0" otherwise.
Belt	Percentage of people who wear seatbelt while driving (%).
Rural	Median mile vehicle traveled over rural highway length (ratio).
Urban	Median mile vehicle traveled over urban highway length (ratio).
HiRsk	Percentage of drivers younger than 25 or elder than 65 (%).
PubTr	Public transportation usage for commuting to work (%).

3.4.1 Dependent Variable: Fatality Rate

The main interest of this study is to identify the effects of socioeconomic and policy determinants to fatality rate. The fatality rate is typically recognized with four standardized forms, which are fatalities per 100 million vehicle miles traveled, fatalities per 100,000 population, fatalities per 100,000 registered vehicles, and fatalities per 100,000 licensed drivers. In this paper, the fatalities per 100 million vehicle miles traveled are used as the fatality rate since it is the most popular measurement of "fatality rate" used in research most similar to this study.

3.4.2 Independent Variables

The selection of the independent variables includes two propositions: the effects of socioeconomic status and the effectiveness of policy making. To test the first proposition, we use five socioeconomic factors. The first measure, the percentage of people who have at least bachelor's degree, provides the education level from the nationwide survey system. It is noted from previous studies that the higher education level attained, the lower probability of accident involvement

(Factor et al., 2008). We expect to see the same influence on the fatality rate in our model. Accordingly, we test the following hypothesis:

Hypothesis 1: The education level of people has an inverse effect on the fatality rate.

The second measure, the percentage of people who are not covered by health insurance, is another potential factor to evaluate in the fatality rate. When a severe accident occurs, the occupants who do not have health insurance could receive less or less effective medical treatment (Doyle Jr, 2005). Moreover, these patients sometimes cannot afford the high medical costs without health insurance, leading these patients to refuse necessary care. Therefore, there should be an inverse relationship between the health insurance variable and the fatality rate:

Hypothesis 2: People with no health insurance will have higher fatality rates in traffic accidents.

The third variable, the percentage of new vehicle registration out of all vehicle registrations, serves as a proxy measure for vehicle age. This measure may indirectly pick up the effects of overall economic activity. As economic conditions improve, new car buying will increase. However, the amount of miles driven during times of robust economic conditions will also increase, and the reason why the dependent variable is expressed as a rate per miles driven is to (in a way) hold economic factors somewhat constant. Specific to this study, the economic crisis in 2008 severely impacted the automobile industry and the number of sales of new vehicles decreased significantly. As expected during this time period, miles driven and the number of crashes decreased. The more important factor is that newer vehicles include technologies and devices to improve the driver's and vehicle's safety. These compound factors will affect the direction of the influence of the variable. While the data collected are from a long term period, we assume the long term relationship will be inverse:

Hypothesis 3: As the percentage of new vehicle registration over all vehicle registrations increases, the lower possibility of fatal traffic accidents occur.

The fourth variable is the average highway maintenance costs. Every year, state governments disburse funds for highway in the following categories: capital outlays, maintenance and service costs, research and administration disbursements, and enforcement and safety disbursements. However, the highway infrastructure and the road conditions have found to affect transportation safety (Miller & Zaloshnja, 2009; Noland & Oh, 2004). It is noted that larger states usually have more disbursements for highways, therefore, we use average highway maintenance costs per highway length for the standardization. For this variable, we want to test:

Hypothesis 4: Higher average highway maintenance spending per mile is associated with decreased fatalities.

The fifth variable, unemployment rate, is the rate of measurement of the unemployed people over all individuals in the labor force (there are various measures for unemployment used by different governmental agencies). In this study, we use the measure of unemployment rate used by the Bureau of Labor Statistics (BLS): "The ratio of unemployed to the civilian labor force expressed as a percent" (Bureau of Labor Statistics). The definition of unemployed persons from BLS is "Included are all persons who had no employment during the reference week, were available for work, except for temporary illness, and had made specific efforts to find employment some time during the 4 week-period ending with the reference week. Persons who were waiting to be recalled to a job from which they had been laid off need not have been looking for work to be classified as unemployed" (Bureau of Labor Statistics). It can be expected that the unemployment rate would be inversely correlated to the annual vehicle miles traveled. Because the unemployed do not need to commute to work, the annual vehicle miles traveled decreases. This reduces congestion (particularly in urban-exurban areas), potentially making the roads less hazardous. This is a possible variable related to the frequency of crash involvement. Hence, we test the hypothesis as following:

Hypothesis 5: There is an inverse relationship between the unemployment rate and the fatality rate.

The last two variables are to measure the effectiveness of safety policies, which are the adoption of distracted driving and seatbelt laws. The adoption of distracted driving law in the model is a binary variable that one means the states have adopted the distracted law and zero means the states have not passed the law. Annual seatbelt use, estimated from the observations of seat belt use randomly selected at roadway sites in the United States was used for the seatbelt variable (as all states currently have adopted seat belt laws) (National Highway Traffic Safety Administration, 2012). Therefore, the last two hypotheses are:

Hypothesis 6: The states with distracted driving laws have lower fatality rates.

Hypothesis 7: Higher seat belt usage is correlated with lower fatal accident rates.

Several control variables are also included in the regression model demonstrated to have an effect on the dependent variable from previous literature. These must be accounted for *a priori*. Factors such as rural and urban congestion, percentage of high risk drivers, and the percentage of workers who commute to work using public transportation in U.S. metropolitan statistical areas were accounted for in this model. The definition of congestion is the million miles vehicle traveled over the highway length. The percentage of high risk drivers is the drivers whose age is under 25 and over 65. Young drivers are with less driving experience, and senior citizens over 65 may have problems from aging.

Based on the hypotheses, the regression equation for the model is as follows:

$$Fatality_{it} = b_0 + b_1 * (Edu)_{it} + b_2 * (NoIn)_{it} + b_3 * (NewV)_{it} + b_4 * (MCost)_{it} + b_5 * (Unem)_{it} + b_6 * (DisD)_{it} + b_7 * (Belt)_{it} + \sum_{j=8}^{11} b_j * (x)_{it} + u_{it}$$

It is noted that variable “Law” is the only binary variable in the model; all the others are continuous variables.

3.5 Descriptive Statistics

The data included 336 observations over the period 2005-2011. Table 3.2 shows the basic descriptive statistics for each variable. The first row indicates that the average fatality rate within seven years was 1.32. Since the fatality rate has exhibited a decreasing trend over time, the maximum value 2.45 appears in the earlier year. The second row presents the education level; 25% of the population sample had at least a college degree. The third row shows an interesting result that about a quarter of people in some states had no health insurance while the average is 14%. The fourth row indicates that people lived in some states purchased new vehicles (20 %) comparing to the nation’s average 5.58%. The sixth row shows the unemployment rate with an average 6%. The eighth row displays the seatbelt use that some states have good safety education and/or enforcement with the highest seat belt use.

Table 3.2: Descriptive Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Fatality		1.32	0.39	0.62	2.45
Edu	336	24.6	4.5	15.44	36.04
NoIn	336	14.07	3.93	3.4	25.5
NewV	336	5.58	2.33	2.25	20.21
MCost (log)	336	2.99	0.67	1.39	4.95
Unem	336	6.32	2.43	2.6	13.8
DisD	336	0.19	0.39	0	1
Belt	336	83.5	7.98	60.8	98
Rural	336	0.2	0.11	0.03	0.5
Urban	336	0.74	0.17	0.36	1.31
HiRsk	336	29.15	2.6	18.86	34.72
PubT (log)	336	0.53	0.99	-1.17	3.3

Each observation indicates data in one State in one year. Because there were 48 States in the "lower 48" within the seven year period, we collected 336 data points.

3.6 Results

3.6.1 Ordinary Least Squares (OLS) Results

The Ordinary Least Squares (OLS) regression model is a widely used method for the initial start from the empirical perspective. OLS is a model to find the relationship between response variables and predictors with the goal of minimizing the sum of the squared vertical distances from the regression line to the observed data points. Therefore, OLS would also be used to compare the results. We dedicated eight OLS models shown in Table 3.3 that the first seven models presented the estimated effects from single main factors with control variables, and the last complete model included all of the variables. From the first seven models, education level, no health insurance, new vehicle registration, unemployment rate, and distracted law variables are the significant factors at the 99% confidence level (ruling out random correlation), while seatbelt usage is significant at the 95% level. For the complete model, the effects of education level, no health insurance, costs of highway maintenance, unemployment rate, and seatbelt usage are all significant at 99% level. The variable costs of highway maintenance was not significant alone, but in combination with other factors in the full model it presents its independent contribution.

Table 3.3: OLS Results with Robust Standard Errors

	Dependent variable: Fatality (%)							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Edu	0.06*** -0.004							0.05*** -0.004
NoIn		0.04*** -0.004						0.03*** -0.003
NewV			0.03*** -0.01					0.01 -0.005
MCost (log)				-0.08 -0.06				0.10*** -0.03
Unem					0.04*** -0.006			0.04*** -0.006
DisD						0.22*** -0.04		-0.01 -0.03
Belt							0.007** -0.003	0.01*** -0.002
Rural	0.32* -0.18	0.06 -0.2	-0.13 -0.21	0.16 -0.32	-0.15 -0.21	-0.18 -0.21	-0.32 -0.22	0.72*** -0.18
Urban	-0.32** -0.16	-0.29 -0.18	-0.1 -0.17	0.09 -0.16	0.14 -0.16	0.04 -0.17	0.22 -0.18	-0.29** -0.12
HiRsk	-0.02*** -0.006	-0.009 -0.006	-0.01** -0.007	-0.01** -0.007	-0.01** -0.006	-0.01** -0.006	-0.01* -0.006	-0.003 -0.005
PubT (log)	-0.04** -0.02	-0.18*** -0.02	-0.22*** -0.02	-0.21*** -0.03	-0.22*** -0.02	-0.20*** -0.02	-0.21*** -0.02	0.03 -0.02
R^2	0.56	0.45	0.35	0.33	0.37	0.37	0.34	0.74

Note: Standard errors that are clustered at the State level are presented in parentheses. *, ** and *** denotes statistical significance at a 90%, 95% and 99% level.

3.6.2 Test for Multicollinearity

In the OLS regression we assumed that the Classical Linear Regression Model (CLRM) assumptions would hold true. However a correlation matrix (Table 3.4) of the variables from the complete model of the OLS regression suggests that some of the predictors are marginally or strongly correlated, violating one of the key prerequisites for drawing inference from analysis of variance models like regression. A multicollinearity issue may occur when high correlations between several predictors, and this problem will decrease model reliability and lead to misleading results. For example the rural congestion is strongly correlated with the costs (log) ($r = 0.83$); this interaction makes it difficult to separate the individual contributions of each variable. The results also show that the public transport is marginally correlated to education and costs ($r = 0.65$), and the same situation also appears in urban congestion. However, when we regressed the dependent variables with all the predictors, we observed that the Variance Inflation Factor (VIF) values are fairly low (Table 3.5). VIF is an index of measuring multicollinearity within the OLS model. A value of VIF greater than 10 is indicated to have multicollinearity problems (Chatterjee & Hadi, 2015). A model with this problem has to remove high correlated factors to get accurate results. The result shows that the variables with highly correlated may be only due to coincidence. Therefore, we do not need to drop any of the variables in order to eliminate the multicollinearity issue.

Table 3.4: Correlation Matrix

	Edu	**NoIn**	**NewV**	**MCst**	**Unem**	**DisD**	**Belt**	**Rural**	**Urban**	**HiRsk**
NoIn	**-0.41**	1								
	0.000									
NewV	**0.15**	0.14	1							
	0.007	0.011								
MCst	**0.39**	-0.03	**0.18**	1						
	0.000	0.528	**0.001**							
Unem	-0.02	**0.25**	**-0.29**	**0.29**	1					
	0.472	**0.000**	**0.000**	**0.000**						
DisD	**0.24**	-0.03	**-0.19**	**0.21**	**0.38**	1				
	0.000	0.645	**0.001**	**0.000**	**0.000**					
Belt	**0.14**	**0.21**	0.05	**0.26**	**0.31**	**0.21**	1			
	0.010	**0.000**	0.358	**0.000**	**0.000**	**0.000**				
Rural	**0.37**	-0.03	**0.20**	**0.83**	0.14	0.08	**0.16**	1		
	0.000	0.591	**0.000**	**0.000**	0.011	0.153	**0.004**			
Urban	**0.34**	0.11	**0.35**	**0.70**	**0.18**	0.10	**0.43**	**0.68**	1	
	0.000	0.041	**0.000**	**0.000**	**0.001**	0.066	**0.000**	**0.000**		
HiRsk	**-0.17**	-0.09	**-0.13**	**-0.14**	-0.00	-0.01	-0.04	**-0.17**	**-0.28**	1
	0.002	0.091	**0.017**	**0.008**	0.958	0.823	0.474	**0.002**	**0.000**	
PubT	**0.65**	-0.12	**0.20**	**0.65**	0.14	**0.22**	**0.41**	**0.48**	**0.64**	**-0.28**
	0.000	0.023	**0.000**	**0.000**	0.011	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**

Note: Values in bold are statistically significant at the 99% or better confidence level; values that are not statistically significant at the 90% level or better are shaded.

Table 3.5: Variance Inflation Factor

	VIF	**1 / VIF**
Edu	2.42	0.41
NoIn	1.56	0.64
NewV	1.46	0.68
MCost (log)	5.27	0.19
Unem	1.66	0.60
DisD	1.32	0.76
Belt	1.54	0.65
Rural	4.21	0.24
Urban	3.25	0.31
HiRsk	1.18	0.85
PubT (log)	3.73	0.27

3.6.3 Test for Autocorrelation

Because the data traces fatality patterns over a seven year period, it becomes imperative to test for autocorrelation as well. Gujarati defined autocorrelation as “correlation between members of series of observations ordered in time [as in time series data] or space [as cross-sectional data] (Gujarati, 2012). It is a problem in a time series analysis if the error terms are correlated. If autocorrelation exists, the OLS model may not be the best model to use. We first test to check if this is an Autoregressive (AR) (1) or AR (2) process. These two are the most common process to model dependence over time. AR (1) can be denoted as the value of regression model lagged one period. Since the coefficient for the first-order and second-order lagged residual are significant for AR (1) (p-value = 0.00) and AR (2) (p-value = 0.00), but the coefficient for the third-order lagged residual is not significant for AR (3) with 0.06 p-value, so we can conclude that it is an AR (2) process at 95% confidence level.

If autocorrelation exists in OLS model such as ours, the estimators will still be unbiased, but the results will be inefficient (Gujarati, 2012). To solve for the autocorrelation problem, we use Generalized Least Squares (GLS) based on the ρ_1 and ρ_2 value obtained in the second auxiliary regression or AR (2) process. While standard errors have minor changes compared to the OLS model, the significance of seven variables of interest remained unchanged (Table 3.6). Thus, the OLS results are efficient enough for further analysis.

Table 3.6: GLS Results

	Dependent variable: Fatality (%)	
	OLS	**GLS**
Edu	-0.05*** (0.004)	-0.05*** (0.004)
NoIn	0.03*** (0.003)	0.03*** (0.003)
NewV	0.01 (0.005)	0.01 (0.006)
MCost (log)	-0.10*** (0.03)	-0.10*** (0.04)
Unem	-0.04*** (0.006)	-0.04*** (0.006)
DisD	-0.01 (0.03)	-0.01 (0.03)
Belt	-0.01*** (0.002)	-0.01*** (0.001)
Rural	0.72*** (0.18)	0.72*** (0.21)
Urban	-0.29** (0.12)	-0.29*** (0.11)
HiRsk	-0.003 (0.005)	-0.003 (0.005)
PubT (log)	0.03 (0.02)	0.03 (0.02)
R-squared	0.74	

Note: Standard errors that are clustered at the state level are presented in parentheses. *, ** and *** denotes p- value significance at a 90%, 95% and 99% level.

3.6.4 Random Effect Panel Data Analysis

As the OLS results are tested and showed without severe identification problems in the previous sections, we decided to apply panel data approach to determine the effects of factors between states within a time period, which is consistent with our data properties. Thus, we need to choose between fixed effects or random effects. The key issue distinguishing between fixed effects and random effects is whether the unobserved individual effects are correlated with the observed explanatory variables in the model. We use Mundlak's approach (which adds the group means of the independent variables to the model) to choose between the two effects (Mundlak, 1978). While we reject the null hypothesis that the mean coefficients are zero with p-value = 0.00 (F-value = 3.93), we believe it is more appropriate and conservative to use random effects model. The results are shown in Table 3.7. It should be noted that the models are generally in agreement (internal validity) and the random effects model could be considered more robust.

Table 3.7: Random Effect Results

	Dependent variable: Fatality (%)	
	OLS	**Random effects**
Edu	-0.05*** (0.004)	-0.06*** (0.007)
NoIn	0.03*** (0.003)	0.005 (0.005)
NewV	0.01 (0.005)	0.02* (0.01)
MCost (log)	-0.10*** (0.03)	-0.12*** (0.04)
Unem	-0.04*** (0.006)	-0.04*** (0.007)
DisD	-0.01 (0.03)	0.03 (0.03)
Belt	-0.01*** (0.002)	-0.006** (0.003)
Rural	0.72*** (0.18)	0.66** (0.29)
Urban	-0.29** (0.12)	-0.11 (0.21)
HiRsk	-0.003 (0.005)	-0.005 (0.005)
PubT (log)	0.03 (0.02)	-0.02 (0.05)
R-squared	0.74	0.69

Note: Standard errors that are clustered at the state level are presented in parentheses. *, ** and *** denotes p-value significance at a 90%, 95% and 99% level.

Table 3.7 presents the empirical results from the regression model, which indicates a good model-specification with relatively high R-squares (0.74; 0.69) and a 99+% confidence level in the overall fit of the data. The variables used in this model explain almost 70 percent of the behavior of the overall fatality rates, and we are more than 99% confident statistically that the relationships are not random. In this model, four out of five socioeconomic factors are statistically significant and one safety policy is statistically significant; meaning we are “confident” at some calculated level that the relationship (covariance) between the independent and dependent variables is the result of some underlying association, and not the result of random chance for each variable pairing. It is noted that three socioeconomic factors are the significant variables at the 99% level, which provides strong evidence ruling out random correlation, and that the effect sizes (strengths of association) can be trusted. The following results of analysis are interpreted variable by variable.

Education Level: Confirming extant research, education level is one of the significant variables to affect fatality rate. The negative sign of the association indicates that people with higher education level have a lower probability of being involved in fatal accidents. Based on the measurement of “education” as the percentage of the population with a bachelor’s degree or higher, a 1% change in education is associated with a change in the fatality rate of 0.06 fatalities per 100 million miles driven.

Health Insurance: In this model, the variable representing the percentage of people with no health insurance does not appear to have significant effects on the fatality rate. We cannot have confidence that any relationship noted would be anything more than a completely random coincidence; therefore we are unable to draw any conclusions.

Vehicle Age: The parameter, new vehicle registration, has moderately significant effects on the fatality rate with 90% confidence. The coefficient estimate confirms the positive direction (vary together) of this variable in the model; as the percentage of newer vehicle registrations increases the fatality rate also increases. A 1% increase in new vehicle registrations is associated with 0.02 fatalities per 100 million miles driven. This is a surprising result, and merits additional investigation. The casual observer and safety expert alike might normally surmise that as the percentage of newer vehicles increases (newer vehicles having more advanced safety features) the fatality rate would decrease.

It is posited that the concept of "moral hazard" may be at work here. As the safety features of their vehicles improve, the owners/drivers may engage in riskier driving behaviors assuming that the net risk effects remain constant. We may posit that the drivers have worse behavior since they think the newer vehicles are safer than their old one; however, further investigation would be needed to confirm this hypothesis.

Highway Maintenance: The average highway maintenance costs also appear to influence the fatality rate in this model. The model confirms (indicated by the negative sign) that lower maintenance costs result in higher fatality rates. A 1% decrease in maintenance spending is associated with 0.12 additional fatalities per 100 million miles driven. However, this relationship- as powerful as it is- must be viewed with caution. Lower maintenance spending may be associated with many other unmeasured factors that might have a more direct effect on fatalities. Lower maintenance costs may be due to the better weather and better road condition, a lack of commercial (heavy use) trucks on the roadways, superior initial roadway design, or many others; however, the well-funded highway projects do maintain safer highways as has been noted in other research (Burningham & Stankevich, 2005). This particular variable- roadway maintenance spending- is particularly important in the arena of public policy and planning. The lives saved by additional spending is a particularly compelling argument to make.

Unemployment: The unemployment rate appears to be inversely related to the fatality rate in the model. The States with lower unemployment rates have higher fatality rates than the other States; a 1% decrease in unemployment is associated with 0.04 additional fatalities per 100 million miles. The result would confirm the proposition that higher levels of economic activity lead to increased roadway congestion, a known factor for hazard in transportation safety. This result is therefore not unexpected; however, the ability to quantify the social cost (in terms of human lives lost) has public policy implications.

Distracted Driving Laws: There is insufficient data, or the data are too random, to conclude that the distracted driving laws share significant variation with the fatality rate between states over the seven year period. We cannot rule out simple random coincidence between the variables. This is unexpected; as the NHTSA has claimed that distracted driving laws decrease fatalities, but our model does not show any support for this claim. Because the law was passed in 2008 by only few States, our seven year period may not include sufficient data to properly assess the effects of the law.

Seat Belt Use: The model confirms that a very slight, inverse relationship between the percentage of seat belt use and the fatality rate does exist. Within the seven years period, the data support the proposition that a 1% increase in seat belt use is associated with 0.006 fewer fatalities per 100 million miles.

Overall Model: In general, the empirical results, using a variety of models (including the random effect model), are consistent with our hypotheses. The variables used in this model explain almost 70 percent of the behavior of the overall fatality rates, and we are more than 99% confident statistically that the relationships are not random. In this model, four out of five socioeconomic factors are statistically significant and one safety policy is statistically significant; meaning we are "confident" at some calculated level that the relationship (covariance) between the independent and dependent variables is the result of some underlying association, and not the result of random chance for each variable pairing. It is noted that three socioeconomic factors are the significant variables at the 99% level, which indicates strong evidence ruling out random correlation, and that the effect sizes (strengths of association) can be trusted. The results of random effect model are not dramatically different from OLS results; however, the effect of new car registration is detected in the random effect model while the effect of no health insurance coverage is no longer significant. This contrast may bear further investigation in future studies.

3.7 Concluding Remarks

Transportation accidents are one of the leading causes of death in the United States. This research effort sought to look at the influence of select socioeconomic factors and safety policies on highway safety. This research used "panel data" analysis to examine the effects of five socioeconomic factors and two safety policies during the years 2005 to 2011. The answers to three research questions were sought: first, what are the most influential socioeconomic and demographic factors involved in highway safety research; what have been the significant factors that impact highway fatality rates over time in the United States from a macro perspective; and what are the implications for U.S. public policy with respect to highway safety policy? Our findings suggest that some socioeconomic and demographic factors do influence highway safety, and public policy decision makers should consider these factors.

In this study, we use panel data with seven main variables to test the relationship between these predictors and fatality rate. We firstly used OLS method for the initial test. After testing the possible issues such as multicollinearity and autocorrelation, there are no severe identification problems to affect the results. We then perform the panel data analysis and find that the random effect is more appropriate to used. The results show that the education level, new vehicle registration, annual highway maintenance costs, unemployment rate, and seatbelt usage have significant effects to the fatality rate.

States with lower average education levels have higher fatality rates. The suggestion for public policy may be to consider the benefits of reduced fatality rates in any cost-benefit calculation of educational programs. The States with higher percentage of new vehicle registrations also have higher fatality rates. It has been noted in previous research that older vehicles have a higher probability of being involved in fatal accidents; our findings are contrary and require further investigation to resolve the contradiction. The theory of “moral hazard” may be at work here; our perception of safer technology may result in our bad driving behaviors as we take more risks than we might have otherwise. The effect of annual highway maintenance costs shows that higher spending is associated with lower fatality rates; this could be explained by state government efforts on keeping the roads in good condition and free of congestion. However, while this may be a compelling argument to make (“lives saved per dollar spent”), there are most likely other, more probative underlying issues that need to be examined. The unemployment rate was expected to have an inverse relationship to the fatality rate, with lower unemployment being associated with higher fatality rates. This was confirmed, with a 1% decrease in unemployment being associated with a 0.04 increase in fatalities per 100 million miles driven. An argument could be made that as economic conditions improve, infrastructure must be increased to support higher levels of activity. Roadway infrastructure is no exception- state governments should have a better strategy to reduce both unemployment rate and the fatality rate. Perhaps the increased revenues from increased economic activity could be allocated toward increasing the load-carrying capacity of the roads; that is a public policy issue that merits consideration in the political/legal domain. With respect to distracted driving laws, no association between the laws and fatalities could be found. It is posited that the effect of the law does not show the significance in the model since this is a relative new law. More data needs to be collected in the future for a better estimation. The last variable, seat belt use, is found again to be statistically significantly correlated to reduced fatalities; for every 1% increase in seat belt use, fatalities decrease by 0.006 fatalities per 100 million miles driven. This effect has become slight over time, as compliance with the law is now widespread and the safety returns are diminishing. The public policy implications may include stabilized or reduced emphasis on seatbelt enforcement and awareness campaigns.

Transportation accidents continue to be one of the leading causes of death in the United States, at an estimated annual economic cost of $300 billion. This research found that it is important to look at the influence of socioeconomic factors and safety policies on highway safety. This research focused on the most influential socioeconomic and demographic factors involved in highway safety research, and the significant factors that impact highway fatality rates over time in the United States from a macro perspective. Several implications for U.S. public policy with respect to highway safety policy were uncovered using a “panel data” analysis to examine the effects of five socioeconomic factors and two safety policies during the years 2005 to 2011. Our findings suggest that some socioeconomic and demographic factors do influence highway safety, and public policy decision makers should consider these factors.

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4 Relative Efficiency of Highway Safety Investments on Commercial Transportation

4.1 Abstract

Highway traffic safety, especially for large trucks, has been one of the most important public policy issues discussed in recent years. Although the numbers of highway accidents have been declining in the past decade, the economic and personal costs of accidents involving Commercial Motor Vehicles is still a challenge for public policy and safety professionals. An effective method to measure the performance of investments in safety is needed to decrease the total number and cost of these incidents. This research effort uses Data Envelopment Analysis (DEA) for benchmarking the efficiency of differential investment in factors known to have an influence on safety performance. In addition, the work focuses on evaluating the change of safety performance over time. The findings of this study constitute a framework for determining which factors could be continuously improved to decrease the likelihood of these incidents occurring. The results of this research can provide an objective safety performance and improvement recommendation for commercial transportation and therefore serve to be instructive to those states with lower efficiencies. The findings suggest that government agencies should focus on more effective policy making towards road condition improvement and capital outlay utilization to reduce the fatality rate.

4.2 Introduction

Commercial motor carriers play an important role in providing transportation services in any modern industrialized economy. Accidents involving commercial motor vehicles (CMVs) have a two-fold penalty: 1) the direct loss of resources as a result of the accident, and 2) the indirect loss of efficiency, as goods are slowed and damaged in transit. CMV accident costs can include increased travel time, a large property damage penalty, and the loss of human life. The major difference between driving CMVs and driving non-CMVs is the complex operational environment required of commercial drivers, including work requirements, government regulations, and company practices; company practices require optimal safety with consistent productivity (Zogby et al., 2000).

In 2013, nearly 4,000 people were killed and 95,000 were injured in highway crashes involving CMVs (it implies large trucks in this study) in the United States (National Highway Traffic Safety Administration, 2013). For carriers, safety technology adoption was at an early stage. Hence, firms should learn about the safety technology that needs to be adopted to increase their safety performance (Cantor et al., 2006). In addition, adopting more practical safety training and awareness programs would make drivers operate vehicles in a safer manner (Swartz & Douglas, 2009).

Government agencies, on the other hand, improve highway safety by supervising driver and carrier operations. They also conduct efficient safety programs and regulations, such as the Motor Carrier Safety Assistant Program (MCSAP). Although the improvement of safety policies, training practices, and vehicle technologies have dramatically cut the number of truck-involved fatalities by 21%, from 2003 to 2013 (America Trucking Association, 2013), there is still a long way to achieve the ultimate safety goal: to eliminate all losses of life and decrease the number of injuries. As such, carriers and government agencies should both work to achieve this goal.

Driver behaviors, roadway characteristics, funding for federal and states highway safety programs, socioeconomic environments, and other related issues contribute to the differences in the number of fatalities and injuries from one state to another. Although a wide variety of CMV accident research has been conducted to identify critical risk factors and improve CMV safety (Federal Motor Carrier Safety Administration, 2007a, 2007b), it is also important to analyze and compare safety performance in order to better understand how to reduce CMV fatalities effectively (Britto et al., 2010; Green & Blower, 2011; Margaret Weber & Weber, 2004; Mejza & Corsi, 1999). In terms of highway safety, the relationship between a set of safety performance indicators (factors) and outcomes needs to be determined carefully. A safety performance indicator is defined as “any measurement that is causally related to crashes or injuries, used in addition to a count of crashes or injuries to indicate safety performance or understand the process that leads to accidents” by the European Transport Safety Council (2001). However, it is very difficult to choose the number of important indicators and assign unbiased weights for each one.

Data Envelopment Analysis (DEA) is a methodology that can be used to measure operational efficiency. In recent years, DEA has been used to rank organization safety performance in several fields (Beriha et al., 2011; Mejza & Corsi, 1999; Reiman & Pietikäinen, 2012; Tinmannsvik & Hovden, 2003). Generally, DEA provides non-biased results without the problem of assigning statistical weights. As such, lessons can be learned from other firms with relatively better practices by using DEA.

The application of DEA has been used to measure road safety performance in European countries. It has recently been applied to compare U.S. states' road safety performance by Egilmez and McAvoy (2013). In Hermans' study, the objective was to minimize fatalities with a certain level of safety indicators including the percentage of road users respecting the blood alcohol concentration (BAC) limit, speed limits, seatbelt laws, the age of the vehicles under six years old, motorway density, and trauma management. These variables are all strong safety indicators. Nevertheless, U.S. government agencies did not provide a comprehensive database for these indicators.

In Egilmez and McAvoy's study, highway expenditures, Vehicle miles travelled (VMT) intensity, road condition, road length, and seatbelt usage were included in the analysis. In terms of highway expenditures and road conditions, different categories should be dismantled and addressed for a better funding utilization. Regarding road safety, it is necessary to treat CMV safety separately. Although the relative CMV safety research has been studied from the carriers perspective (Margaret Weber & Weber, 2004; Wanke, 2013), government performance should also be measured for a better understanding of the current practices. The remainder of this paper is organized as follows. In section Two, the concept of the DEA model and the Malmquist index is introduced. Section Three provides the description for the selection of safety indicators and outcomes. In section Four, the corresponding results are discussed. The concluding remarks and future direction of research is summarized in the last section.

4.3 Methodology

4.3.1 Basic Data Envelopment Analysis Model

The proposed methodology uses Data Envelopment Analysis (DEA) for benchmarking the safety performance of CMV transportation in the southeastern states of the United States. DEA is a linear programming approach for measuring the relative efficiency of a set of comparable groups called Decision Making Units (DMUs); in this case, the state governments. The idea was initially used by Farrell (1957) for evaluating economic productivity, but was only able to measure the efficiency of a single output. The definition of efficiency, or productivity, is to evaluate how well the resources are used to produce the outputs in organizations. The difficulty of the original use was the selection of inputs, outputs, and the weights for measuring single input to single output ratio for multiple times. DEA was used for assessing multiple inputs and outputs by Charnes et al. (1978) in the approach designated the "Charnes, Cooper and Rhodes" (CCR) model. The major benefits of using DEA is that it does not require the user to assign a complete specification for the functional form of the production frontier (between investment choices and safety results); the conversion process of inputs to outputs does not need to be completely understood *a priori*. In addition, the distribution of inefficient deviations from the frontier need not be assumed in advance. DEA requires general production and distribution assumptions only, it is very robust in that it eliminates the need to apply restrictive requirements of formulated assumptions and variations, compared to other regression models (Cooper et al., 2011). It is therefore particularly useful in investigating the efficiency of inputs against outputs in complex adaptive systems such as those that exist outside of the laboratory or on the factory floor.

The investigated DMUs, processes and organizational units are characterized by the conversion of multiple disproportionate inputs to outputs. For given inputs and outputs with unknown weights, each DMU will be assessed for a relative efficiency score, which is called technical efficiency (TE). In general, a DMU with an efficiency score of 1 is considered as a relative efficiency unit, and a relative inefficiency unit is the DMU with score less than 1. The basic assumption of the CCR model is that the returns to scale are constant (a stable underlying process). However, an increase in inputs does not always have the same proportional change in outputs, therefore, another model was developed by Banker, Charnes, and Cooper (the BCC model) considering variable returns to scale (Banker et al. (1984). Instead of measuring the technical efficiency, the BCC model decomposes the technical efficiency into pure technical efficiency (PTE) and scale efficiency (SE). In terms of variable return to scale, the PTE only measures the managerial efficiency of the allocation of inputs or the capacity of outputs in the organization, and the SE indicates the ability of choosing the optimal scale. The use of the SE makes it possible to determine whether the relationships between input and output variables involved increasing, constant (the nominal CCR assumption), or decreasing returns to scale. Two terms considered for scale efficiency are increasing return-to-scale (IRS) and decreasing return-to-scale (DRS). Cooper et al. (2011) provides a comprehensive discussion for returns to scale in DEA. The general output-oriented BBC model is presented symbolically:

Objective function:

$$\min z = \sum_{i=1}^{m} v_i x_{ij} + u_0 \tag{1}$$

subject to:

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} + u_0 \geq 0, \quad for\ j = 1, \ldots, n, \tag{2}$$

$$\sum_{i=1}^{m} u_i y_{i0} = 1 \tag{3}$$

$$v_i, u_r \geq \varepsilon,\ u_0 \text{ free in sign} \tag{4}$$

where, r = output 1 to output s; i = input 1 to input m; y_{rj} = amount of output r from unit j; x_{ij} = amount of input i from unit j; u_r ›= the weight given to output r; v_i = the weight given to input i. ε is a small non-Archimedean number (Charnes et al., 1979) in order to prevent the DMUs from assigning a weight of zero.

For each inefficient unit, a peer group is assigned from a set of corresponding efficient units. These efficient units are able to be the reference points to those inefficient units. Meanwhile, the efficient units can be said to have the same inputs and outputs orientation as inefficient units, but the difference is the weight. The aspect of peer group can help other units with lower efficiency to improve. Nevertheless, these efficient units usually do not have same importance even though they are all shown in the peer groups. The key features presented by Norman and Stoker (1991) provide insights to identify the efficient units appearing in the peer groups in an input-oriented model:

- The robustly efficient units are emerged many times from different peer groups. These types of efficient units are more likely to remain efficient unless huge shifts of inputs and outputs occur. The value of the units is larger than any other efficient units because these units can offer more information of improvement than others.
- The weakly efficient units are revealed few times in the peer groups, usually only one or two counts. These units may become inefficient when a minor change of inputs or outputs shift such as a small increasing of an input or deceasing of an output.
- The marginal inefficient units are those units that have efficient score in excess of 0.9 and less than 1.0. These units are potential efficient units in the future with a small amount of improvement.
- Medium inefficient units have efficiency between 0.7 and 0.9.
- Distinctively inefficient units have difficulties to improve their performance from under 0.7 to 1 in a short period, unless some major shifts of inputs and outputs are made.

As a result, DEA can be used in number of ways to determine how the units can be more efficient. The processes can be illustrated as the following (Boussofiane et al., 1991):

- using peer groups,
- identifying efficient operating practices,
- target setting,
- identifying efficient strategies,
- monitoring efficiency changes over time.

After performing DEA and obtaining the performance by each DMU, the Malmquist index is used to measure whether the productivity of DMUs increase or decrease over time.

4.3.2 *Malmquist Index*

A quantity index was introduced to analyze data in a consumption framework by Malmquist (1953), and then the developed index was applied into a production analysis to measure the productivity change over time by Caves et al. (1982). R Färe et al. (1992) defined the Malmquist index (MI) as the geometric mean into two indices as shown in Eq. (5)-(7). The efficiency change measures the distance from the observed production to the optimal maximum production between period t and t+1. The technical change (TECHCH) measures the shift in the frontier (innovation) over time. When a value of MI is equal to 1, there is no productivity change in inputs and outputs between the periods. A value of MI less than 1 indicates a decreasing productivity, whereas a value more than 1 denotes productivity growth.

$$\text{efficiency change} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \tag{5}$$

$$\text{technical change} = \left[\left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^{t+1}, y^{t+1})}\right) \times \left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right)\right]^{1/2} \tag{6}$$

$$M_o(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \times \left[\left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^{t+1}, y^{t+1})}\right) \times \left(\frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right)\right]^{1/2} \tag{7}$$

This Malmquist index, known as FGLR model, is based on constant return to scale. The assumption of the CRS model does not reflect the real situation, which is that the proportion of input change does not usually change the same proportion of an output. Rolf Färe et al. (1994) introduced a VRS Malmquist model (FGNZ model) to further decompose the efficiency change into pure efficiency change (PECH) and scale change (SECH). The model is formulated as follows

(Eq.(8)). The first expression measures the PECHCH, the second expression measures the SECH, and the third expression measures the TC.

$$\mathrm{MI}_{(x_t, y_t, x_{t+1} y_{t+1})} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1} | V)}{D_o^{t}(x^{t}, y^{t} | V)} \times \left(\frac{D_o^{t+1}(x^{t+1}, y^{t+1} | C) / D_o^{t+1}(x^{t+1}, y^{t+1} | V)}{D_o^{t}(x^{t}, y^{t} | C) / D_o^{t}(x^{t}, y^{t} | V)} \right) \times \left[\left(\frac{D_o^{t}(x^{t}, y^{t} | C)}{D_o^{t+1}(x^{t+1}, y^{t+1} | C)} \right) \times \left(\frac{D_o^{t}(x^{t}, y^{t} | C)}{D_o^{t+1}(x^{t}, y^{t} | C)} \right) \right]^{1/2} \tag{8}$$

4.4 Data

4.4.1 Selections of DMUs

The targets of this study focus on the CMV safety performance between 12 southeastern states in the United States. These states include Alabama, Kentucky, Mississippi, South Carolina, North Carolina, Georgia, Florida, West Virginia, Virginia, Tennessee, Arkansas, and Louisiana. The results can be compared to the annual efficiency change. More importantly, the suggestion of assigned targets can offer future direction for decision makers.

The purpose of selecting these states is one of pseudo experimental control (Shadish et al., 2002), attempting to hold three of the most serious confounds to inference “constant.” The mix of traffic by type of vehicle, cargo, and mode, type of road surface, and weather externalities are similar among the states chosen. Except Arkansas and Louisiana, other states are classified as southeastern states by the Association of American Geographers. Considering similar weather conditions, Arkansas and Louisiana are added into the selection of DMUs to minimize the effects of differences in climate.

Regarding the analysis, data for the years of 2003 through 2011 was chosen. Due to the limited data sources and the lack of data for some years, data for the years 2003, 2005, 2007, 2009, and 2011 (every two years) are considered in the analysis. Hence, a total of 60 DMUs are evaluated by designated inputs and outputs. The raw data was provided by the Federal Motor Carrier Safety Administration in the Motor Carrier Management Information System (MCMIS), where CMV inspections and crash data were collected. It was provided by the Highway Statistics from the Federal Highway Administration (FHWA), which contained statistical information for highway finance and highway infrastructure. More detail is presented in the subsection.

4.4.2 Identification of Safety Performance Indicators (SPI) and Safety Outcomes

The independent variable of interest in this study was the "Fatality Rate", defined by the FMCSA as the fatalities per 100 million vehicle miles traveled (MVMT). The fatality rate is a commonly used variable in the highway safety literature. The objective function of an output-oriented DEA model requires values to be maximized. Consequently, an inverse value transformation was performed, since our objective was to reduce the fatality rate. Therefore, the minimization of the fatality rate was represented as the maximization of the mean travel distance between fatalities. To select the most appropriate input variables, some critical factors from the previous research were chosen. Egilmez and McAvoy (2013) considered four main SPIs: economic investment on the system, the usage of the system, the condition of the system, and the personal safety in the system. Hermans et al. (2009) defined alcohol and drugs, speed, protective systems, trauma management, infrastructure, and vehicle life as SPIs. Although some significant variables were applied from earlier studies (Tsai et al., 2015), not all can be incorporated in our DEA model. Nevertheless, some new factors related to CMV were imported.

It is almost impossible to collect data from every truck driver and company, due to the issue of time consumption and large costs. For example, lower seatbelt usage is one of the critical factors that increases the probability of fatal crashes. For example, lower seatbelt usage is one of the critical factors that increases the probability of fatal crashes. According to Cook et al. (2008), the CMV seat belt usage is lower than passenger vehicle seatbelt usage. Still, there is no existing database to record or compare CMV seatbelt usage. Two steps were followed to choose the inputs. Because we want to provide southeastern state governments with an easy conductible tool to analyze and monitor safety performance, the inputs should choose from data that can be collected easily as the initial step. In addition, these factors must be controllable for improving the safety performance.

The inputs were collected from two online databases: the Motor Carrier Management Information System (MCMIS), from the Federal Motor Carrier Safety Administration (FMCSA), and the Highway Statistics from the Federal Highway Administration (FHWA). In this study, four main subject areas were evaluated: (1) the economic investment on the system, (2) the condition of the system, (3) the inspection status, and (4) traffic enforcement. The economic investment on the system and the condition of the system were extended from the work of Egilmez and McAvoy (2013). Because federal and state agencies may concentrate on different categories of highway expenditures, the economic investments on the system were detailed into three categories: capital outlay, maintenance and services, and highway law enforcement and safety.

Capital outlays are expenditures associated with highway improvements. Maintenance and traffic services include road maintenance, traffic control operations, snow and ice removal, and other items. Highway law enforcement and safety consists of state agencies, inspection programs, safety programs, and other items. These variables were standardized by dividing road lengths. We also separated the condition of the system into rural system and urban system. Road condition was categorized on scale-based data as, “very good”, “good”, “fair”, “mediocre”, and “poor”, by the

Research and Innovative Technology Administration (RITA). The road condition score is transformed into a value between 0 and 1, which is defined as the total weighted-miles of road divided by the total graded road length (Egilmez & McAvoy, 2013). The next subject area is the inspection status, which consists of three variables: drivers with a bad inspection status per MVMT, vehicles with a bad inspection status per MVMT (number of Out-of-Service driver and vehicle violations), and full inspection rates. It was expected that fatigued drivers and vehicles with bad maintenance records would lead to a higher crash risk. The effect of inputs on the outputs has to have the same direction of impact; therefore, a transformation is used. These two variables are calculated as one divided by the number of Out-of-Service violations per MVMT. In terms of CMV inspections, there are six levels. Full inspection rates represent the rates of comprehensive inspection of CMVs per MVMT. The last SPI index is traffic enforcement. The evidence shows that some types of moving violations are highly correlated with future crash involvement (Murray et al., 2006). It is also suggested that more traffic tickets reduce accidents (Luca, 2015). Therefore, the number of operation violations per MVMT was included in the study. Four SPI indices are listed in Table 4.1:

Table 4.1 Input and Output Variables for Safety Performance

Inputs	SPI_1: The economic investment on system (expenditure) • I_1 capital outlay • I_2 maintenance and services • I_3 highway law enforcement and safety SPI_2: The condition of system • I_4 Rural road condition • I_5 Urban road condition SPI_3: Inspection status • I_6 1/Out of service drivers per MVMT • I_7 1/Out of service vehicles per MVMT • I_8 Full inspection per MVMT SPI_4: Traffic enforcement • I_9 Operation violations per MVMT
Outputs	O_1:1/Fatality rates

For our variable selection, the variables belonging to the first SPI, the economic investments on the system, indicate the impact of investment on highway to fatalities. It is a premise of a public policy that effective spending on highway improvements, maintenance, and law enforcement and safety have a positive effect on lowering the fatality rate. Therefore, there should be a positive relationship in our model. The same assumption can be applied to the second SPI, the condition of the system, which is that better road conditions lead to a lower fatality rate. The third SPI, inspection status, was also expected to have a positive relationship based on our transformation. The last SPI, traffic enforcement, should have a positive impact in reducing the risk of traffic crashes.

To investigate our assumption, the next step is to perform a correlation analysis to find the relationship between the inputs and the output. The variables with significant positive coefficient values are the valid inputs in the model. The results are provided in Table 4.2. With the exceptions of full inspection rates (Full_ins) and operation violations per MVMT (Violations), other inputs have a significant positive linear sense to the output. There could be a reversal of causality in the model at work. States with worse vehicle inspection results would place an emphasis on increased enforcement in this area. This concept could also be at work in the case of the violations as well. Hence, these two variables should be investigated further; the a priori expectation would be for there to be a positive impact on the output.

Based on the Pearson product moment correlation coefficient, maintenance, and traffic enforcement and safety expenditures have the most significant relationship with the fatality rate. It is noted that the number of DMUs should be at least twice the number of inputs and outputs multiplied to sustain the accuracy of the results (Golany & Roll, 1989). Bowlin (1998) suggested having three times the number of DMUs as there are input and output variables. In our study, a total number of 60 DMUs satisfied these assumptions.

Table 4.2 Correlation Analysis

		Capital	Maintenance	Law_Safety	Urban	Rural	Full_ins	DOOS	VOOS	violations	Fatality_rates
Capital	Pearson Correlation	1	.453**	.572**	0.195	.369**	-0.115	0.178	0.106	-0.178	.392**
	Sig. (2-tailed)		0	0	0.135	0.004	0.381	0.173	0.422	0.173	0.002
Maintenance	Pearson Correlation	.453**	1	.815**	0.086	0.116	-0.235	.403**	0.184	-0.135	.611**
	Sig. (2-tailed)	0		0	0.514	0.377	0.07	0.001	0.159	0.304	0
Law_Safety	Pearson Correlation	.572**	.815**	1	0.111	0.145	-.402**	.437**	0.221	-0.088	.663**
	Sig. (2-tailed)	0	0		0.4	0.27	0.001	0	0.089	0.505	0
Urban	Pearson Correlation	0.195	0.086	0.111	1	.808**	-0.203	-0.039	0.169	-.375**	.286*
	Sig. (2-tailed)	0.135	0.514	0.4		0	0.12	0.77	0.197	0.003	0.027
Rural	Pearson Correlation	.369**	0.116	0.145	.808**	1	-0.239	-0.013	.297*	-.514**	.332**
	Sig. (2-tailed)	0.004	0.377	0.27	0		0.066	0.924	0.021	0	0.01
Full_ins	Pearson Correlation	-0.115	-0.235	-.402**	-0.203	-0.239	1	-.403**	-.553**	0.143	-0.25
	Sig. (2-tailed)	0.381	0.07	0.001	0.12	0.066		0.001	0	0.276	0.054
DOOS	Pearson Correlation	0.178	.403**	.437**	-0.039	-0.013	-.403**	1	.806**	0.054	.344**
	Sig. (2-tailed)	0.173	0.001	0	0.77	0.924	0.001		0	0.681	0.007
VOOS	Pearson Correlation	0.106	0.184	0.221	0.169	.297*	-.553**	.806**	1	-0.12	.287*
	Sig. (2-tailed)	0.422	0.159	0.089	0.197	0.021	0	0		0.36	0.026
Violations	Pearson Correlation	-0.178	-0.135	-0.088	-.375**	-.514**	0.143	0.054	-0.12	1	-.338**
	Sig. (2-tailed)	0.173	0.304	0.505	0.003	0	0.276	0.681	0.36		0.008
Fatality_rates	Pearson Correlation	.392**	.611**	.663**	.286*	.332**	-0.25	.344**	.287*	-.338**	1
	Sig. (2-tailed)	0.002	0	0	0.027	0.01	0.054	0.007	0.026	0.008	

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

4.5 Results and Discussion

Using DEA to examine the efficiency of the data collected from the seven inputs and one output for 12 southeastern states from 2003 to 2011, the results are presented as follows: 1) identification of road safety scores and relevant benchmarks, 2) an overall efficiency score based on the Malmquist index, and 3) a sensitivity analysis.

4.5.1 *Identification of relevant benchmarks*

The results of solving the proposed model provided two efficiency indices (PTE and SE) for each DMU, as well as the returns to scale. As previously stated, the PTE measures the managerial efficiency in increasing the outputs by allocating the inputs in the organization. In this study reflects the safety performance of a state under the variable returns to scale. The SE indicates the ability of the model to select the optimal scale under the variable returns to scale. TE is the overall efficiency under constant returns to scale. In this study, it represents the overall safety performance of a state.

In the output-oriented DEA model, a DMU with a value greater than 1 is relatively inefficient, as compared to other efficient DMUs. The results are shown in Table 4.3. In 2003, only two states were observed as “technically efficient” (Mississippi and Tennessee). Four other states were identified as efficient states under increasing returns to scale. The results showed that four states (Arkansas, Georgia, Louisiana, and South Carolina) utilized their resources well, but they could adjust the size of their resources to reach constant returns to scale. For other inefficient states, the focus would be the target setting of reducing the fatality rates without changing the current resource allocation.

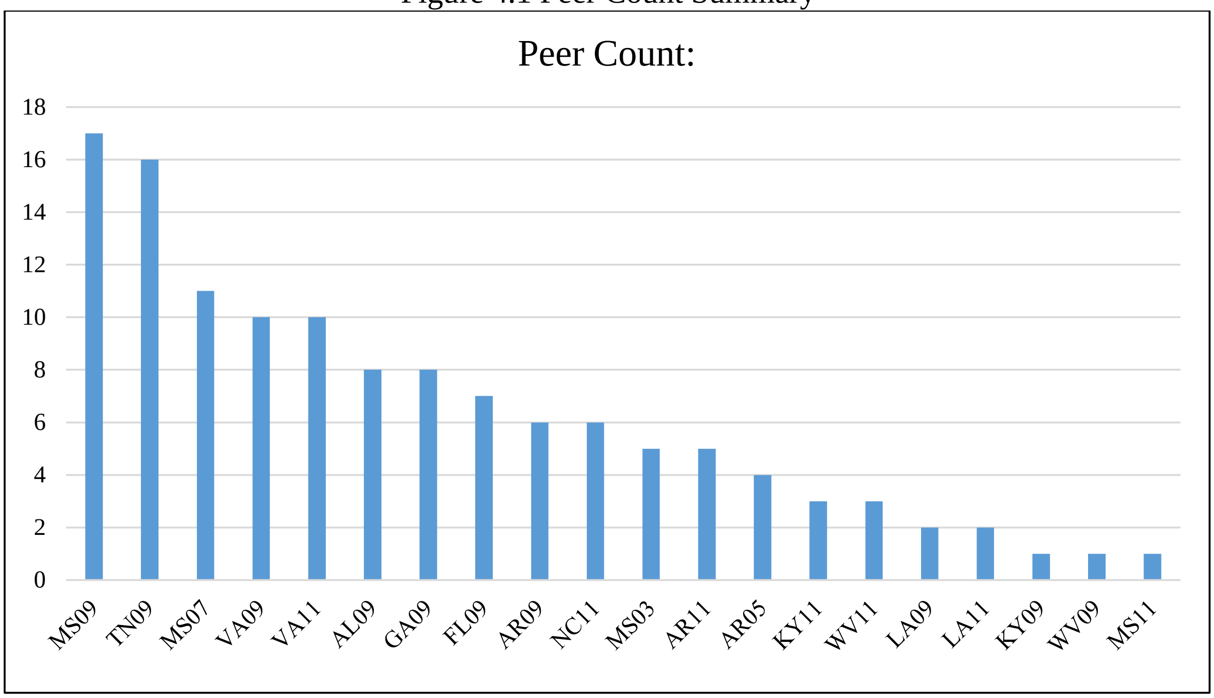
In 2005, only two states had a pure technical efficiency equal to 1: Arkansas and Georgia. In 2003, six states had increasing returns to scale; therefore, a DMU should reconsider its funding strategy and law enforcement operations for reducing the fatality rates to obtain the optimal return to scale. In 2005, the four states with decreasing returns to scale should have considered utilizing the inputs to have better safety performance. In 2007, only three states were relatively efficient, as compared to the other DMUs. It is noted that 10 states demonstrated pure technical efficiency, out of the 12 states in 2009, which means the resources allocation and traffic enforcement reduced the fatality rates without wasting money. The values of the PTE in 2011 had a slight increase; regardless, more than half of the states still remained relatively efficient. In terms of efficiency, there were several efficient units on the frontier. These efficient units can still be compared for the best practice performance.

Table 4.3 Efficiency Scores for 12 States

States(year)	TE	PTE	SE	RTS	States(year)	TE	PTE	SE	RTS
AL03	1.610	1.597	1.007	drs	**MS07**	1.000	1.000	1.000	-
AR03	1.038	1.000	1.038	irs	**NC07**	1.277	1.276	1.001	drs
FL03	2.028	1.869	1.086	drs	**SC07**	1.167	1.101	1.059	irs
GA03	1.003	1.000	1.003	irs	**TN07**	1.253	1.000	1.253	irs
KY03	1.381	1.339	1.032	irs	**VA07**	1.074	1.074	1.000	-
LA03	1.672	1.000	1.672	irs	**WV07**	1.458	1.233	1.181	irs
MS03	1.000	1.000	1.000	-	**AL09**	1.000	1.000	1.000	-
NC03	1.433	1.427	1.004	drs	**AR09**	1.000	1.000	1.000	-
SC03	1.319	1.000	1.319	irs	**FL09**	1.000	1.000	1.000	-
TN03	1.000	1.000	1.000	-	**GA09**	1.000	1.000	1.000	-
VA03	1.346	1.321	1.018	drs	**KY09**	1.054	1.000	1.054	irs
WV03	2.033	1.873	1.087	irs	**LA09**	1.000	1.000	1.000	-
AL05	1.479	1.464	1.009	drs	**MS09**	1.000	1.000	1.000	-
AR05	1.018	1.000	1.018	irs	**NC09**	1.043	1.041	1.002	drs
FL05	2.092	1.946	1.075	drs	**SC09**	1.095	1.087	1.008	irs
GA05	1.000	1.000	1.000	-	**TN09**	1.000	1.000	1.000	-
KY05	1.376	1.319	1.043	irs	**VA09**	1.000	1.000	1.000	-
LA05	1.718	1.477	1.164	irs	**WV09**	1.060	1.000	1.060	irs
MS05	1.244	1.215	1.024	irs	**AL11**	1.013	1.001	1.012	irs
NC05	1.704	1.689	1.009	drs	**AR11**	1.082	1.000	1.082	irs
SC05	1.698	1.678	1.012	irs	**FL11**	1.117	1.109	1.007	irs
TN05	1.425	1.420	1.002	irs	**GA11**	1.078	1.047	1.030	irs
VA05	1.252	1.230	1.016	drs	**KY11**	1.000	1.000	1.000	-
WV05	1.980	1.789	1.107	irs	**LA11**	1.000	1.000	1.000	-
AL07	1.684	1.667	1.010	drs	**MS11**	1.152	1.000	1.152	irs
AR07	1.198	1.000	1.198	irs	**NC11**	1.000	1.000	1.000	-
FL07	1.412	1.389	1.016	drs	**SC11**	1.200	1.193	1.007	drs
GA07	1.056	1.013	1.043	irs	**TN11**	1.034	1.013	1.021	drs
KY07	1.272	1.247	1.020	drs	**VA11**	1.000	1.000	1.000	-
LA07	1.346	1.140	1.179	irs	**WV11**	1.221	1.000	1.221	irs

The peer group is an efficiency reference set in which the members are identified as similar efficient performance units; inefficient DMUs are compared directly with these efficient DMUs in the group. When a DMU is referred to more times by other inefficient DMUs in the group, the input utilization and the produced outputs have more importance. The reference of the DMUs can be used as realistic targets for other DMUs for efficiency improvements. The results are illustrated in Figure 4.1. The performance of Mississippi in 2009 were compared 17 times to the other inefficient units; Tennessee in 2009 was compared 16 times. How these two state governments utilized the resources and operated their enforcement would be the targets for other state governments.

Figure 4.1 Peer Count Summary



4.5.2 Road Safety Performance Scores Based on Malmquist Index

By solving the Malmquist-VRS model, road safety performance scores are shown in Figure 4.2. The values are the means of the biennial periods between 2003 and 2011. Three metrics, (i.e., PECH, TECHCH, and SECH) represent the components of the DEA model as introduced in the Methodology section. Regarding road safety performance, PECH measures the positive/negative efficiency growth of the fatality rate affected by the composition of the inputs. During the periods of 2003 to 2005 and 2007 to 2009, the average safety performance had a positive efficiency growth level of 2.5 percent and 2.1 percent, respectively. Although the fatality rate decreased from 2005 to 2007, the negative efficiency growth indicated that the fatality rates should have decreased more in terms of the amounts of resource allocation. This could indicate that spending was misallocated during that period. Another negative efficiency growth level occurred during the period of 2009 to 2011 (–0.6 percent). During that time, the auto industry was starting to recover; shifting the expansion to the Southeast might have increased the highway driving risk. The results of TECHCH show inconsistent performance over time. A negative growth of TECHCH was observed from 2003 to 2005, but there was more than 20% positive growth from the periods of 2005 to 2007 and 2007 to 2009. After that, a downward trend of TECHCH was detected from 2009 to 2011. A positive technical change implies an innovation or technology improvement over time such as new roadside technology corridors and safety program campaigns. Decreasing technological efficiency denotes that government agencies did not use the technology effectively. In terms of the MI, the value was significantly affected by the TECHCH since it is the multiplication of SECH, PECH, and TECHCH.

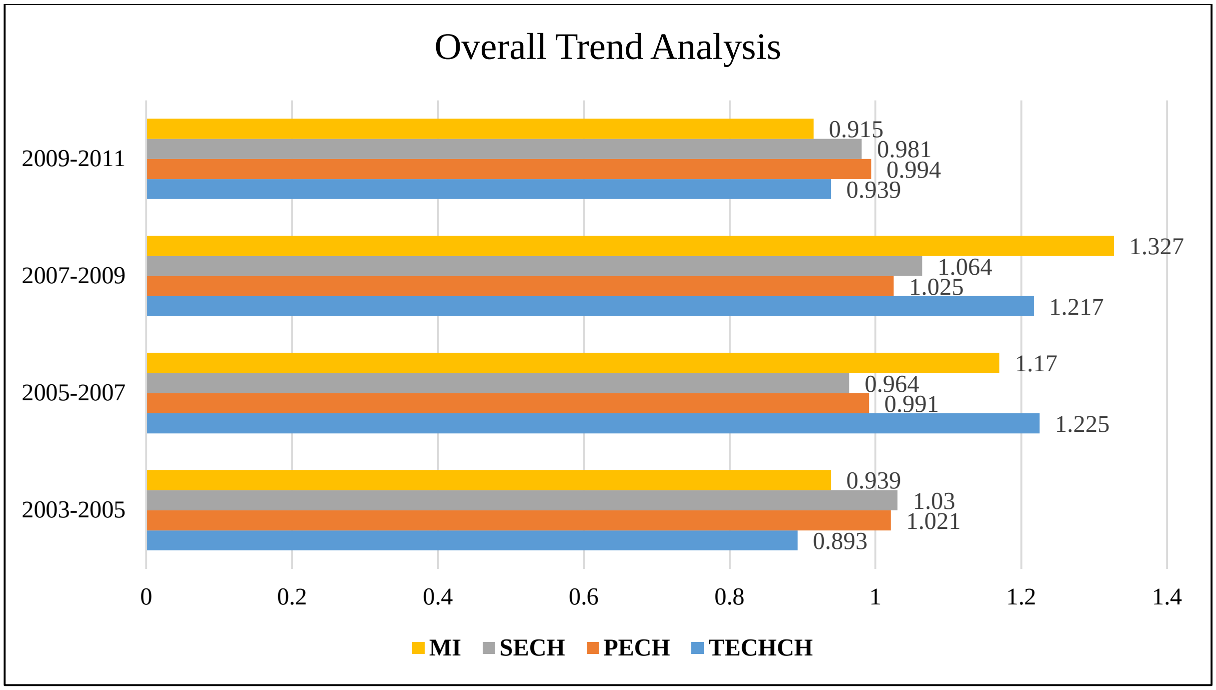


Figure 4.2 The Overall Trend Performance

4.5.3 Results of Malmquist Index

In terms of PECH, nine states showed constant efficiency, two states (i.e., Alabama and Florida) had increasing performances in efficiency, and only one state, South Carolina, was observed to have a decreasing performance in efficiency (Table 4.4). The results of TECHCH indicate a positive safety improvement from resource allocation and technology within the period of 2003 to 2011 in 12 states. Mississippi was observed to have a decreasing technological change over time. In terms of the overall productivity index (MI), only Mississippi and South Carolina had negative growth from the inefficient technology use and resource utilization.

Table 4.4 Malmquist Index

States	TECHCH	PECH	SCH	MI
Alabama	1.058	1.084	1.003	1.150
Arkansas	1.024	1.000	1.000	1.024
Florida	1.083	1.033	1.029	1.151
Georgia	1.043	1.000	1.000	1.043
Kentucky	1.116	1.000	1.000	1.116
Louisiana	1.088	1.000	1.050	1.142
Mississippi	0.977	1.000	0.993	0.97
North Carolina	1.082	1.000	1.000	1.082
South Carolina	1.030	0.975	0.994	0.998
Tennessee	1.022	1.000	1.000	1.022
Virginia	1.105	1.000	1.000	1.105
West Virginia	1.069	1.000	1.041	1.114

4.5.4 Sensitivity Analysis

A sensitivity analysis was performed to test the robustness of the model by selecting different numbers of inputs. In the study, the VRS-DEA model was solved seven times by only selecting six out of seven inputs to measure the variation in the efficiency. Also of note and requiring further investigation is the mediocre associations between the CMV operations related inputs, which display a moderately strong association with fatality rates in the biserial correlations that are not supported by the sensitivity analysis.

Figure 4.3 presents the average sensitivity of each input variable on the impact of the efficiency of DMUs for each period. The highest variation occurs when the rural road condition, urban road condition, or capital outlay expenditure is dropped, especially within the first three periods. For the first two inputs, the average variation is around 6% for the entire period. When the urban road condition is dropped, eight of the weakly efficient units of 28 efficient units become inefficient units. When the rural road condition is unselected, five of the weakly efficient units become inefficient units. The capital outlay is ranked third among all the variables. Therefore, it can be concluded that the road condition (rural/urban) and the capital outlay are the most significant inputs out of the seven inputs. From the biserial correlations (Table 4.2), this is supported by the effect sizes of Rural 0.332, Urban 0.286 and Capitol 0.392, which are robust factors. An increased investment in these areas has a strong likelihood of reducing fatalities. Highway law enforcement and safety is found to be the least significant factor. This relationship is contradicted by the simple biserial correlation data, and merits further investigation. This could be an anomalous result of a restriction of the range and variation of the input variable relative to the outcome variable, which would indicate a consistent contribution from government agencies over the time period investigated. Also of note, and requiring further investigation are the mediocre associations between the CMV operations related inputs, which display a moderately strong association with fatality rates in the biserial correlations but that are not supported by sensitivity analysis.

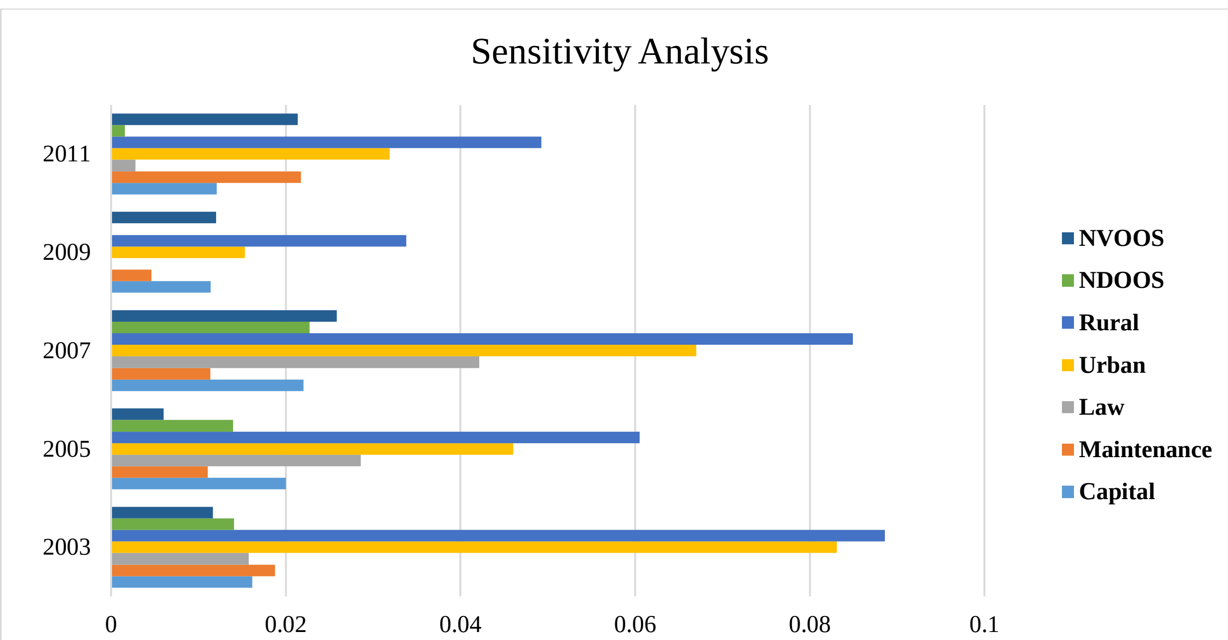


Figure 4.3 Sensitivity Analysis

4.6 Concluding Remarks and Future Research Directions

In this study, the CMV highway safety performance was measured every two years from 2003 to 2011. The fatality rates were dramatically reduced by adopting new safety programs, innovative vehicle technology, and investments on highway maintenance and condition. The state government agencies also set up their own strategies to reduce the rate of CMV fatalities from different safety projects. To monitor how state government agencies utilized the resources with the aim of reducing crashes involved in CMVs, highway safety performance should be analyzed. DEA and the Malmquist index were applied to measure the efficiency over time. Seven safety performance indicators were considered in the model: (1) capital outlay, (2) maintenance and service expenditures, (3) highway law enforcement and safety spending, (4) rural road conditions, (5) urban road conditions, (6) number of Out-of-Service driver violations per MVMT, and (7) the number of Out-of-Service vehicle violations per MVMT. The only outcome was (the inverse of) the fatality rate. The southeastern states were selected for the period between 2003 and 2011.

The results of the DEA and Malmquist index indicated an overall positive efficiency growth among the southeastern states. The majority of overall safety performance is affected by the change of technology. Rather than a consistent increasing or decreasing trend in efficiency from the period by period analysis, the unstable performance change raised two concerns: (1) the utilization of inputs from the stakeholders should be improved, and (2) the economic issues played an important role in affecting the efficiency. Although each indicator should be improved for better CMV safety, some factors have to be prioritized, such as rural road condition, urban road condition, and capital outlay.

This research developed a framework for evaluating southeast CMV highway safety. There were several studies addressing the road safety problems, and some indicators were selected. It must be noted that, CMV safety is another lesson that needs to be analyzed as a separate category. There is still more work to do in studies. First, the injury rate should be considered as a potential output. Second, a more detailed investment on highways, particularly for CMV, should be considered for a more precise result. Finally, a regional comparison should be obtained for federal agencies.

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5 Conclusions

5.1 Dissertation Contribution

The data analytic tools and underlying theme of the selected variables presented in this dissertation address the lack of current highway safety research data and the need to increase decision-making effectiveness. Highway safety studies have typically investigated causal factors from crash data and then provided results to stakeholders. A deeper and more comprehensive study should have been considered to facilitate policy-making, given that reducing accident fatalities has been a consistent highway safety priority. This research makes several contributions to the field of highway safety, which include the following: 1) the potential for gaining better understanding of current highway safety by transforming low-level traffic-related data into high-content information; 2) the development of a visual data-mining tool to assist decision-makers in developing sound theory and policies; 3) an investigation of pre-crash data to determine the influence of socioeconomic factors and safety policies on highway safety; 4) a call for long-term monitoring of safety performance trends by state government agencies to evaluate their highway safety investments. These contributions, described in detail in the following subsections, offer current governmental systems the potential for improved use of resources and the reduction of traffic fatalities.

5.1.1 A Visual Data-Mining Toolkit

Previous highway safety research has typically examined highway safety by solving statistical models and providing supplemental graphical information such as histograms, line charts, or maps to present results. The data and models sometimes require the assumption of a number of restrictions, without which decision makers would not adequately understand these results. The goal of the majority of the content in Chapter 2 is the description of a visual data-mining toolkit, as developed in this study, to assist stakeholders to better understand the impact of public policies and to uncover hidden transportation safety information. This toolkit can transform temporal, spatiotemporal, and policy-related data into high-content information. Using a calendar-based K-means clustering tool, the results reveal daily, weekly, seasonal, and unusual traffic flows with no assumptions or prerequisite knowledge. The developed mapping tool presents flexible information on a variety of variables in different dimensions, such as shapes, colors, and charts. This tool provides stakeholders with an easy way to understand the effectiveness of policies by transforming complicated statistical results into a heat map.

5.1.2 The Impacts of Socioeconomic factors and safety policy

In Chapter 3, we demonstrate that macro-perspective pre-crash data should be considered to better understand highway safety factors. While traffic crashes are influenced most by driving behaviors, there have been fewer studies of socioeconomic factors, which might also be causal factors leading to bad driving behavior and future crash risks. In addition, panel data analysis can measure the long-term effects of selected variables on outcomes. As such, the evaluation of the effectiveness of current public policies could provide decision makers with a basis for setting future policy directions. Most importantly, this research correlates driving behaviors from crash data with socioeconomic factors and safety policies from pre-crash data.

5.1.3 A Long Term Safety Performance Monitoring

Government agencies invest huge funding amounts on highway improvements and maintenance, law enforcement, safety programs, and vehicle inspections. The effectiveness of this allotment of funds should be determined to ensure the optimal use of limited public resources. An overfunding in certain areas might lead to better investment in other safety programs. A DEA-based Malmquist productivity index was applied to determine the effectiveness of the allocation of state government agencies' resources effectively for a given period of time. As reported in Chapter 4, this represents the first time this method has been applied in CMV safety research.

5.1.4 Summary of Contributions

The overall goal of this dissertation is to fill a knowledge gap in highway safety research regarding the factors leading to traffic fatalities. Effective highway safety research must include a comprehensive surveillance system to better facilitate policy development. Four components are required for constructing a highway safety surveillance system framework. The first component is a better understanding of current data, as introduced in Chapter 2. The second component is an understanding of the impact of socioeconomic factors and safety policies on road safety, as presented in Chapter 3. The third component is a determination of causal factors based on human behaviors, as is typically studied in general highway safety research (excluded from this dissertation). The final component is the evaluation of safety performance measures taken by federal and state government authorities. This dissertation presents a practical tool for linking different information sources in a framework from data collection to monitoring, as shown in Figure 5.1.

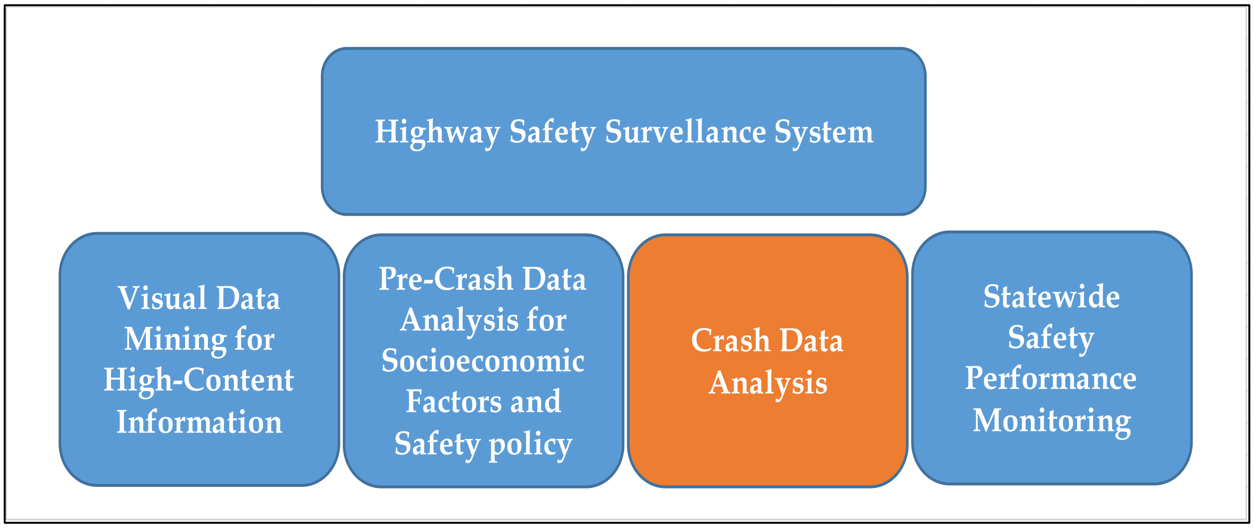

Figure 5.1 The Expected Highway Safety Surveillance System

5.2 Reference

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