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16. Abstract Anticipating changes to public transportation ridership demand is important to planning for and meeting service goals and maintaining system viability. These changes may occur in the short- or long-term; extensive academic work has focused on bettering long-term forecasting procedures while improvements to short-term forecasting techniques have not received significant academic attention. This dissertation combines traditional forecasting approaches with multivariate regression to develop a transferable short-term public transportation ridership forecasting model that incorporates fuel price as a prediction parameter. The research herein addresses 254 US transit systems from bus, light rail, heavy rail, and commuter rail modes, and uses complementary methods to account for seasonal and non-seasonal ridership fluctuations. Models were built and calibrated using monthly data from 2002 to 2007 and validated using a six-month dataset from early 2008. Using variable transformations, classical data decomposition techniques, multivariate regression, and a variety of forecasting model validation measures, this work establishes a benchmark for future research into transferable transit ridership forecasting model improvements that may aid public transportation system planners in an era when, due to fuel price concerns, global warming and green initiatives, and other impetuses, transit use is seeing a resurgence in popularity.					
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**A Methodology for Incorporating Fuel Price Impacts into
Short-term Transit Ridership Forecasts**

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Research Report SWUTC/09/169203-1

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August 2009

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ABSTRACT

Anticipating changes to public transportation ridership demand is important to planning for and meeting service goals and maintaining system viability. These changes may occur in the short- or long-term; extensive academic work has focused on bettering long-term forecasting procedures while improvements to short-term forecasting techniques have not received significant academic attention. This dissertation combines traditional forecasting approaches with multivariate regression to develop a transferable short-term public transportation ridership forecasting model that incorporates fuel price as a prediction parameter. The research herein addresses 254 US transit systems from bus, light rail, heavy rail, and commuter rail modes, and uses complementary methods to account for seasonal and non-seasonal ridership fluctuations. Models were built and calibrated using monthly data from 2002 to 2007 and validated using a six-month dataset from early 2008. Using variable transformations, classical data decomposition techniques, multivariate regression, and a variety of forecasting model validation measures, this work establishes a benchmark for future research into transferable transit ridership forecasting model improvements that may aid public transportation system planners in an era when, due to fuel price concerns, global warming and green initiatives, and other impetuses, transit use is seeing a resurgence in popularity.

EXECUTIVE SUMMARY

Currently, most public transportation agencies use tools developed either in-house or by their metropolitan planning organization, while in smaller communities, techniques such as sketch planning are still employed. The subject of ridership forecasting and its transferability has not, to date, received widespread academic attention, and therefore formalized methodologies are lacking.

This research attempts to fill the academic and technical void by developing a transferable methodology for transit planners to create system-specific short-term ridership forecasts, so that the needs of potential transit passengers can be anticipated and met quickly. Rapid response to new ridership aids in the ability to provide a pleasant travel experience for new and existing passengers; trip makers tentatively trying public transportation as an alternative are unlikely to continue using it if transit vehicles are late or uncomfortably crowded, both of which situations might be avoided if ridership can be forecast accurately.

In addition to providing a methodology for system-specific forecasts, this work establishes region- and mode-specific forecasting procedures. Models were developed by combining traditional forecasting techniques with multivariate regression to allow for greater explanatory power, localized calibration, and national applicability.

The short-term ridership forecasting model created here starts by assembling ridership and other data types for 254 US transit systems during the 2002-2007 period, transforming the dependent ridership variable to attain stability, and seasonally decomposing the ridership time series datasets to establish seasonal models and derive non-seasonal ridership components for each system. Using multivariate regression, encompassing a variety of internal and external factors, these non-seasonal components are then dissected to ascertain the non-seasonal relationships between ridership and the independent parameters, including, among others, fuel price.

After establishing the seasonal models for each system, as well as non-seasonal regression models on system-, region-, and mode-specific bases, the seasonal and non-seasonal models are combined to form a composite model, which, on average, explains roughly 70 percent of ridership variability across the entire evaluation set of 254 transit systems. The model is then validated using data from the first six months of 2008.

Most transit agencies establish their own forecasting methods in-house or through cooperation with their local metropolitan planning organization. This research combines established forecasting methodologies, such as data decomposition, with more advanced multivariate regression in a complementary manner that leads to robust prediction abilities. By calibrating and examining each individual system within the evaluation set, the model is transferable, and comparisons can be made across systems, regions, and modes, which, in the absence of such disaggregate model-building, cannot otherwise be accomplished.

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Chapter 1: Introduction

1.1 OVERVIEW

The topic of fuel price change has, for the last several years, captured media headlines on national, regional, and local levels. Not since the 1970's have fuel prices received such attention and induced such speculation on impacts to the economy and future implications of continued price growth.

We live in a world where the price of a gallon of oil affects nearly every aspect of our lives. Oil prices continue to fluctuate on an almost daily basis and elevated prices are subsequently reflected in numerous ways. The cost to transport goods increases as oil and fuel prices rise and these transportation costs are transferred to the consumer through higher prices on the goods. Similarly, the cost of transporting livestock feed grows and thus, coupled with higher goods transport expenses, the price of milk and meat at the grocery store inflates. In alternative businesses, taxi fares are growing as cab companies must pay more for fuel, and delivery services increase their delivery charges to offset their increased transportation-related business expenditures.

Perhaps the most publicized effect of rising fuel prices has been at gasoline pumps. Regional fuel prices are now a common part of local news broadcasts, and occasionally of national news broadcasts. As transportation costs consume an ever-greater proportion of household expenditures, looking for less expensive alternatives becomes a necessity for many trip makers. Public transportation operators have experienced a resulting growth in ridership and have created advertising campaigns to encourage drivers to save money by switching to transit.

In 2007, transit ridership reached 10.3 billion annual trips, the highest level witnessed in 50 years. Much of this growth is attributed to elevated gasoline prices (Miller, 2008). Growing transit ridership presents exciting opportunities and challenges for transit agencies with regard to planning their systems to accommodate growth and supplying sufficient services to support and retain new ridership. Anticipating the degree to which ridership may grow and be maintained is an important part of providing a satisfactory experience for new and habitual transit passengers. Clearly, the extent to which trip makers will switch to the transit mode is affected by many factors—two of the most important factors being (1) the nature of the existing transportation system and local infrastructure layout and (2) the quality of the existing transit network and service. These two factors vary considerably on a local basis and therefore, the inclination of trip makers to see public transportation as a viable option will depend on local conditions and more importantly, trip makers' perceptions of those local conditions. In some transit markets, the price of fuel may have no real impact on transit ridership if potential patrons do not view transit as a practical option, due to the quality of the travel experience or its inability to serve their travel needs. In other markets, transit use may already be very high because of limitations or costs of using other modes, and in such cases, ridership may not be measurably affected by fuel price.

Because of the variability in regional and system-based factors affecting the proclivity of trip makers to switch to transit mode, it is desirable to provide a ridership forecasting tool that can be

calibrated to local conditions. Currently, most public transportation agencies use tools developed either in-house or by their metropolitan planning organization, while in smaller communities, techniques such as sketch planning are still employed. The subject of ridership forecasting and its transferability has not, to date, received widespread academic attention, and therefore formalized methodologies are lacking.

This research attempts to fill the academic and technical void by developing a transferable methodology for transit planners to create system-specific short-term ridership forecasts, so that the needs of potential transit passengers can be anticipated and met quickly. Rapid response to new ridership aids in the ability to provide a pleasant travel experience for new and existing passengers; trip makers tentatively trying public transportation as an alternative are unlikely to continue using it if transit vehicles are late or uncomfortably crowded, both of which situations might be avoided if ridership can be forecast accurately.

In addition to providing a methodology for system-specific forecasts, this work establishes region- and mode-specific forecasting procedures. Models were developed by combining traditional forecasting techniques with multivariate regression to allow for greater explanatory power, localized calibration, and national applicability.

The short-term ridership forecasting model created here starts by assembling ridership and other data types for 254 US transit systems during the 2002-2007 period, transforming the dependent ridership variable to attain stability, and seasonally decomposing the ridership time series datasets to establish seasonal models and derive non-seasonal ridership components for each system. Using multivariate regression, encompassing a variety of internal and external factors, these non-seasonal components are then dissected to ascertain the non-seasonal relationships between ridership and the independent parameters, including, among others, fuel price.

After establishing the seasonal models for each system, as well as non-seasonal regression models on system-, region-, and mode-specific bases, the seasonal and non-seasonal models are combined to form a composite model, which, on average, explains roughly 70 percent of ridership variability across the entire evaluation set of 254 transit systems. Lastly, the model is validated using data from the first six months of 2008. Overall, the composite model performs quite well; errors are fairly small for single-month projections, while multi-month projections, although acceptable, suffer lower accuracy levels due to error propagation through the forecast series.

Academically, the research herein explores a topic which has received little attention, most transit agencies establishing their own forecasting methods in-house or through cooperation with their local metropolitan planning organization. The procedures here are unique in that they combine established forecasting methodologies, such as data decomposition, with more advanced multivariate regression in a complementary manner that leads to robust prediction abilities. By calibrating and examining each individual system within the evaluation set, the model is made truly transferable, and comparisons can be made across systems, regions, and modes, which, in the absence of such disaggregate model-building, cannot otherwise be accomplished.

Technical contributions of this work include its transferability via individual system calibration of the seasonal and non-seasonal parameters. Additionally, the modeling procedure is straightforward to apply, making use of commonly-available data, and readily adaptable to mathematical programming interfaces for unique system treatment.

The remainder of this work is organized as follows. Literature review is provided in two chapters: Chapter 2 presents the history of fuel price effects on transportation since the mid-1970's and Chapter 3 outlines the current state of practice and knowledge with regard to ridership forecasting. Chapter 4 explores the impact of fuel price growth on transit ridership in five historically auto-oriented US cities. In Chapter 5, the data collected and utilized in building and calibrating the ridership forecasting models are outlined and problems inherent in time series data are addressed. The removal of seasonal fluctuations from ridership data using a statistical decomposition technique is covered in Chapter 6, while Chapter 7 outlines the results of multivariate regression analyses performed on the remaining non-seasonal portions. In Chapter 8, the seasonal and non-seasonal models are combined to establish the final composite model form, which is validated in Chapter 9. The final chapter, Chapter 10, discusses the conclusions from this research and contributions thereof, and future steps to improve the work developed herein.

Chapter 2: Fuel Price Impacts on Transportation, 1970's – Present

2.1 INTRODUCTION

The price of crude oil and automobile fuel receives considerable attention in our daily lives. Even before prices began to rise dramatically around the year 2000, gas prices were a regular topic of conversation, and since prices have grown exponentially in recent years, they have gone from being a topic of light conversation to one of much argument and debate.

Figure 2.1 shows the national monthly average price for a gallon of regular gasoline between August 1990 and March 2008. One can readily see from this plot how prices started their growth in mid-2000, jumping to over \$1.50 per gallon, and despite many wild fluctuations, have continued their upward trend such that a gallon of gasoline in 2008 cost easily twice what consumers paid only five years previously. Prices dropped precipitously in late 2008 to levels not seen since 2004, but show signs of renewed growth.

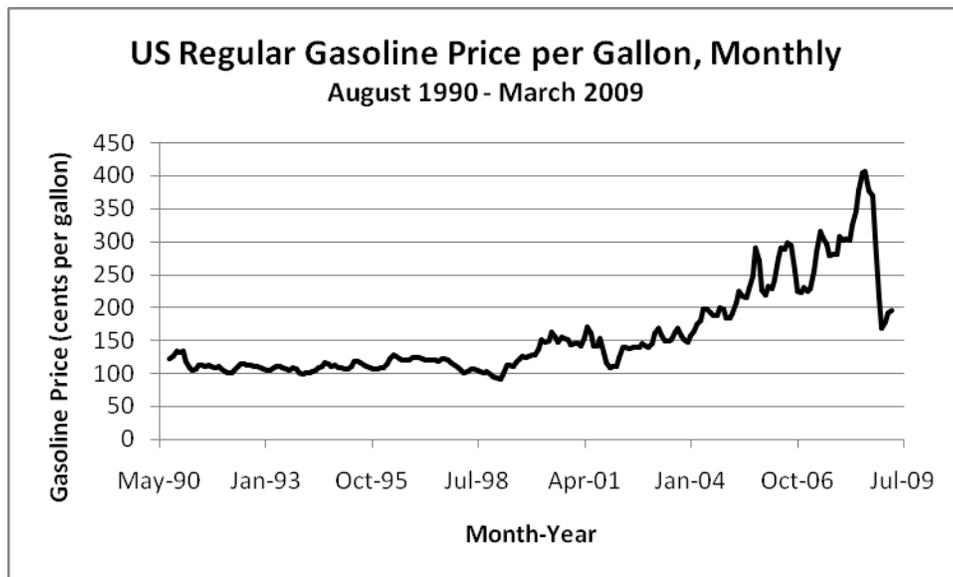


Figure 2.1 US National Monthly Gasoline Price per Gallon, August 1990 – March 2009

Much attention and research have lately gone into analyzing the effects in various sectors of this growth in fuel price. However, these recent efforts are not the first time that the cost of gasoline and its impacts on our economy and specifically, on our transportation systems, have been evaluated. The oil crises of the 1970's presented researchers with ample opportunity to investigate the role that fuel prices play in our society. This chapter explores the history of fuel price change during the last four decades and corresponding research correlated with these changes, beginning with the oil crises of 1973 and 1979, continuing through the institutional changes in oil trade that occurred in the 1980's as a result, and follows with recent developments in the 1990's and in our current century.

2.2 THE OIL CRISES OF 1973 AND 1979 AND THEIR EFFECTS

Political and institutional circumstances in the oil industry, beginning as early as the 1950's, brought about the oil crises of the 1970's. Particularly following World War II, with the rise in automobile use and dependency, world demand for fuel grew, and as now, most of the available petroleum deposits lay in what were then developing countries in the Middle East. In the 1960's, seven major oil importers (the "Seven Sisters", listed in Table 2.1 with their country of origin) dealt directly with oil-exporting countries, whose governments owned the oil deposits. These companies had direct influence, in the beginning, on the prices set on oil exports. There was little need for competition between these seven companies because demand was continually high; at times, they often had difficulty providing sufficient gasoline supply.

Table 2.1 The Seven Major Oil Importers in the 1950's-1970's

Company	Nationality
Chevron	US
Exxon	US
Gulf	US
Mobil	US
Texaco	US
British Petroleum	Britain
Royal Dutch/Shell	Anglo-Dutch

As the years progressed, however, the relationships between oil companies and oil-exporting nations changed and became strained by internal and external causes. Many wrongly believe that the two oil crises of 1973 and 1979, six years apart, were caused by the same political and market forces. In fact, the circumstances creating these scenarios were quite different. Here we will explore the causes in some detail (see Parra, 2007).

2.2.1 The Oil Embargo and Crisis of 1973

Fuel shortages in 1973 came about due to Arabian countries' use of oil as a strategic weapon against nations supporting Israel. Israeli troops had invaded and occupied several formerly Arab-held lands in 1967 during the Six Days' War, including the West Bank, Jerusalem, the Golan Heights, and the Sinai Peninsula. With Israel backed by the US and Britain, the Arab countries recognized that their military forces were no match for those of the western supporters. As political tensions in the area rose, the president of Egypt, Anwar Sadat, chose to develop a complex solution to the situation, which involved attacking Israeli forces across the Suez Canal from Egypt, orchestrating this attack with one from Syria to the north of Israel, and debilitating US efforts by withholding oil supplies from Saudi Arabia unless the US changed its foreign policy with respect to Israel.

Previous agreements signed by the seven major companies and the oil-exporting countries (OPEC, the Organization of Petroleum Exporting Countries) broke down and meetings

attempting to rectify the situation and establish market prices for oil met with failure. In early October 1973, the seven major companies permanently lost any say in the prices set for oil.

Shortly after the failure of price negotiations between OPEC and the importing companies, production cutbacks began. For every month that Israeli forces remained in the contested areas, oil ministers jointly decided to curtail oil production by five percent. On October 18, Saudi Arabia chose to reduce production by ten percent—but the following day, the US launched a colossal new campaign of militaristic support for Israel, so on October 20, Saudi Arabia enacted a full embargo of oil exports to the US. Saudi Arabia's full embargo against the US was joined quickly by all other Arabian countries.

Despite a UN cease-fire agreement of the Arab-Israeli war which was accepted by all warring parties, the oil embargo towards the United States continued. Prices at the pump rose greatly, due to a number of factors, including shortages and rising freighting costs as the US scrambled to procure oil from other sources. Peace talks convened in Geneva in December 1973 between Israel, Egypt, and Jordan, and in mid-March of 1974, the oil embargo directed at the US was finally lifted, five months after it had begun.

During the embargo, President Nixon encouraged use and development of alternative energy sources and conservation measures. However, many people were terrified of economic catastrophes that they saw as imminent. Economic experts warned of an impending economic crash and looming period of world economic darkness to rival that of 1929 and the Great Depression (see Cairncross and McRae, 1975; Parra, 2007). The US Subcommittee on Multinational Corporations reported in January 1975 that (excerpted from Parra, 2007):

The United States and the rest of the non-Communist world face the most serious economic crisis since the depression of the Nineteen Thirties. If strong policies are not immediately adopted, this crisis can undermine the economic foundation of the non-Communist world and jeopardize our democratic form of government.

In the five months of the 1973-74 oil embargo, crude oil prices tripled. Prices in oil markets finally stabilized somewhat in 1974 once OPEC countries put in place production ceilings and set official market prices that were more or less independent of supply and demand forces.

As a result, OPEC morphed into what essentially constituted a cartel, setting prices on oil where they wished and attempting to balance production among members with little, if any, outside influence. They believed that shortages and depletion were imminent and that supply and demand forces would eventually balance prices out at what the market would bear. However, during the embargo, world oil usage had dropped and in mid-1974, the result was an international over-supply of oil. After significant internal (and external) struggle regarding prices and production levels, OPEC set prices where they would, and these prices remained fairly intact for a number of years.

2.2.1.1 The Effects of the 1973 Oil Embargo on US Transportation

How did the 1973 oil embargo and subsequent crisis affect the US transportation system, and specifically, how did it affect transit usage? It is important to keep in mind that public transportation was undergoing major institutional changes during this same time period. The Urban Mass Transportation Act of 1964 had established what is now the Federal Transit Administration and provided federal funding of \$375 million for bringing transit systems into the public realm (FTA, 2006). Up to this point, most public transportation systems had been privately owned and financed, and most were doing quite poorly in attempting to stay afloat as viable transportation alternatives. On the heels of the 1964 act came the Urban Mass Transportation Act of 1970, which increased the level of funding. Thus, in the early 1970's, most transit systems, particularly the smaller systems, underwent massive changes in their operating structures as they grew from floundering, disorganized attempts to prove financially profitable to well-planned, federally-supported transportation systems.

Due to data collection techniques at the time, the bulk of research conducted evaluating reactions to the changes enacted by the embargo focused primarily on specific regions of the US, rather than the nation as a whole.

Between July 1973 and July 1974, national use of public transportation grew by 12.3 percent. However, research during this period pointed out that sustained growth in transit use could be accomplished only through coordinated land use and urban growth planning over the long-term (Leotta, 2007).

A study published in 1975 (see Curry, *et al.*, 1975) calculated cross-elasticities of demand for various aspects of regional travel in Washington, DC; Boston; and Denver during the period November 1973 through July 1974. This study found short-term price elasticities of fuel demand of -0.1 for DC and Boston and -0.12 for Denver (thus, as fuel price increased by 10 percent, gasoline sales declined by about one percent). It also calculated a short-term elasticity of transit demand in DC with respect to fuel price of 0.04 (prior to the METRO heavy rail construction), indicating a growth in transit ridership of 0.4 percent for a 10 percent increase in fuel price. The authors note, however, that various unaccounted-for influences in Boston's transit system regarding fares during the analysis period and a transit operators' strike in DC in May 1974 make the calculated results ambiguous and evaluation of their accuracy difficult. They also point to the short "post-'crisis'" period as limiting the usefulness of the findings and emphasize that the elasticities derived were for short-term changes.

In a second 1975 study that focused on the Hudson River crossings into Manhattan and Staten Island from New Jersey (see Lessieu and Karvasarsky, 1975), decreases in traffic volume were measured during the first and second quarters of 1974. The authors attribute the considerable drop in traffic volumes during the first quarter to fuel shortages, and indicate that high fuel price was less a deterrent to volumes in the second quarter than availability had been in the first, since volumes recovered somewhat following the end of the oil embargo in March 1974. The researchers also examined peak versus off-peak travel and concluded that fuel availability and price played no role in changing the peaking pattern and that both peak and off-peak travel were affected by fuel price growth. Finally, they concluded that peak-period travelers reacted to fuel shortages and price escalations by increasing carpooling and transit usage, while off-peak and

leisure travelers reacted by making fewer and/or shorter trips. They add, however, that transit passenger volumes at the two crossings analyzed were (at the time) three times what automobile user volumes were and that (due to lack of passenger counting technologies at the time), isolating transit passenger increases was virtually impossible and thus transit ridership growth was hypothesized.

In a study commissioned by the U.S. Department of Commerce, a survey conducted of households in suburbs north of Chicago indicated that availability of gasoline played a greater role in producing changes in travel behavior, rather than fuel price (see Peskin *et al.*, 1975). Furthermore, the research concluded that while work and non-discretionary trips were not affected by the fuel shortage or accompanying price surge, discretionary travel fell by 13 percent and trip chaining became more prevalent in an effort to conserve fuel. Most respondents viewed the fuel shortage and higher prices as little more than an inconvenience and there was virtually no change in their mode choice for any type of trip.

The findings of this Chicago-based study were echoed in a study analyzing travel behavior in Columbia, South Carolina (see Sacco and Hajj, 1976). The authors found that while auto travel did not drop appreciably, what little reduction occurred, through reducing driving speeds and limiting discretionary trips, happened mostly on weekend days. They concur that fuel supply appeared to affect travel behavior more than price, and concluded that public transit would not garner increased ridership due simply to higher fuel prices, based on transit's poor service quality (as mentioned in this sub-section's introductory paragraph). Overall, reliance on automobiles was not reduced, but instead travel behavior and driving habits were adjusted to conserve fuel.

Reactions were similar in southeastern Wisconsin, according to a survey conducted in late 1975 (see Corsi and Harvey, 1977). While more than 75 percent of households in this region admitted changing their travel behavior, they did so through "careful retreat, making changes that caused the least disruption to their precrisis travel patterns and putting off hard decisions that would involve major changes," such as changing modes or residential relocation. Trip chaining and altering travel patterns to locations less distant were the primary reactions; switching to more fuel-efficient vehicles was also common. While respondents expressed support for public transportation systems, most of that support came in the form of professed backing of additional property, fuel, or income taxes to fund transit. The researchers also explored respondents' gasoline "price thresholds", or the price per gallon that would cause households to make significant changes in their travel behavior. For about 30 percent of households, this value was 80 cents per gallon, although roughly ten percent of respondents indicated that the price at the time, between 50 and 59 cents per gallon, was sufficient to cause them to change their habits. The final conclusion of the researchers was that households were unlikely to make major changes in their travel behavior under the impetus of moderate and gradual growth in gasoline prices, that only strong rationing and/or "excessive" price increases would cause substantial behavioral shifts.

Reactions of households to high fuel prices shared similarities with reactions to conservation strategies. As would be expected, knowing human nature, most surveys collecting respondents' reactions to potential conservation strategies found that households preferred options that

impacted their own personal travel habits the least. In rural Iowa, for instance, given the options of (1) severe rationing, (2) severe price increases, (3) various speed restrictions (all at or below 55 mph), (4) taxes based on vehicle fuel efficiency, or (5) incentives and subsidies for transit use, carpooling use, or voluntary reductions in household travel, stratification by age and income group revealed that household support of one policy versus another was determined mostly by the impact to a particular household and that household's perception of the policy's adverse effects on lifestyle (Brewer and Grey, 1977).

It is important to point out that the short-term nature of the changes in fuel price affected by the embargo, as compared to the much longer-term growth in price in today's market, made observing change difficult, and any changes would have constituted short-term changes, rather than reactions to prolonged exposure to higher fuel prices. Additionally, and on a related note, it may be assumed that changes in travel behavior due to increased fuel prices take time to occur and thus present a lag between the price change and behavior change. For instance, if fuel price grows by some large percentage, one can hypothesize that it may be weeks or months before consumers feel the pinch and begin to investigate alternative travel means, and perhaps an additional period of time before they act on that information.

A study conducted in 1979, which looked at the changes in fuel price during the 1973-74 period, used flow-adjustment models (a type of econometric model) to account for this time lag (see Pucher and Rothenberg, 1979). The researchers point out, however, that the flow-adjustment models do not provide insight on the nature of the lag itself, except as far as its timing and relative size. The study also summarized the findings of eight aggregate econometric models of gasoline demand with respect to vehicle kilometers of travel, most of which had either linear or logarithmic functional forms and used ordinary least squares or two-stage least squares estimation techniques. Generally, the studies (which did not differentiate between urban and ex-urban travel, regional differences within the US, trip purpose, or income level) converged on a short-term elasticity of -0.2 to -0.3, and the authors suggested that public policies governing the price of gasoline could dramatically affect automobile usage and overall travel behavior.

It appears that, although researchers recognized the implications for public transportation use brought on by higher fuel prices, conducting research geared specifically towards measuring the effect on ridership during the 1970's was mostly infeasible because of technological limitations regarding data collection. Until very recently (the last decade or so), ridership totals were gathered through on-board surveys, which were conducted infrequently and at great cost to the data collector. The proliferation of automatic passenger counters (APCs) has simplified this process and made ridership data more readily available, although smaller transit agencies may still be unable to afford this technology. However, in the 1970's, despite researchers' best intentions, on-board surveys simply did not produce the rich database for analysis that we may take for granted today. Thus, many estimates of the effect of fuel price on transit patronage are relatively inconclusive as far as producing concrete relationships.

The overall conclusions of researchers following the consequences of the oil embargo of 1973 indicate that in the wake of the embargo's fuel shortages and higher fuel prices, travel behavior changed only moderately, and mostly only when considering discretionary travel, particularly on weekends. Substantial effort focused on determining the relationship between fuel price and fuel

consumption and found that, as expected, consumption dropped as prices rose. Purchases of smaller, more fuel-efficient automobiles grew and speculation about further reduction of vehicle size resulted from findings of research in this period. Trip-makers also conserved energy by reducing their travel and, to a much lesser extent, by using alternative modes such as carpooling or public transportation, although the propensity of travelers to change modes depended on regional factors, such as the higher accepted use of transit in New York City.

2.2.2 The Oil Crisis of 1979

Conversely to the oil crisis in 1973, the crisis in 1979 was not created as a strategic political weapon against the US. Instead, it occurred as a result of the Iranian Revolution of 1979. OPEC had continued to virtually ignore the market laws of supply and demand, and the world was waiting with bated breath for certain news of the depleted oil sources that all had been convinced were just around the corner, however unfounded the claims actually were.

In October 1978, Iranian oilfield workers went on strike. The strike permeated the rest of Iran and until the Shah left the country and was replaced by a heartily welcomed Ayatollah Khomeini, the strike continued. The revolution and accompanying transfer of power changed Iran from a monarchy to an Islamic republic under the Ayatollah. Oil exports, which had been stopped, resumed finally in March 1979. Between September 1978 and November 1979, “spot crude” oil prices, which acted as a barometer of sorts for oil prices, exploded from \$12.80 a barrel to nearly \$40 a barrel.

During the Iranian Revolution, as had been earlier agreed upon, OPEC raised oil prices as they had planned. This step, however, induced North Sea producers in Norway and Britain to raise their crude prices, too, refusing to allow the Middle Eastern countries full leverage over price-setting. Consequently, a battle began between the two groups, each raising prices higher than the other, until the future of prices could not be anticipated.

Members of the worldwide community witnessed the ever-increasing oil prices resulting from this pricing battle, and, coupled with the still-present fear of impending oil shortages, stockpiling and hoarding of oil supplies became rampant. Through 1979, prices continued to climb, fueled mostly by fear. Eventually, however, by mid-1980, oil storage facilities were full to bursting and prices began to fall. In October 1980, Iraq invaded Iran and the two nations went to war, which effectively eliminated oil exports from both countries, but amassed supplies were such by that time that it had little effect on the market and other producers stepped in to make up the difference. Oil exports from Iran and Iraq resumed again in mid-1981, although the Iran-Iraq War lasted until August 1988.

Despite falling prices and bursting oil stockpiles, the world continued to believe that an energy crisis loomed. Conservation efforts expanded as everyone prepared for the worst. Eventually, though, market forces took over and prices began to drop, and by mid-1981, calm had been restored.

2.2.2.1 The Effects of the 1979 Oil Crisis on US Transportation

Facing a second oil crisis and fuel price jump in less than a decade, how did Americans react regarding their travel habits?

The primary reactions to decreased gasoline availability and higher prices at the pump, as in the research pertaining to the 1973 embargo, focused on fuel conservation, by adopting less wasteful driving habits and changing to smaller, more mechanically-efficient vehicles (Dansker *et al.*, 1981). Interestingly, supporting the idea that fuel price and fuel demand are generally recognized to have an inelastic relationship, the Dansker study found that sensitivity to fuel price spikes (through the form of elasticities) fell over time as consumers became rather desensitized to the price surges.

A study published in 1984 by Greene and Hu found that the inclination to reduce travel versus switching to more fuel-efficient auto use depended on the number of vehicles in a household. They concluded that single-vehicle households reduced their trip-making, while multi-vehicle households reduced their use of poorer-fuel efficiency (larger) autos and made a larger proportion of their trips in their more fuel-efficient (smaller) vehicle(s). Overall, they found that gasoline price increases led to a reduction in vehicle-miles traveled (VMT), the effect of which outstripped the savings incurred by switching vehicle types. In developing a corresponding model based on household travel survey data between 1978 and 1981, they found that, for a 25 percent increase in fuel price, the model predicted a 4.7 percent drop in overall vehicle use and that fleet fuel economy improved by 0.2 percent.

A second study by this team, using a 1978-1981 data set for single-vehicle households, investigated the short-run elasticity of vehicle travel and gasoline demand and found that price elasticity grew with fuel price; lower values were on the order of -0.5, while higher values obtained a value of -0.6 (Greene and Hu, 1986). Thus, as gasoline price increased, consumers became more sensitive to additional positive changes in price and demand consequently dropped.

While most studies in the 1970's pertaining to the fuel crises found that most conservation behavior came about through reductions in discretionary trip-making, a study in 1981 of the latter crisis concluded that, although most reductions resulted from non-work travel, energy use for work trips showed the greatest sensitivity to energy supply and price (Neveu, 1981). Calculations of elasticities using gallons purchased as a surrogate for VMT led to elasticity values of +1.132 for work travel energy use with respect to fuel supply, versus +0.915 for non-work travel energy use, and travel energy use elasticities with respect to fuel price of -0.335 for work travel and -0.270 for non-work travel. From these calculations, the researchers concluded that fuel supply was three to five times more influential in reducing energy use than fuel price. They explained these seemingly unintuitive values through noting that work trips produced the greatest inclination towards use of higher-occupancy modes (transit, carpooling, etc.) and changes in fuel efficiency of vehicles purchased. Government conservation propaganda at this time focused on work trip energy conservation, which was at odds with what most research determined people were actually doing—reducing their non-work travel. This particular study suggested that perhaps travelers were actually doing both. Furthermore, the findings from this study in New York State were used to make recommendations regarding proposed conservation strategies, primarily to the effect that “blanket policies” were not advised, as socio-economic

groups react differently to a given strategy and therefore, strategies should be prepared to reach specific groups to allow for greater equity and effectiveness.

A report compiled and prepared for the US Department of Energy in 1981 discussed the price inelasticity of fuel demand and pointed out that the very low values of these price elasticities implied a future of increased dependence on foreign oil sources in providing for US energy needs (Morlan, 1981). It also indicated that since the elasticities were so low, it was important to invest research funding in exploration of alternative energy sources and new petroleum supply technologies because otherwise, the proportion of a household's income dedicated to fuel purchase would continue to increase, as would the net profits gained by oil exporters. Short-term gasoline price elasticities of demand surveyed in this study (those for one-, three-, and five-year periods) varied from -0.1 to -0.3, while long-term values (for 10-year evaluation periods) ranged from -0.3 to -0.9. Perhaps the greatest finding of this research was the conclusion that in investigating the long-term effects of heightened prices for all petroleum products, more than half of the effect achieved on demand was accomplished within the first three years of the higher price levels. This effect, when considering only gasoline prices (compared to all petroleum products), came about, not through travel reductions, but primarily via improved vehicle fuel efficiencies.

However, although travel reduction was not the main reaction of consumers, it still occurred to some extent and not all trip purposes experienced equal decline. While most studies found that discretionary travel during the oil crises dropped, a study published in 1983 found little change in attendance at national parks during these periods (Kihl, 1983). The study was fairly inconclusive and could not explain why some parks' attendance exhibited no change and others' seemed to be adversely affected. The author hypothesized that trip-makers were observing conservation habits during their workweeks and reserving automobile travel for weekend excursions to the parks investigated.

In 1981, it was forecast that through the 1980's and 1990's, travel (in New York State) would increase because of improved vehicle efficiencies, population growth, suburbanization and sprawl, and increased auto ownership (Hartgen, 1981). Growth in travel was projected to meet difficulty with higher energy prices, additional oil embargoes, and higher inflation and employment. Fuel prices were expected to grow rapidly and it was anticipated that gasoline demand would fall by ten to 20 percent.

Instead, the mid-1980's through the 1990's brought no more embargoes and an extended period of the lowest and most stable fuel prices in history.

2.3 RESEARCH GENERATED IN THE MID-1980'S THROUGH THE 1990'S

Contrary to the 1970's and 2000's, the 1980's and 1990's brought with them nearly two decades of low and stable gasoline prices.

In 1987, after several years of continually low fuel prices, a study was published that speculated about the implications of lower prices, compared to the fervor in the past with which the government and consumers had pursued conservation and travel reduction techniques. The researchers concluded that (1) domestic oil production would drop; (2) use of petroleum products,

particularly with regard to transportation, would grow; (3) the US would become ever more dependent on foreign sources of oil and more sensitive to price shocks and supply disruptions; and (4) research into fuel-efficient technologies would decline due to lack of incentive (Mintz, *et al.*, 1987). Today, we can look back and see how prophetic these conclusions seem.

Obviously, given the history of fuel prices, it was impossible to know how consistently low prices during this period would prove and therefore, planners tried to anticipate the worst and develop contingency plans accordingly. Contingency strategies for interruptions in fuel supply were created by the Massachusetts Institute of Technology (MIT) in 1982 for the U.S. Department of Energy and presented at a workshop entitled “Strategies for Calm and Order”. (Humphrey, 1983). Another incidence of oil supply disruption in the future was considered to constitute a “high probability”.

The strategies developed by MIT for dealing with four distinct scenarios included: (1) “Actions to facilitate more energy-efficient travel and maintain mobility”, including consumer education, promotion of higher-occupancy modes, improvement of transit systems and ride-sharing programs, flexible work schedules, and reduced speed limits; (2) “Tax excess profits and provide rebate to consumers” by lessening the effects to the economy of fuel price growth; (3) enforcement of “Demand-restraint measures” such as limiting consumers’ access to fuel pumps, carless days using vehicle stickers, banning Sunday driving, and restricting single-occupant vehicle use; and (4) a “Coupon-rationing program” (of which there had been one such program in the late 1970’s until it was repealed by President Reagan early in 1981).

The conservation trends observed during the 1970’s continued into the early 1980’s, including nationwide shifts to smaller, more fuel-efficient vehicles. Immediately following the fuel shortages of the 1970’s, there were reductions in travel and attempts made to conserve energy resources. However, as was hypothesized in the late 1970’s, the financial savings garnered through conservation efforts on a household level were then “re-invested” in recreational and other non-work travel (Brunso and Hartgen, 1985). Despite trip-makers’ claims of reduced non-work travel during the period 1979-1982, evaluation of trip rates, trip distances, and incidence factors revealed that non-work travel had not suffered as much as alleged.

Bicycle use enjoyed a resurgence in popularity in the wake of the oil crises. The energy crisis created a demand for bicycles as an alternative mode of transportation in the late 1970’s and early 1980’s. The demand elasticity for bicycles at that time with respect to fuel price was 0.51; as fuel price grew by 10 percent, bicycle sales grew by 5.1 percent (Kerr, 1987).

One study developed a model using the Almost Ideal Demand System (AIDS) methodology created in the 1980’s to replicate household vehicle fuel expenditure allocation in the US (Oladosu, 2003). The research used data sets from the late 1980’s and early 1990’s and determined that vehicle characteristics were the greatest determinants of household fuel expenditure.

Fuel prices around the world were affected in similar ways and timeframes as those in the US. In the UK, price elasticities of demand for gasoline between 1980 and 1988 were calculated for time-series and cross-sectional data in the short- and long-term, where “short-term” constituted

periods of less than one year. For the time-series data, these British elasticities were -0.27 and -0.71 (short- and long-term, respectively) and -0.28 and -0.84 for the cross-sectional data (Goodwin, 1988). These values concur with those found by US researchers looking at 1978-1981 US data, which had calculated values between -0.5 and -0.6 (Greene and Hu, 1986). A third study, examining behavior of drivers in the Netherlands, used fixed and random effects models to investigate price elasticities of demand for auto fuel in that country (Rouwendal and de Vries, 1999). Their findings ranged from 0 to -0.37 when using the fixed effects model and 1986 panel data, or -0.44 to -0.50 for the same 1986 data set and -0.63 to -0.65 for a data set from 1991 when employing the random effects models. Again, these ranges agree with the findings in the US and UK.

Most studies and researchers recognize that fuel demand is price inelastic, elasticity values falling at or near zero (see Morlan, 1981; Schimek, 1996; Eltony, 1999), although one study using data from 1950 to 1994 found that, in the short-term, fuel demand was price inelastic, but that in the long-term, its elasticity was -0.7 (Schimek, 1996).

How was public transportation affected by fuel price? Transit systems are not created equal, and across regions of the US, or even within regions, there will be substantial differences in effects. However, the most notable differences occur when comparing trends in one country with another, where not only policies differ, but so do land use controls and city structure. Although a London study at the time showed an elasticity of transit demand with respect to fuel price of +0.34, a different study in Orange County, California found that, due to the large proportion of captive riders in the local system (70 percent), changes in fuel price produced no effect on ridership, although a change had occurred in 1979 from the oil shortage (which quickly dissipated following the end of the shortage) (Ferguson, 1991). These differences in regionality will be explored in more depth in the next section of this chapter and in Chapters 4 and 7.

2.4 FOCUS ON FUEL PRICES IN THE NEW CENTURY

After many years of relative calm, the 21st century ushered in a new decade of concern over fuel prices. Beginning quietly in the year 2000, prices grew and fluctuated rapidly as world events and market forces came to the forefront in oil pricing. Figure 2.3 shows weekly prices from January 2004 through early April 2009, a period of exceptional growth and flux. As shown in the plot, consumers in 2008 paid twice or more what they did in 2004 for a gallon of regular gasoline. While the oil embargo of 1973-74 caused prices to balloon by nearly 300 percent, the magnitude of this increase is dampened when comparing the absolute price of fuel in 1974 to the prices paid today. The average price of a gallon of gasoline in June 1974, following the embargo when prices surged, was 55 cents. In 2008, consumers paid more than four dollars for the same gallon.

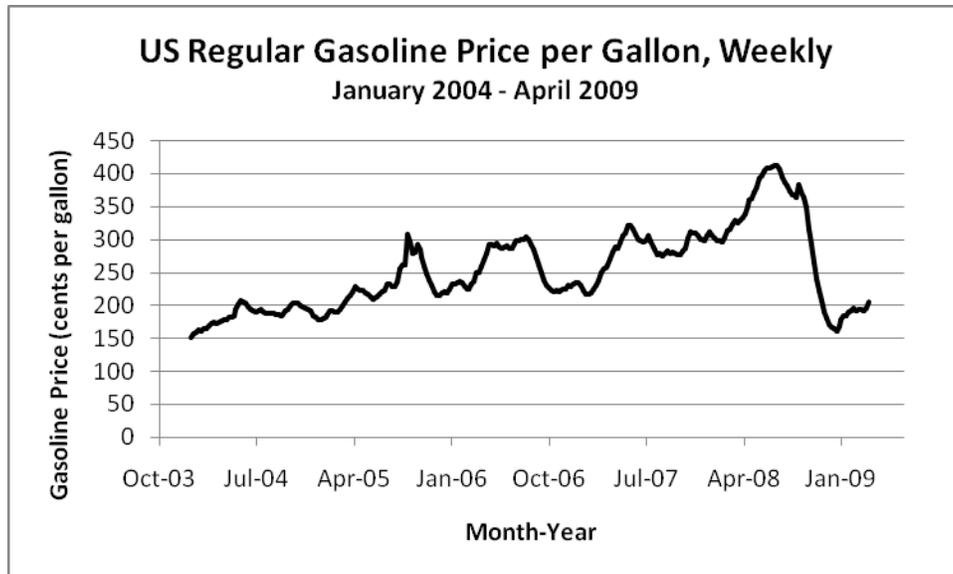


Figure 2.2 US National Weekly Gasoline Price per Gallon, January 2004 – April 2009

One of the primary and significant differences between the oil crises of the 1970's and today's price explosions is the duration of the events. The 1973 oil embargo lasted five months, and although the effects were felt for many months afterwards, the actual shortage and corresponding price increases were fairly short-term, compared to today. Similarly, the 1979 oil crisis, although its effects caused roughly two years of higher prices, did not produce lasting impacts on oil prices. The availability (or lack thereof) of gasoline during these crises was the main influence in reducing travel by automobile, rather than the inflated prices consumers paid. Contrast these situations with today's scenario, in which consumers have been dealing with continually higher prices for nearly eight years, but during which supply has never been at issue.

Many researchers believe that we cannot expect to find the same elasticity values in today's market as were realized in the 1970's. Given how much our transportation systems and attitudes have changed in the last 30 years, it seems realistic to expect consumers to react differently today. One study determined that a shift in that reaction has occurred since the oil crises, and found that short-run price elasticities have fallen from a range of -0.21 to -0.34 between 1975 and 1980 to a range of -0.034 to -0.077 between 2001 and 2006 (Hughes *et al.*, 2007). Thus, consumers are much less sensitive to price changes today when it comes to purchasing automobile fuel than they were 30 years ago. The study did not address the *availability* of fuel as an influence in the higher fuel price elasticity values in the earlier time period.

This change in elasticity and sensitivity over time is stressed by Basso and Oum, who recommend that those relating fuel price to fuel consumption recognize that time-series analyses may be flawed if the "non-stationary nature" of the time series and changing reactivity are not expressly considered (Basso and Oum, 2007).

Sensitivity to fuel price as it pertains to gasoline demand is also affected by household income. A 2007 study found that, interestingly, the lowest and highest income groups respond most

strongly to higher fuel prices (price elasticities of 0.35 for the lowest income group and 0.29 for the highest), while households falling into mid-range income groups react less strongly (price elasticity of demand of 0.20) (Wadud *et al.*, 2007).

In the year 2000, the US constituted 55 percent of total world oil demand. Two-thirds of that demand goes towards transportation purposes (Leotta, 2007). As pump prices grow, so does the proportion of household expenditure that must be dedicated to transportation, barring the adjustment of travel behavior.

A team of Australian researchers evaluated the correlation between major world events during the period 1998-2006 and aggregate US transit ridership to investigate correspondence between the two. They calculated cross-elasticities of public transportation demand with respect to fuel price for transit as a whole (0.12), and separate elasticities for bus (0.04 to 0.08), light rail (0.27 to 0.38), and heavy rail (0.17 to 0.19). Short-run elasticities prior to September 11, 2001 showed less sensitivity to fuel price than the post-9/11 period, although long-run elasticities post-9/11 showed that sensitivity fell over time (Graham and Currie, 2007).

These results are consistent with a much more disaggregate-level study performed by Haire and Machemehl in 2007(b), which evaluated the correlation between fuel price and transit system ridership for five historically auto-oriented cities in the US. This research can be found in its entirety in Chapter 4. The empirical relationships (similar to elasticities) found in their study varied by mode and city, but ranged between 0.22 to 0.54 for the evaluated bus systems, 0.06 to 0.11 for the light rail systems, 0.11 to 0.40 for the heavy rail systems, and 0.21 to 0.49 for the included commuter rail systems. These results can be expected to differ from the results in Graham and Currie's study because this research looked at specific modes in specific cities, rather than at total US transit ridership, which includes cities with more transit-dependent riders in areas not historically auto-oriented.

In a meta-analysis of transit demand, the effect of fuel price in various western countries was evaluated (Holmgren, 2007). For the US, a short-run value of demand elasticity with respect to fuel price was calculated as 0.82. However, the research found that these short-run demand elasticities were much higher in the US and Australia than in Europe, where an elasticity of 0.4 was determined, indicating that fuel price plays a much smaller role in European public transportation ridership than in the US and Australia. Comparable long-run elasticities were 0.73 in Europe and 1.15 in the US and Australia, further supporting greater sensitivity to fuel price in the latter countries.

In a study completed for Land Transport New Zealand, cross-elasticities of transit demand with respect to fuel price in New Zealand, Australia, and international locations were explored in the literature and tabulated (Kennedy and Wallis, 2007). The researchers found wide variations, not only between nations, but within a single nation. Estimates in New Zealand ranged from +0.07 to +0.40, while Australian estimates varied from +0.01 to +0.8 (the higher value was attributed to rail transit in Australia, and when omitting such modes, the upper value for bus and tram was +0.2). International experience with such calculations gave resulting ranges of +0.08 to +0.80 in the US (from studies conducted in the mid-1980's); +0.07 in Germany; +0.22 in Italy (short- and long-run); +0.18 and +0.16 (short- and long-run) in the Netherlands; +0.38 and +0.37 in

Brussels; +0.06 and +0.09 in France; and in Paris, specifically, a short-run range of +0.04 to +0.11 and a long-run range of +0.12 to +0.19. Clearly, of these results, the US and Australian values exhibit not only the greatest range but also the greatest magnitude, agreeing with the Holmgren study that concluded higher sensitivity to fuel price in the US and Australia than in Europe.

These variations by nation in sensitivity to fuel price and consequential use of public transportation are further supported by a study comparing responses to fuel price in the US and Canada (Haire and Machemehl, 2007a). The study found virtually no correlation between fuel price and Canadian transit use in four historically auto-oriented Canadian cities. Reasons for this lack of association were hypothesized to lie primarily in urban form, which is much more centralized in Canada, much higher population densities compared to US cities, shorter commute distances, and greater acceptance of transit as a transportation option.

In a 2008 study, Mattson used a polynomial distributed lag model, allowing for both short- and long-term elasticities, to discern the reaction rates between fuel price and transit patronage. He concluded that responses differ based on city size. In large cities, the response to fuel price was found to be rapid, occurring within one to two months of rising prices. In medium-sized cities, a lesser response occurs immediately after price growth, drawn out over a period of up to seven months. In the smallest cities, any transit ridership response to heightened fuel prices took place between five to seven months following the change.

Urban form and household location play substantial roles in proclivity to use transit and as a factor affecting sensitivity to fuel price. Households in out-lying suburbs and rural areas have fewer choices when making their mode choice and thus are more dependent on their automobiles to maintain mobility. One study found that price elasticity of fuel demand in rural areas is on the order of 0.17, while the comparable value in urban areas is 0.30 (Wadud *et al.*, 2007). A research team in Austin, Texas explored the effects of the spike in fuel price that occurred in late 2005 and concluded that survey respondents reacted to higher fuel prices in a manner similar to that of the 1970's—trip-makers reduced their overall driving and chained trips in more efficient ways, and adopted driving behaviors that conserved fuel while behind the wheel (Bomberg and Kockelman, 2007). However, the researchers found that households tended to make these adjustments and other travel choices based on their residential location; those living in more centralized areas with greater land use diversity were more apt to choose alternative modes (including transit, walking, or bicycling) to reach their destinations versus households in locations further from the central business district, which were more confined to relying on their automobiles regardless of fuel price. Thus, the more centrally-located households were likely to respond to higher fuel prices by changing their travel mode, while out-lying households were more likely to adapt by changing their driving behavior.

Household location is one of many factors that can produce differing reactions in travel behavior when trip-makers are faced with fuel price growth. Community and regional characteristics can have great effects on transportation system quality, as well as on public perception of alternative transportation modes. Haire and Machemehl used a sampling of 22 US public transportation systems (bus, light rail, heavy rail, and commuter rail) of various size and location to explore relationships between high correlation between fuel price and transit ridership and community

characteristics, including transit mode share, vehicle ownership among public transportation users, route miles of service per service area, and average transit system trip length (Haire and Machemehl, 2008). For the cities analyzed, they found no universally-explanatory trend within the examined parameters, suggesting that the reactions within each city rely heavily on regional characteristics and perceptions.

Research in the areas summarized here is likely to remain a hot topic and probably grow over time if prices do not stabilize. In the absence of oil embargoes or striking oil field workers, why have prices exploded in the last decade? Why, unlike in the 1970's, have prices continued to climb ever higher over time, rather than spiking and returning to prior levels? What forces led to the volatility in today's gasoline markets?

International politics and economic forces continue to play strong roles in gasoline price futures. A Congressional research report in early 2006 outlined several specific causes for the higher fuel prices consumers had experienced to that point (Behrens, 2006). Briefly, the reasons pointed to:

- Increased demand for crude oil and resulting higher prices from economic principles of supply and demand
 - Self-imposed restrictions on production quotas by OPEC
 - Growth in crude oil demand in China
 - Oil production interruptions in Venezuela, Iraq, and Nigeria
 - The dropping value of the US dollar in world markets
 - Concerns over supply disruptions in Iraq and Saudi Arabia due to the US war in Iraq and terrorism threats
- Structural and policy restrictions on US refineries
- In 2005, supply issues surrounding Hurricane Katrina and subsequent questions of price gouging

A second investigation by the Government Accountability Office (USGAO, 2007) agreed with the impetuses outlined in the Congressional report and included the effects of declining gasoline inventories; regulatory factors, such as requiring new environmentally-sensitive gasoline formulations; and mergers within the petroleum industry. They found that during the 1990's, more than 2600 mergers took place within the US petroleum industry and these consolidations ultimately led to higher gasoline pump prices. GAO looked specifically at eight of the mergers and used econometric analyses to determine that each of the evaluated mergers led to price increases of one to seven cents per gallon. GAO further speculated that the mergers occurring since 2000 also led fuel prices higher, although at the time of publication they had not completed analyses of those mergers.

2.5 SUMMARY

The literature regarding the impacts today of higher fuel prices seems taken from that of the 1970's. Having failed to learn the lessons of the 1973 and 1979 oil crises, we appear to be repeating them. Consumers are responding in the same ways today as they responded 30 years ago to higher prices—reducing travel, buying more fuel-efficient vehicles, chaining more trips, and switching to higher-occupancy or non-motorized modes. The same issues plague us today as

three decades ago: dependency on foreign oil, inefficient and polluting internal combustion engines, and questions about domestic oil reserves. However, today's world introduces even more problems and motivations to change our travel behavior: the environmental crisis of global warming, ever-increasing congestion on our nation's highways, and urban forms that show no boundaries in their expansion.

All of these critical reasons beg us to really take notice *this* time, to not slip into complacency as happened in the 1980's when fuel prices stabilized at low levels. If prices continue to increase, perhaps *this* time the changes to our transportation systems will become long-lasting and permanent.

Chapter 3: Ridership Forecasting Techniques and Needs

3.1 INTRODUCTION

Obtaining reliable forecasts of ridership is an important goal for public transportation agencies for many reasons. Providing satisfactory levels of service to transit patrons is paramount and only through anticipating rider demand and need can such satisfaction be delivered. Another main concern for agencies is the allocation of limited funds and the use of those funds by the most effective and efficient means possible. Forecasting plays into this careful allocation by allowing planners to determine how best to spend funds in order to provide adequate service to the most critical parts of the transit network. For instance, if a planner knows that fuel price affects the agency's bus ridership more strongly than its light rail ridership, and that fuel prices will rise dramatically in the near future, it may be well worth allotting a greater proportion of funds to the bus network than to the light rail network in coming months. Yet another reason for producing accurate ridership forecasts lies in presenting these forecasts to decision makers in an easily understood format so that pending decisions can be made confidently.

3.2 *TCRP SYNTHESIS 66: FIXED-ROUTE TRANSIT RIDERSHIP FORECASTING AND SERVICE PLANNING METHODS*

Currently, most public transportation forecasting tools are developed either by a transit agency itself or by the agency's local metropolitan planning organization. These tools take many factors into account, but according to a 2005 Transit Cooperative Research Program (TCRP) survey of 36 US and Canadian transit agencies, gas prices were not a major consideration in the forecasting processes used by survey respondents (see TCRP, 2006). Other factors such as proposed new or adjusted routes, new modes or types of service, and/or scheduling changes were more prevalent inputs into forecast calculations. Problems associated with forecasting methods currently in place, or that have been proposed and left unused in the past, include a lack of transferability (since the models are developed and applied on local bases), requirements in the models for inaccessible data, and results that are difficult to interpret.

Respondents to the TCRP survey indicated a number of desirable attributes for future proposed forecasting methodologies. Among these requests was that for a transferable methodology. The authors state, "Transferability across different metropolitan areas has not been established and is an important factor inhibiting widespread use of ridership forecasting models."

Another property deemed necessary, which ties in with the problems associated with transferability, is an ability to include local factors in the analysis. This need was observed within the context of analyzing fuel price effects, as seen in the fuel price research by Haire and Machemehl (2007b, discussed in Chapters 2 and 4) and Mattson (2008), because each transit community experiences a different reaction to fuel price. Other regional and local factors, such as population density and existing public transportation patronage, will also have varying effects on forecasted ridership. One of the lessons learned from the research was that local factors should be developed and calibrated, rather than reliance on external sources. The researchers

state, “Develop local factors—forecast models from external sources do not work well. They are complicated, time-intensive, data-intensive, and provide inferior results; local elasticities preferred over industry; use experience and results from the past.”

Any forecast that produces a single value of future ridership is guaranteed to be wrong, and therefore, respondents to the TCRP survey expressed interest in forecasting methodologies that generate projections consisting of ranges and confidence intervals, rather than single values. It is also important that these results be easily interpretable and capable of presentation in lay terms for stakeholders and decision makers. The ability to interpret and present the forecast results in simple terms is viewed by practitioners as having equal importance with the results themselves.

One of the primary problems with forecasting models proposed and produced in the past lies in the data requirements asked of planners using them. Respondents to the survey stated that they frequently did not have access to all the data required for proposed models; never was there a case where having too much available data created a problem. Thus, simplicity regarding data entry and data requirements is a considerable need. The authors instruct to “Simplify the approach—focus on one or two tools for synergy and absence of conflicting forecasts; trend forecasting and professional judgment can be as accurate as regression and econometric models; in-house expertise is more effective and less expensive than consultants.” Any proposed methodology should also be straightforward to apply, in part because the model will be used to compare multiple scenarios and must therefore be easily adjustable.

Finally, the scope of forecasting results differs between large and small public transportation agencies. While smaller agencies look for more disaggregate forecasts for their transit networks, larger agencies expressed a desire to know results on a system-wide, network basis.

3.3 SHORT-TERM FORECASTS VERSUS LONG-TERM FORECASTS

Long-term forecasts, with horizons of multiple years and even decades, are time-consuming practices that involve such techniques as the four-step planning model (trip generation, trip distribution, mode split, and route assignment). However, despite the time and resources required to develop these forecasts, they are necessary when attempting to anticipate and plan for a region’s travel needs in the distant future.

Completed research and literature abounds with studies focused on long-term forecasting, as is used for prospective or start-up projects, rather than short-term forecasts used for existing systems. The Federal Transit Administration (FTA) currently requires New Starts rail projects to provide ridership forecasts, which are accomplished using the four-step model.

The data used as input in long-term forecasts differs in many cases from that used in short-term forecasts. Long-term forecasts make use of substantial amounts of economic, demographic, and land use data, from household income and vehicle ownership to maps of existing transportation infrastructure. From these data, origin-destination pairs are discerned and trips between the origin-destination pairs are assigned to existing and future transportation modes and routes.

Conversely, planners creating short-term forecasts do not typically use origin-destination data to develop their forecasts, although such data are frequently considered in other ways (see TCRP,

2006). Demographic data are often components of short-term forecasts, however, as are transit ridership data. Short-term forecasts make use of system-wide and route-level ridership counts, and although planners indicate that stop-level boarding and alighting data would enhance their forecasting efforts, most agencies have technological and institutional problems with collecting such data.

The primary difference between long-term and short-term forecasts lies in their respective levels of analysis. As mentioned, long-term forecasts have planning horizons of several years and often multiple decades, and attempt to anticipate the changes that may occur in the economic, demographic, or geographic realms. As such, they are concerned with the net changes in these factors through the forecast horizon, not the frequent fluctuations in regional and national characteristics, or the magnitude of these fluctuations.

For our purposes, paramount among the potential input to forecasts are economic data, which arguably may have the greatest short-term fluctuations of the data types. As an example, if fuel price effects were to be included in a long-term forecast with a 20-year planning frame, the modeler would be interested in the overall change in fuel price within that 20-year period, not the yearly or monthly changes that accrued to equal that net change. If the year-to-year changes in fuel price fluctuate up and down by ten or 20 or 50 or 300 percent, but the summation of changes resulted in a net growth in price of five percent, the long-term forecast would capture the five percent change, not the greater short-term changes, which may have a more dramatic effect on travel behavior than the five percent net growth. From the elevated perspective that long-term forecasts take, they are simply incapable of capturing the effects of short-term changes in forecast inputs.

The inability of long-term transportation plans to capture these shorter-term effects does not reflect any deficiency on their part. They are not intended to reflect these changes or provide forecasts responding to changes occurring on horizons shorter than their design horizon. Long-term transportation planning forecasts are designed to aid planners in anticipating the travel needs of their constituents far into the future, and to prepare the transportation system to meet these needs. They examine the “big picture”, looking at regional connectivity and other issues, rather than focusing on the requirements of individual modes and systems to better provide service over the coming weeks and months. The numerous studies available in the literature reflect the long-range goals of these types of forecasts, inasmuch as they are geared towards building transportation systems that meet the future travel needs of the community as a whole. The inputs to these studies and the resulting projections reflect the long-term net changes in regional characteristics. One oft-used purpose of long-term forecasts is to derive benefit-cost analyses of potential transportation projects. Section 3.3.1 examines these studies dealing with long-term forecasts.

Conversely, short-term forecasts are designed to respond to relevant changes on shorter bases. Unlike long-term forecasts, short-term planning forecasts are suited to anticipating changes that may occur over coming weeks and months and preparing the transportation system for the impacts of such changes.

3.3.1 Long-term Forecast Inputs and Horizons

As stated, long-term regional transportation models are usually time-consuming procedures that require extensive small-scale input data, including origin-destination data, demographic and employment information, and numerous other transportation system characteristics and regional attributes. Despite the intricate level of data and intensive labor used in developing these travel forecasts, these types of models are ill-suited to calculating disaggregate transit ridership forecasts. Several researchers have attempted to remedy this problem by combining model types or introducing various levels of smaller-resolution factors.

Researchers in Seattle combined regional transportation planning with transit ridership forecasting by using the regional models to derive estimates of future population growth and highway congestion, while relying on observed transit origin-destination pairs, transit line passenger volumes, and transit system characteristics to establish anticipated ridership levels (Dehghani and Harvey, 1994).

Often, long-term forecasts are created for transit services that do not exist in the base year. In these feasibility studies, sketch-planning models are useful tools for planners. An early study in 1986 sought to develop a sketch model of light rail and commuter rail transit ridership for nationwide use. This study collected data from 17 US regions regarding ridership, demographics, and the transportation systems in place. After evaluating 163 potential variables, two multivariate regressions were achieved that proved fairly reliable when transferred to other systems for validation. The model was capable of measuring the impacts to the light and commuter rail systems of improvements in operating speed and headways and changes in fares.

Many transit feasibility studies focus on station-level characteristics to determine transit system success for proposed services. A study of potential extensions of San Francisco's BART rail system developed a forecasting methodology that combined a direct ridership forecasting approach using multivariate regression models with the traditional four-step model to produce estimates of ridership at several proposed station locations (Walters and Cervero, 2003). The chief variables were based on station-area population and employment (within walking radius), catchment-area population, feeder bus service level, parking supply, train frequency, and train service type (BART heavy rail versus Caltrain commuter rail). The authors indicate that by combining the two forecasting approaches, the resulting model proved capable of responding to long-term projections including track alignments, station locations, and effects of nearby land use density and walkability, as well as shorter-response issues such as parking, feeder bus service, and rail service frequencies. Although the researchers addressed short-term responses to a few station-related concerns, the primary horizon for their forecasts was 2020, a year two decades distant from the analysis period.

Another study focusing on station-level qualities of potential rail alignments used multivariate analysis to investigate the factors contributing most to rail ridership in the San Francisco and Sacramento areas (Saur *et al.*, 2004). Similarly to the Walters and Cervero study, the researchers used station-level data to characterize ridership in a horizon year of 2020, based on parking and feeder bus service, rail service level and characteristics, and station-area demographics and employment.

In an later study, Saur developed “Transit Likelihood Indices” to compare base and 2025 future cases of commuter rail transit service in Petaluma, California, and predict the likely change in proclivity to use transit (Saur, 2005). The index was developed using changes in station-area development density and levels of service of the rail system.

The Petaluma study made use of Geographic Information System (GIS) data in developing the Transit Likelihood Indices. GIS is becoming a more commonly-used application in gathering transit data, including ridership counts. Although its use is fairly widespread now, an early project at MIT proposed the usefulness of GIS in planning transit systems, particularly with respect to vehicle routing tasks (Azar and Ferreira, 1995).

Long-term forecasts are often used to establish benefit-cost analyses for proposed transit projects (see Brod, 1997). Ridership forecasts play a large role in determining the success and cost-effectiveness of an investment; if a service extension results in a ridership level that does not justify the cost involved in building the extension, those funds may have been invested more wisely in another way. A study evaluating the cost-effectiveness of a rail extension to San Luis Obispo from Los Angeles used a five-year time horizon and a limited database to develop ridership forecasts for the proposed service (Rice, 1998). The methodology assumed that population drove ridership and used historical passenger ridership trends, origin-destination data, details of service frequency, and station locations.

3.4 FACTORS CONTRIBUTING TO TRANSIT RIDERSHIP

Many characteristics of a community, its transit system, and individual household traits affect the success or failure of a public transportation network. These characteristics fall into one of two categories: factors outside the control of the agency (external factors) and factors within the agency’s control (internal factors). *TCRP Report 111* (2007; see also Fleishman and Fay, 2005; TCRP, 2005) breaks external factors into six broad types and then lists individual elements contained within each type:

- Population characteristics/changes
 - General growth in the region
 - High/increased immigration
 - High/increased number of seniors
 - High/increased tourism
 - High number of college students
- Economic conditions
 - Employment/unemployment levels
 - Per capita income levels
 - Household auto ownership levels
- Cost and availability of alternative modes
 - Fuel and toll pricing
 - Parking pricing and availability
 - Taxi fares
 - Fuel taxes
 - Auto purchase and ownership costs
 - Availability of commuter benefits programs by employers

- Land use/development patterns and policies
 - Density of development
 - Relative locations of major employers and residential areas
 - Land use/zoning controls and incentives
- Travel conditions
 - Climate/weather patterns
 - Traffic congestion levels/highway capacity
 - Traffic disruptions (e.g., from major construction projects)
- Public policy/funding initiatives
 - Air quality mandates
 - Auto emission standards
 - Federal/state transit funding levels (capital and operating)
 - Local transit funding (e.g., sales or other tax receipts)

Regarding internal factors of which the transit operator has control, the authors break the system's features into three types: (1) pricing/availability mode choice considerations (including fare levels and amount and types of service available), (2) service quality mode choice considerations (such as route design, service schedules and frequency, accessibility features, perceptions of agency safety and security, and the public image of the agency, to name a few), and (3) aspects of the organizational and management structure that facilitate the agency's ability to enact strategies to influence ridership levels.

Another study, conducted in Canada, used Canadian transit data for the period 1992-1997 from 85 urban transit networks (carrying 97 percent of all Canadian transit passengers) to develop a model for transit ridership. The final model produced highly statistically significant results that showed a positive relationship between revenue hours of service and ridership (using revenue hours of service as a proxy for service coverage and population) and a negative relationship between fares and ridership, both of which results are intuitive (Kohn, 2000).

3.5 SHORT-TERM FORECASTING TECHNIQUES AND APPLICATIONS

TCRP Synthesis 66 summarizes the state-of-the-practice with respect to short-term forecasting techniques in use by planners at most of the nation's transit agencies. As cited, trend analysis and other means, including professional judgment, comprise the bulk of techniques currently used. Most short-term models are developed in-house by the transit agency, or by the regional metropolitan planning organization.

Efforts to create short-term forecasting procedures by external researchers have resulted in novel developments. Among these is a methodology proposed in 2005 using Madrid transit data (García-Ferrer *et al.*, 2005). This study developed a causal econometric model using a monthly dataset from 1987 to 2000 and a dynamic harmonic regression model for comparative purposes. Dynamic harmonic regression models are a type of unobserved component model. The researchers made use of intervention variables to counteract disruptions in ridership resulting from consequences of transit worker strikes and holidays. The researchers found that these types of models handled the seasonal nature of ridership data well and provided decent short- and

medium-term forecasts of ridership, although they admit that the importance of inevitable outliers within the dataset makes the process quite complex.

Other applications of short-term forecasting techniques may have alternative goals besides projecting transit ridership. The US Department of Energy's Office of Integrated Analysis and Forecasting develops the National Energy Modeling System (NEMS), one module of which focuses on transportation energy demand (USDOE, 2007). Among other transportation types including air, recreational boating, freight (highway, rail, and waterborne), and light-duty vehicles, the NEMS provides forecasts of energy use in mass transit applications. In the transit submodules used for the NEMS, passenger-miles are used as a surrogate for energy demand, and growth in transit mode usage (passenger-miles) is assumed to be proportional to the growth in light-duty vehicle passenger-miles. The validity of this relational assumption seems questionable on the surface, since one would assume that as transit patronage grows, some of those patrons have come to transit as former automobile users, thus decreasing the overall use of light-duty vehicles; one would expect the two to be inversely proportional. However, one must then consider the fact that national VMT continues to grow, despite all economic and other factors that would normally suggest otherwise.

In the NEMS mass transit submodule, annual passenger rail energy demand by region is determined as the sum of transit rail, commuter rail, and intercity rail demand by census division. For the bus segment of the NEMS model, bus energy demand is calculated by multiplying the previous year's bus demand by the ratio of change in light-duty vehicle usage and a proportionality coefficient (see Equation 3.1).

$$TMOD_{IM,Year} = TMOD_{IM,Year-1} \times \left[\frac{VMTEE_{Year}}{VMTEE_{Year-1}} \right]^{BETAMS} \quad (3.1)$$

where

$TMOD$ = Passenger-miles traveled, by mode

$VMTEE$ = Light-duty vehicle vehicle-miles traveled

$BETAMS$ = Coefficient of proportionality, relating mass transit to light-duty vehicle travel

IM = Index of transportation mode: 1 = Transit bus, 2 = Intercity bus, 3 = School bus

This short-term demand model is quite simple and relies heavily on the $BETAMS$ coefficient to capture the effects of numerous other factors contributing to changes in transit ridership, as well as the assumptions made regarding the proportional relationship between automobile VMT and transit passenger-mile growth. However, the purpose of the model is not to develop ridership forecasts directly, particularly for any given transit agency or system, but to anticipate transit energy consumption at census division levels. Thus, rather than achieving a final numerical estimate of transit patronage, the value of passenger-miles traveled in the target year is then multiplied by a factor calibrated to derive the energy demands for the mode. These energy factors for rail and bus modes are developed from the freight (rail and heavy vehicle) module of the NEMS.

In a paper following similar logic to that presented in Chapter 4 of this document, short-term forecasts were derived using single-variate linear regression following seasonal adjustment of ridership data (Conlon, 1998). The seasonally-adjusted trend of the data was evaluated using least-squares, with the independent variable as time, and the subsequent forecast value was calculated and adjusted for its appropriate seasonal trend value. The author indicates that the developed forecasts of daily ridership for a multi-modal transit system in Maryland (using 1989-1995 data) were within 0.16 percent of actual values.

3.6 SUMMARY

This chapter recounted the state-of-the-practice in short-term public transportation ridership forecasting and discussed recent academic and federal efforts to advance this state in terms of ridership projections and transit system energy consumption. It also elaborated the differences between short- and long-term forecasts and how the two types may be combined synergistically.

Chapter 4 describes research conducted in 2006 that explored the relationship between fuel price and transit ridership in five historically auto-oriented US cities. This research supported and was succeeded by the forecasting model development that comprises the focus of this report.

Chapter 4: The Impact of Rising Fuel Prices on US Transit Ridership

4.1 INTRODUCTION

Several series of recent events, market forces, and countless other catalysts have driven fuel prices skyward over the past many months. As auto-dependent cultures around the world have seen fuel prices rising dramatically during this time, some have speculated that once-auto-oriented transportation patterns may, as a result, begin to lean more heavily upon public transportation.

In 2007, US transit ridership reached its highest level in 50 years; 10.3 billion trips were made using public transportation (Miller, 2008). The American Public Transportation Association (APTA) announced this extraordinary statistic in early 2008 following their analysis of the previous year's ridership, and indicated that high fuel prices and road congestion, coupled with more widespread transit services, led to the growth.

Indeed, it is doubtless that at least some commuters have changed their travel habits and now rely upon transit to lighten the burden to their wallets. In 2003, when fuel prices were less than half where they stood in late 2008, it cost an average of 53 cents per mile to own and operate an automobile. At an average fare of 18 cents per passenger-mile in 2003, transit was a decidedly more affordable option (USDOT, 2005). At their peak in 2008, however, fuel prices forced the price of vehicle ownership higher and although many transit agencies raised fares to offset their own fuel expenditures, transit still proves a more economical choice.

A 2004 study by APTA surveyed transit agencies, asking whether they had observed any change in their transit patronage due to the increase in fuel prices between the beginning of 2004 and June 2004. At that time, the study found that "Transit agencies attribute a very small increase in ridership, less than four-tenths of one percent, to have resulted in part from the increase in the cost of fuel to motorists. Even if higher prices continue or increase, transit agencies anticipate an increase in ridership of only two-tenths of one percent." (APTA, 2004)

Most agencies have since amended that perspective as extreme fuel prices through 2007 and 2008 coincided with a resurgence of national transit use. How much, though, have continuing fuel price increases affected transit ridership? Many transit agencies boast increased ridership and immediately point to fuel prices as the cause. What magnitude increase, however, constitutes sufficient change to cite fuel prices as the impetus?

This chapter describes research conducted by the author in 2006 which sought to determine the validity of the claim that rising gasoline prices have fueled an increase in transit usage, and, if such a claim were warranted, to investigate the nature of such a relationship. Monthly ridership counts (unlinked passenger trips) for January 1999 through June 2006 for five large US cities, obtained through APTA, were the primary source of ridership trend information, and fuel price and consumption data were obtained from the US Department of Energy's Energy Information Administration.

4.2 CITIES INVESTIGATED

In selecting cities for evaluation, it was necessary to choose cities with sufficient transit systems in place to give travelers a choice in mode selection (so-called “discretionary users”). If a city, no matter how large or small, has a transit system which does not provide enough coverage or service regularity to prove a viable alternative to driving, it cannot be expected that travelers will switch their mode selection, no matter the expense savings, since such a choice would undoubtedly reduce their mobility.

However, it was also important to the selection that a city not already be so oriented to transit usage that its residents could be labeled “transit-dependent”. In such cities, fluctuating gasoline prices cannot realistically be expected to have a substantial impact upon transit ridership or mode choice. To this end, cities with historically transit-oriented societies, including New York, Boston, and Chicago, were eliminated from consideration.

Ultimately, five large urban areas were chosen for inclusion in this study: Atlanta; Dallas; Los Angeles; San Francisco; and Washington, DC. It is arguable that these cities may, in fact, have large “transit-dependent” populations, but in such cases it is believed that there are enough commuters and other trip-makers entering and exiting the city centers from areas not as transit-dependent.

4.3 BACKGROUND

4.3.1 Transit Ridership Trends

Using time-series analysis and seasonal averages between 1992 and 2001, the Bureau of Transportation Statistics (BTS) provides a visual representation of national seasonal ridership fluctuations, as illustrated in Figure 4.1 (BTS, 2002).

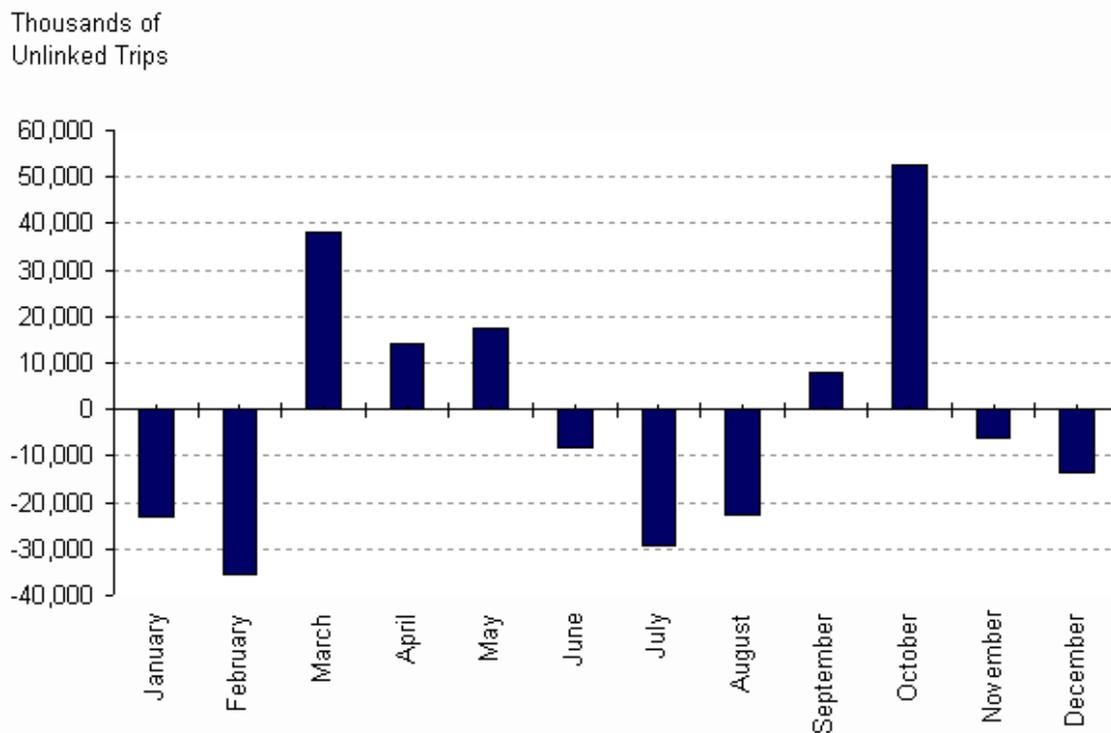


Figure 4.1 Seasonal Fluctuations from Average in Transit Ridership (1992-2001) (BTS, 2002)

Figure 4.1 reflects ten years of national ridership data, including cities across the US in regions with very different weather patterns, as well as cities in the “snow belt”, which experience four distinct seasons. The impact of these seasons can be seen in Figure 4.1; in the milder seasons, spring (March through May) and fall (September through October), ridership tends to be higher than average. In the seasons where it is less pleasant to travel by foot to a transit stop or wait outdoors for the transit vehicle to arrive, winter (November through February) and summer (June through August), transit ridership tends to be lower than average. Also enhancing these seasonal patterns are school and university academic schedules and seasonal migratory populations.

4.3.2 Gasoline Price Trends

It is no secret that fuel prices have risen rapidly in recent years. News agencies now regularly cite the prices of national and local gasoline as part of their normal broadcasts, and various other media have made those prices a conspicuous part of society. The US Department of Energy reports weekly and monthly fuel prices on their website at the national level, for various regions of the nation, and for select large metropolises. As can be seen from Figure 4.2, which depicts these national monthly data between August 1990 and March 2009, prices were relatively stable through the end of 2000, after which they rose quickly and experienced much more prominent fluctuations. Furthermore, prices during the 2005-2008 period were not only much higher than in the past, but also oscillated frequently by more than 50 cents within periods of only a few months. Prices fell precipitously in late 2008 and early 2009 to levels not seen since early 2004, but there

is no indication that they will remain at such levels; in fact, the contrary seems more likely, and as of publication, prices were again on the rise.

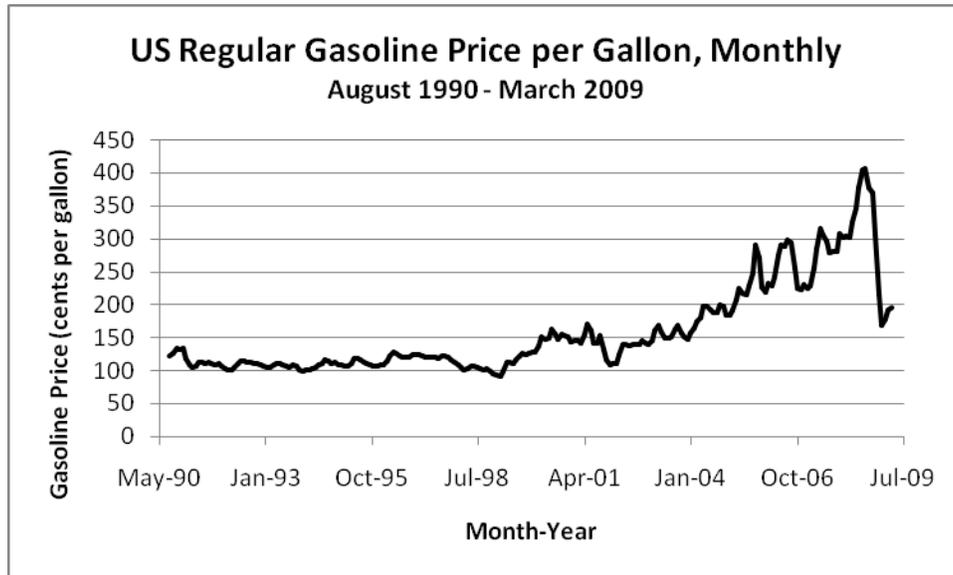


Figure 4.2 US National Monthly Gasoline Price per Gallon, August 1990 – March 2009

4.4 METHODOLOGY AND RESULTS

The modes evaluated in this study include bus (MB), light rail (LR), heavy rail (HR), and commuter rail (CRP). Each city's ridership trends for the available modes were evaluated. The modes for which data were available for each of the five selected cities are as follows:

- Atlanta (ATL): MB, HR
- Dallas (DAL): MB, LR, CRP
- Los Angeles (LA): MB, LR, HR, CRP
- San Francisco (SF): MB, HR, CRP
- Washington, DC (DC): MB, HR, CRP

The modal data for each city are comprised of all such systems operating within the given metropolitan region, as data were available. The research contained herein made use of time series analysis using 12-month moving averages, seasonal indices, and correlation coefficients.

4.4.1 Time Series Analysis

The first step in analyzing the ridership data was to observe the overall trend for the 90 months (January 1999 through June 2006) for which data were available. The data were adjusted using a 12-month moving average to counteract the monthly and seasonal fluctuations in ridership. A trend line was fit to these data using least-squares regression analysis. Most of the data sequences correspond to the averages for July 1999 through December 2005; exceptions are noted.

4.4.1.1 Bus (MB) Mode

Figure 4.3 reveals substantially different ridership growth patterns for the five examined bus systems. Atlanta's bus system shows a fairly steady decline over the period between May 2000 and April 2004, then positive growth through the period centered at January 2005, suggesting that ridership again declined after June 2005. The trend line is decidedly negative with an R^2 value of 0.8015, suggesting that little variability is unexplained by the trend line.

The Dallas bus system plot shows a sharply decreasing ridership trend which suddenly changed to sharply positive at the point centered at March 2003, indicating that ridership began to climb greatly in the months following September 2003. This growth continued through June 2006 at a high rate.

The Los Angeles bus ridership data for the period analyzed had two anomalous points, assumed to be the result of strikes or some other service disruption (these appeared in the HR and LR data sets as well), which were omitted and replaced with interpolated data in Figure 4.3(c), so that the overall trend could be observed. The adjusted data show a general upward trend, although between February 2002 and September 2004 there was a decrease. Since September 2004, ridership has been growing steadily.

The San Francisco data reveal that the system hit its ridership peak at the point centered about May 2001 and has been declining since then. It should be noted that data for the San Francisco Municipal Railway (both MB and LR modes) were either unavailable or too fractured to include in this analysis.

The bus ridership data for Washington, DC indicate general sustained growth in ridership over the period analyzed, despite a slight dip between June 2004 and July 2005; positive growth resumed following July 2005. The trend line fit to these data has a fairly high R^2 value of 0.7303, showing a good fit to the data.

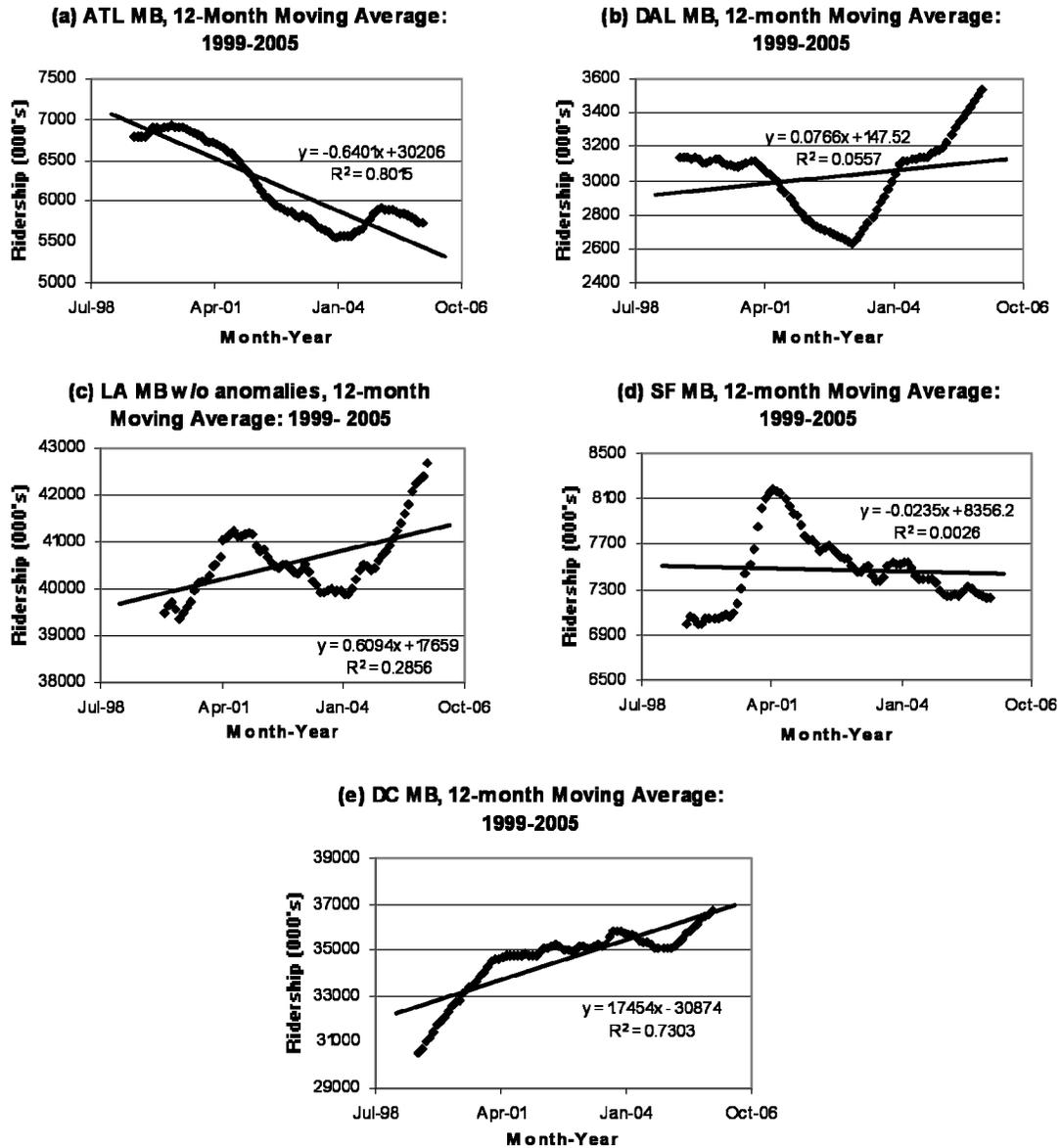


Figure 4.3 (a-e) 12-Month Moving Average Trend, MB mode, (a) Atlanta, (b) Dallas, (c) Los Angeles, (d) San Francisco, (e) Washington, DC

4.4.1.2 Light Rail (LR) Mode

Figure 4.4(a) shows that Dallas' LR system has been experiencing steady slow growth in ridership, when the effect of service expansion is ignored. Between July 2003 and about August 2004, ridership decreased somewhat, but picked up again after August 2004.

The Los Angeles LR system's ridership has grown fairly steadily over the analysis period, with a greater growth rate in the months following February 2005. The R^2 value in Figure 4.4(b) is quite good, 0.9731, showing that the trend line fits the data well and that the system generally gains nearly 580 unlinked passenger trips per month.

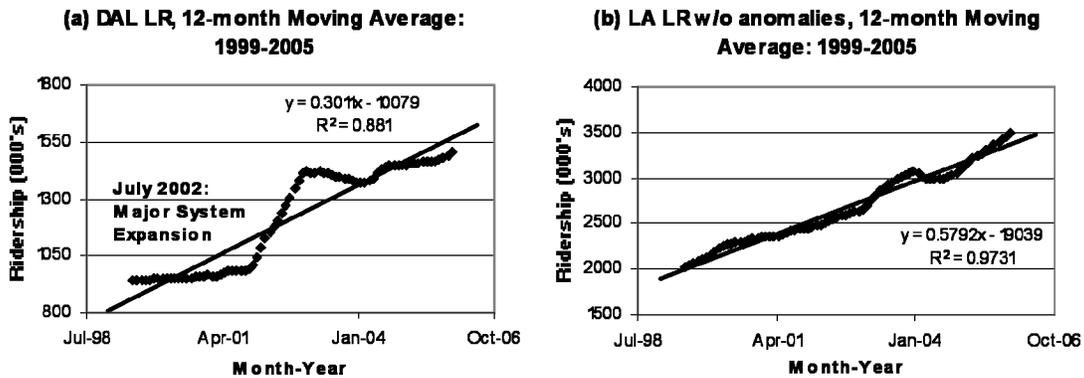


Figure 4.4 (a-b) 12-Month Moving Average Trend, LR mode, (a) Dallas, (b) Los Angeles

4.4.1.3 Heavy Rail (HR) Mode

Figures 4.5(a-d) show the plots of 12-month moving averages for the evaluated HR modes. Like the Atlanta MB data, the Atlanta HR data show a steady fall in ridership, with a slight increase that occurred around June 2004, only to decline again starting May 2005. The R^2 value of 0.8502 shows a good fit with the data.

In Figure 4.5(b), the Los Angeles HR data, adjusted to omit the anomalous points, shows a decline between May 2002 and August 2003, but growing ridership since August 2003. Ridership growth through the end of the analysis period was rapid.

The San Francisco HR data (for the BART system) grew in magnitude between 2000 and early 2002, but declined to a low point attained in June 2003 and rose fairly steadily after that time.

Washington, DC's HR system (METRO) experienced steady growth in ridership at varying rates throughout the period of analysis. The R^2 value of 0.9297 corresponds to a trend line that fits the data well and indicates that the system gains about 1840 new unlinked passenger trips per month.

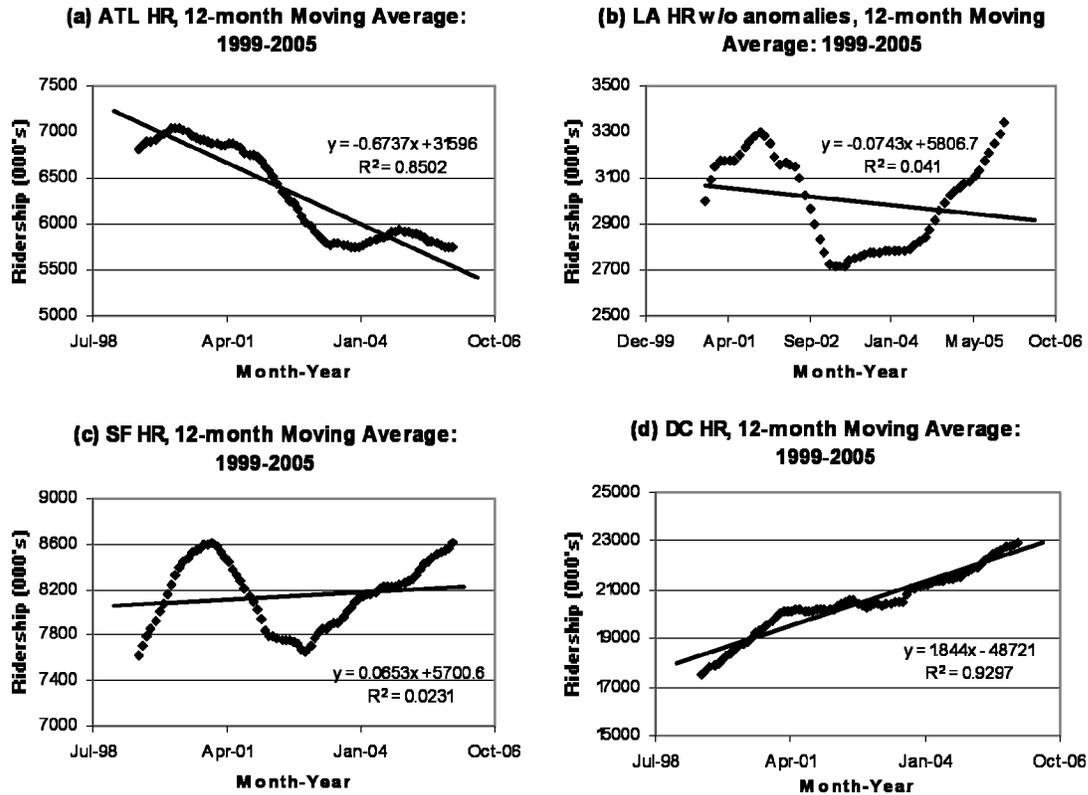


Figure 4.5 (a-d) 12-Month Moving Average Trend, HR mode, (a) Atlanta, (b) Los Angeles, (c) San Francisco, (d) Washington, DC

4.4.1.4 Commuter Rail (CRP) Mode

In Dallas, the CRP system, the Trinity Railway Express, had a major service expansion in December 2001, thus the plotted data points in Figure 4.6(a) begin with the 12-month moving average centered at June 2002. The system had ridership growth after June 2002, but then experienced steadily falling ridership between October 2003 and August 2005, when it began to grow rapidly through the end of the analysis period.

Unlike the other transit modes in Los Angeles, the CRP system there did not have anomalous data points. The data provide a trend with a relatively stable slope, indicating steadily increasing ridership through the analysis period. The R^2 value, 0.9812, shows that the derived trendline equation fits the data points well, and that the system tends to gain approximately 100 new unlinked passenger trips per month.

The San Francisco CRP system, Caltrain, has experienced fluctuations in ridership, reaching a high in September 2001 that decreased continually for many months, attaining a minimum in about February 2004. Since that point, ridership has grown relatively steadily.

For the Virginia Railway Express (VRE), Washington, DC's CRP system, ridership has risen at a steady rate since the beginning of the analysis period, gaining about 73 new unlinked passenger trips each month. Since February 2005, however, ridership has leveled off at about 311,000 trips per month.

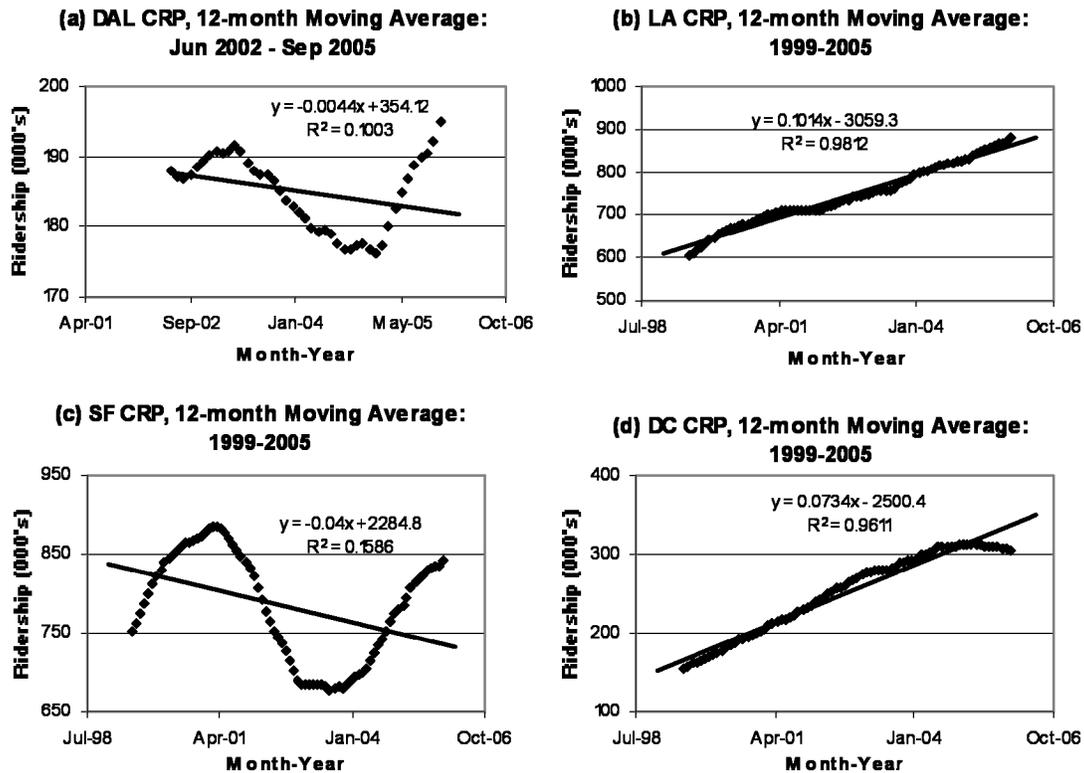


Figure 4.6 (a-d) 12-Month Moving Average Trend, CRP mode, (a) Dallas, (b) Los Angeles, (c) San Francisco, (d) Washington, DC

4.4.2 Seasonal Indices

Using the 12-month moving averages, seasonal indices were developed for each month for each evaluated city's modes, each mode in aggregate form (i.e. the sum of all MB system ridership across the five cities), and values for all modes and cities combined. These indices were developed by dividing the actual monthly ridership values by the corresponding moving average, to find what percentage of the moving average the monthly data point constituted.

In finding the index for a particular month, the median value was used (rather than the mathematical mean) because it proved more accurate, eliminating the effect of strikes or other anomalous data points without requiring use of the interpolated data points (in the case of the Los Angeles data). Table 4.1 provides all city- and mode-specific monthly indices derived in this manner.

While the cities in this study lie in more temperate regions of the US, the impact of seasonal change on their ridership is also apparent. This seasonal change in ridership is displayed in Figure 4.7 through the use of the median-valued seasonal indices for all modes in all five cities. Unlike the plot supplied earlier from BTS, which includes all cities in all climate regions of the US, a drop in ridership during the summer months is not exhibited in Figure 4.7. Although these cities experience seasonal weather fluctuations, they are much less pronounced than in cities

lying farther north; the winter months (November through February) show lower-than-average ridership, while the spring, summer, and fall months (March through October) find higher-than-average ridership. It is hypothesized that while the relatively colder winter weather temperatures have a negative effect on ridership, the residents of these regions are much more sensitive to colder temperatures and more tolerant of the warmer summer weather.

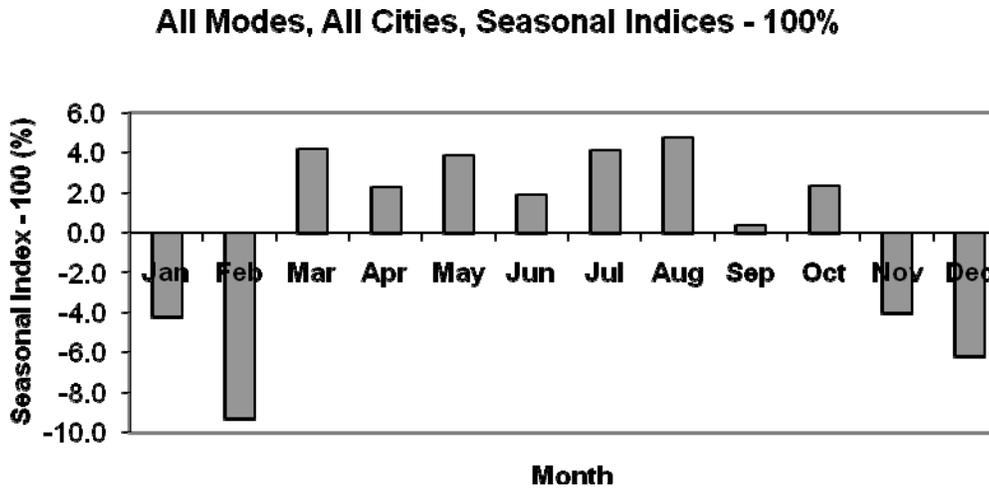


Figure 4.7 Seasonal Index Difference from 100 %; All Modes, All Cities

Table 4.1 Adjusted Seasonal Indices (Median Values), 1999-2005

	Bus (MB)						Heavy Rail (HR)					Light Rail (LR)			Commuter Rail (CRP)					All Modes, All Cities
	ATL	DAL	LA	SF	DC	All MB	ATL	LA	SF	DC	All HR	DAL	LA	All LR	DAL	LA	SF	DC	All CRP	
Jan	94.3	99.0	96.4	99.7	92.8	96.4	95.5	97.3	95.4	92.7	95.0	97.2	98.0	97.9	101.1	98.2	95.8	98.2	98.0	95.9
Feb	96.6	92.1	90.6	91.9	90.0	90.4	89.5	92.8	92.0	89.4	90.4	91.4	91.0	91.2	93.1	93.6	89.9	92.6	91.5	90.7
Mar	101.8	100.6	103.1	100.9	104.5	104.0	102.7	103.6	104.0	106.3	105.7	104.6	104.4	103.6	113.4	108.0	101.1	109.0	105.7	104.3
Apr	101.7	101.5	103.4	95.3	105.1	102.0	97.6	99.9	100.1	107.5	103.7	99.2	101.8	102.4	100.1	101.9	103.2	104.0	103.6	102.4
May	100.1	101.2	104.0	102.3	102.9	103.8	101.0	104.6	103.1	102.9	102.1	102.2	103.9	103.8	91.4	103.3	106.9	104.5	104.2	103.9
Jun	100.0	94.3	100.1	98.0	106.0	100.0	100.2	105.6	101.7	108.1	106.2	99.4	102.5	101.7	97.9	103.7	104.1	104.9	103.4	101.9
Jul	97.7	95.5	103.7	92.1	107.2	103.4	106.7	114.0	100.6	109.3	106.4	101.6	105.5	103.5	104.2	99.2	103.6	101.1	102.6	104.2
Aug	102.9	104.0	104.9	104.3	103.2	104.5	108.3	114.7	101.7	102.0	102.5	103.2	106.2	108.1	103.8	104.2	107.0	104.2	105.0	104.8
Sep	102.9	105.4	99.5	102.3	99.3	101.0	100.9	99.7	102.7	96.3	99.2	101.0	97.8	98.8	100.8	97.4	101.0	97.9	98.4	100.4
Oct	107.6	113.2	102.1	115.1	104.9	103.1	107.7	82.5	104.8	103.4	102.8	105.5	98.8	99.8	104.0	104.5	104.5	105.8	104.8	102.4
Nov	98.4	98.9	96.8	101.6	93.6	95.9	97.3	90.1	96.7	92.3	94.1	100.2	94.4	95.1	95.0	95.4	94.8	92.2	94.6	95.1
Dec	95.9	94.2	95.5	96.6	90.4	95.6	92.5	95.2	97.1	89.9	91.9	94.6	95.8	94.3	95.4	90.6	88.0	85.6	88.5	94.0

4.4.3 Correlation between Ridership Data and Fuel Prices

Using correlation coefficients, this research sought to determine how well the ridership and fuel prices varied together in the period from January 2004 to June 2006. Figure 4.8 (a-b) provides two sample plots of ridership and fuel price, the first for the Dallas MB system and the second for Washington, DC's HR (METRO) system. Examination of these plots reveals interesting correspondence between the price data and ridership data. In many locations, the data fluctuations appear to vary together, particularly in the 2004-2006 data points.

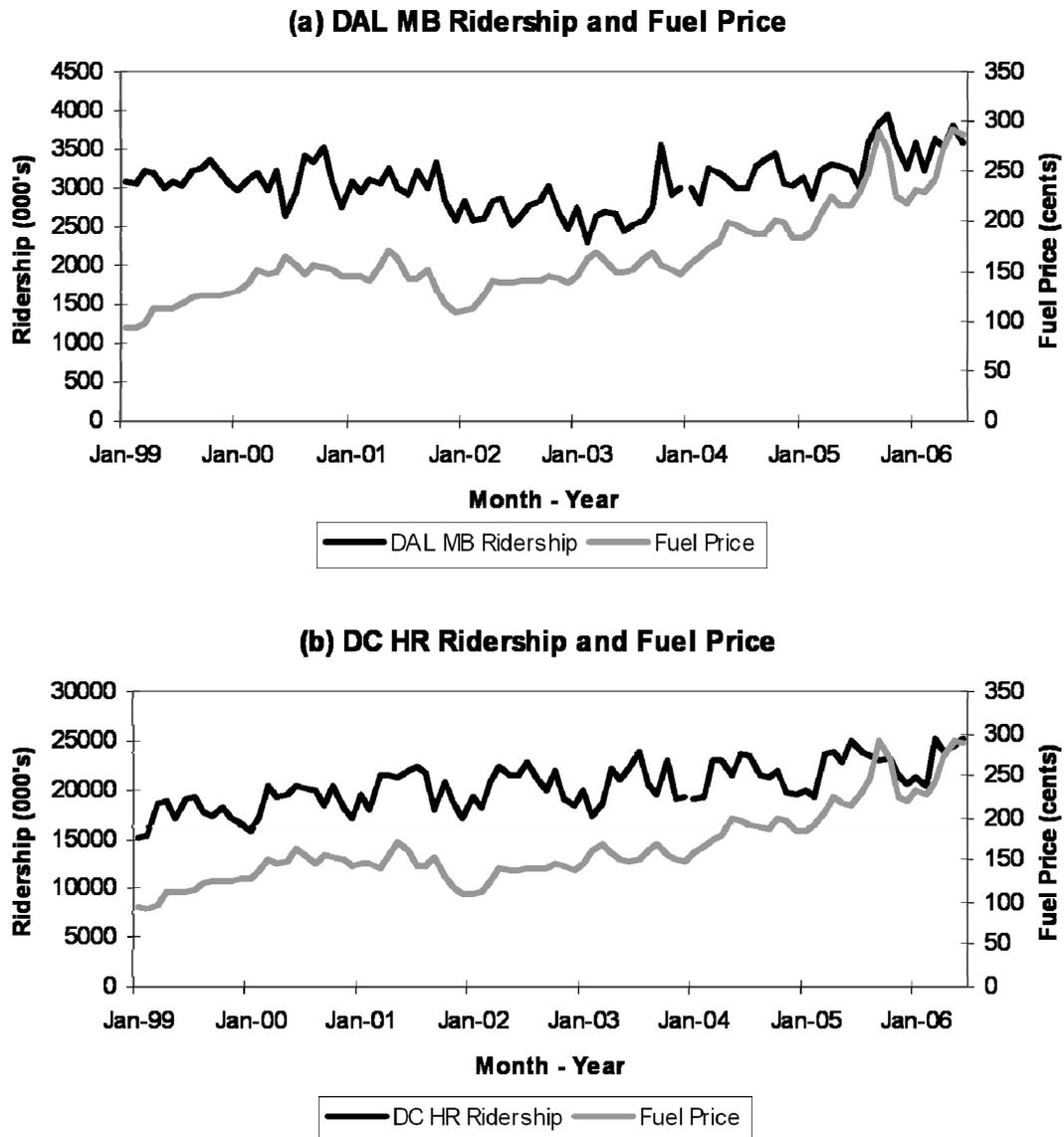


Figure 4.8 (a-b) Ridership and Fuel Price, (a) Dallas MB, (b) DC HR

Finding how well the two variables varied together should reveal clues as to how much growth in ridership may be attributable to fuel price increases. Thus, in calculating the correlation coefficients, fuel price was treated as the independent, or observed (X), variable and ridership

was treated as the dependent, or predicted (Y), variable. Table 4.2 provides the results of the correlation coefficient analysis.

It may also be observed from the plots like those in Figure 4.8(a-b) that there may be a lag period between fuel price increases and what appear to be corresponding ridership increases, perhaps due to new transit riders' reluctance to react immediately to the fuel price increases. To determine the validity of this observation and find how long it takes riders to respond to increasing fuel prices, the fuel price data were shifted forward by single-month increments from one to five months.

However, only the one- and two-month shift cases for the Dallas LR system produced better results than the original un-shifted data points. It may be the case that the shifted correlation values do not capture the behavioral fluctuations accurately; reactions to rising prices may generate a different effect than falling prices, or gradual desensitizing to stable, though high, prices. A better methodology for determining the existence and magnitude of any behavioral lag may be more appropriate.

For the original (un-shifted) data sets, all except the San Francisco MB produced positive correlation coefficients and thus it was desired to know the significance of the computed correlation coefficients. Finding this significance was accomplished using Student's T statistic and a significance α -level of 0.05. Having 28 degrees of freedom (30 monthly data points minus two), the corresponding t -value is ± 2.048 .

The null hypothesis (H_0) was that the population showed zero correlation ($H_0: \rho = 0$) and the corresponding alternate hypothesis, H_A , that the data had some non-zero correlation ($H_A: \rho \neq 0$). The test statistic used for this test is computed as

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}} \quad (4.1)$$

Using this test statistic by plugging in the calculated correlation coefficients for r , and $n = 30$, the obtained value was compared to the significant t -value of ± 2.048 . Any test statistics with absolute values greater than 2.048 led to a rejection of the null hypothesis with 95% confidence, and a conclusion that statistically significant correlation exists between the ridership data and the fuel price data.

Table 4.3 provides the results of this statistical test. The bold-faced values indicate a rejection of the null hypothesis, or, in other words, transit systems showing non-zero correlation between ridership and fuel price. It is notable that only the San Francisco MB system shows a negative correlation (statistically insignificant) with fuel price; all others are positive. However, the Atlanta MB and HR systems and the DC CRP system do not show statistically significant correlation. All the aggregate mode values (those in which data for all systems of that mode type are summed) display significant correlation with the fuel price data. All other city modal data show statistically significant correlation; the greatest significance is shown in the Dallas MB, Los Angeles LR and HR, and the San Francisco CRP systems. The aggregated LR and CRP modes display highly statistically significant correlation as well.

These results suggest that rising fuel prices have, in fact, played a role in encouraging transit usage in the historically auto-oriented cities analyzed here. In general, LR and CRP system ridership appear to exhibit the greatest correlation to fuel price, implying that as fuel prices increase, potential LR or CRP passengers are perhaps more reactionary to price increases. Heavy rail is generally the third-selected of the four analyzed aggregate modes, having the next-greatest statistical significance. However, the aggregated HR correlation value is depressed by the inclusion of the Atlanta data. Bus passengers (with the exception of the Dallas system and Los Angeles systems) appear to react to rising fuel prices the least. This effect may be due to the demographic characteristics of bus passengers or average trip lengths.

It may be argued that these correlation coefficients capture the effects of influences other than fuel price. This is a valid argument; however, other influences may be grouped into one of two categories: supply factors and demand factors. On the supply side, we have aspects of the transit service itself, such as service expansions or disruptions. Also included in this category are fare increases. In the five cities evaluated, there is generally one transit agency that comprises the bulk of the data. These agencies were queried about fare increases during the analysis period. The Atlanta MARTA system and Dallas DART systems had no fare increases during the period 2004 to present, while the San Francisco BART and Los Angeles MTA implemented fare increases on January 1, 2004. BART also had a Consumer Price Index-based 3.7 percent increase and ten-cent capital surcharge added to its fare structure on January 1, 2006, constituting a minimal increase. The DC METRO system had a slight fare increase in June 2004. Thus, no system had a sizeable increase that would be believed to effect ridership detrimentally. Additionally, the research team is unaware of any substantial service expansions or reductions during the January 2004 – June 2006 analysis period.

In the other category, demand factors, it is believed that, because the analysis period is relatively short, only 30 months, any economic factors that may affect demand are minimized. Environmental influences are minimized through the selection of cities with ridership patterns that are less affected by seasonal changes.

4.4.4 Empirical Relationships between Fuel Price Change and Transit Demand

For those modes with statistically significant correlation coefficients, this research attempted to discern basic empirical relationships between fuel price and transit demand, or the percent change in ridership for a one percent change in fuel price. These relationships were obtained by analyzing observed data and thus should not be confused with or misinterpreted as elasticities, which are today derived by more theoretical means.

To accomplish this goal, the monthly percent changes in ridership were plotted against the corresponding percent change in gasoline price. The slopes of the corresponding trend lines are provided in Table 4.3. While the R^2 values on the trend lines were rather low (most on the order of 0.10), the lines tended to fall in the first and third quadrants of the coordinate system, and most passed through or very near the origin.

As can be seen from Table 4.3, the HR and CRP modes enjoy the greatest values (0.2653 and 0.2726, respectively), while LR has a substantially lower value (0.0665) than the other evaluated rail modes. This suggests that although there is high correlation between fuel price and LR

ridership, ridership fluctuates at a much lower rate on LR systems than on other modes. Whereas the HR and CRP modes garner about 0.27 percent more riders for every one percent increase in fuel price, LR mode ridership increases by only 0.07 percent. The MB systems analyzed have higher values than LR, on the same order as those of the HR and CRP systems. Overall, all calculated values were positive, and the general relationship between fuel price and transit demand appears to be 0.2379.

As an extension to finding these relationships, plots of percent change in ridership were set against the actual change in fuel price. The slope values found in this manner are also located in Table 4.3. The relationships, expressed in this alternate form, show similar correspondence to the standard relationships, with CRP and HR ridership being most influenced by increases in fuel price and LR being least influenced. The MB mode ridership shows varying levels of impact by fuel price, although the Dallas bus system is an exception to this generalization. For the aggregate model which contained data for all cities and all modes, this value constituted an approximate 0.09 percent change in ridership for each additional cent of fuel price.

These findings may have important implications for transit agencies. While all the modes showed correlation between fuel price and ridership, some displayed higher correlation than others. After observing the correlation values, it is necessary to then find the corresponding empirical relationship value. In doing this, one can see that although a particular system may have high correlation, the relationship itself may not be great. For instance, the LR systems show highly statistically significant correlation, but the relationship value reveals that ridership is not changing with fuel price as strongly as other modes.

This result brings into question the matter of resource allocation. If transit operators were to track data for their own systems in this manner, it may help them better determine to which modes they should allocate their scarce resources. As an example, if an agency manages LR and HR systems, knowing from the correlation coefficient values that their potential riders are sensitive to rising fuel prices would aid them in anticipating ridership increases. However, knowing the nature of the relationship between fuel price and demand through the empirical relationships could enable them to better respond to demand changes. Based on the findings in this research, an agency would likely choose to allocate more resources to the HR mode than to the LR mode in order to better serve their constituents, since the magnitude of the HR response (shown in the empirical relationship values) is greater than that of the LR response.

The magnitude of the empirical relationships may underscore differences in service structure inherent in the modes. Characteristics of the modes themselves play a role in service quality, particularly with respect to accessibility and reliability. Bus systems are very flexible but not known for their reliability or timeliness, while rail modes, with their fixed guideways, are less flexible but reliable. An exception to the reliability within rail modes are light rail systems running in mixed traffic. Figure 4.9 provides a graphical representation of the spectra of transit mode accessibility/flexibility and reliability. For instance, while bus systems are flexible and offer wide service coverage, they are typically not the most reliable as far as schedule, nor are they the most comfortable of the modes. Light rail, it can be argued, is a step up from bus, offering greater comfort and improved speed, but because it still shares guideway in some locations with automobiles, reliability is decreased. As examples, the Dallas system shares 1.5

miles of its 45-mile system with automobiles in downtown Dallas, even if only at intersections. The Los Angeles system, by comparison, shares approximately 35 percent of its guideway with autos.

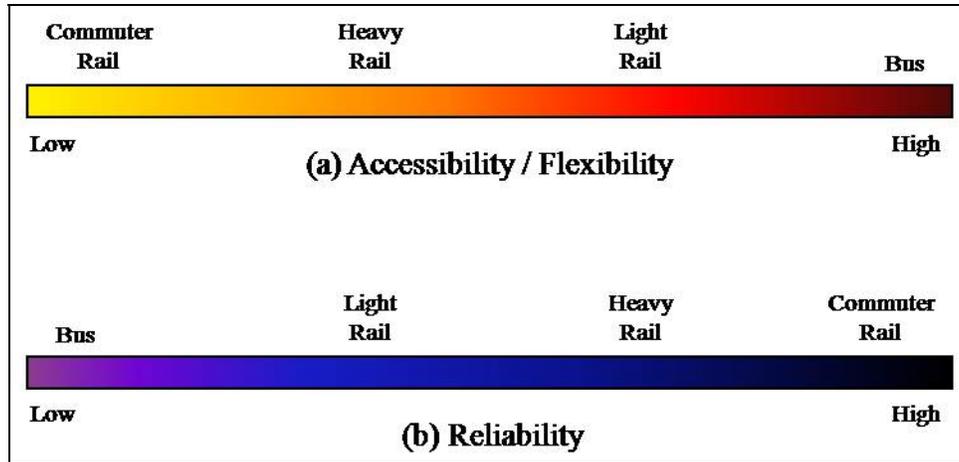


Figure 4.9 Spectra of (a) Accessibility / Flexibility and (b) Reliability for Selected Modes

Those systems with the highest correlation and empirical relationships include the HR and CRP systems. The implications here are that riders switching from auto mode value comfort, speed, and reliability when making their modal choice. The drawbacks of these modes are their limited coverage and accessibility.

The exception to the generalizations drawn in this study for CRP systems is the Virginia Railway Express, the DC CRP system. However, its service routes closely parallel the DC HR routes, except far outside the city. Given that this mode is competing with the DC HR for passengers, it is not surprising that its correlation is less than that of similar CRP systems.

Table 4.2 Significance of Calculated Correlation Coefficients

	Motor Bus (MB)						Light Rail (LR)			Heavy Rail (HR)					Commuter Rail (CRP)					All Modes, All Cities
	ATL	DAL	DC	LA	SF	All MB	DAL	LA	All LR	ATL	DC	LA	SF	All HR	DAL	DC	LA	SF	All CRP	
Computed r-value (Correlation Coefficient)	0.344	0.794	0.521	0.715	-0.029	0.597	0.633	0.797	0.823	0.117	0.605	0.800	0.703	0.659	0.534	0.038	0.688	0.844	0.770	0.665
Test Statistic (Reject H ₀ if >2.048 or <-2.048)	1.937	6.910	3.229	5.408	-0.156	3.934	4.328	6.992	7.663	0.621	4.023	7.044	5.233	4.632	3.341	0.201	5.023	8.320	6.384	4.716

Table 4.3 Empirical Relationships between Fuel Price Change and Transit Demand

	Motor Bus (MB)				Light Rail (LR)			Heavy Rail (HR)				Commuter Rail (CRP)				All Modes, All Cities
	DAL	DC	LA	All MB	DAL	LA	All LR	DC	LA	SF	All HR	DAL	LA	SF	All CRP	
% change in ridership for a 1% increase in fuel price	0.5404	0.3097	0.2229	0.2439	0.1058	0.0582	0.0665	0.4043	0.1053	0.2270	0.2653	0.4923	0.2131	0.3735	0.2726	0.2379
% change in ridership for a 1¢ increase in fuel price	0.2330	0.1203	0.0824	0.0939	0.0407	0.0135	0.0197	0.1620	0.0312	0.0948	0.1021	0.1989	0.0790	0.1456	0.1026	0.0916

4.5 CONCLUSIONS

The research presented here, conducted in 2006, found that of the five cities analyzed, most of their transit systems experienced ridership growth in the months following early 2004. Exceptions to this growth include the Atlanta bus and heavy rail systems and the San Francisco bus systems, which saw declining ridership.

Using time series analysis, seasonal indices, and correlation coefficients, ridership trends were evaluated and compared with corresponding national fuel prices for individual modes in each city and the aggregation of each mode. With the exclusion of the Atlanta bus and heavy rail systems, the San Francisco bus system, and the Washington, DC commuter rail mode (Virginia Railway Express), this research found statistically significant correlation between ridership and fuel prices for all evaluated systems, suggesting that fuel price increases have, in fact, played a role in encouraging transit use in historically auto-oriented American cities. The most significant correlation, on a system basis, appears in the San Francisco heavy rail and commuter rail systems, the Los Angeles bus and heavy rail systems, and the Dallas bus system.

On an overall modal basis, light rail and commuter rail system ridership appear to exhibit the greatest correlation to fuel price, implying that riders of these modes react more to fuel prices than patrons of other modes, although the systems analyzed in this research vary considerably in their service characteristics. Bus passengers (with the exception of the Dallas and Los Angeles systems) appear to react to rising fuel prices the least.

The empirical relationships between fuel price and transit demand were evaluated for those modes showing statistically significant correlation, and these relationships appear to be on the order of 0.24. When converted to percent change in ridership for a one-cent increase in fuel price, the average effect is approximately 0.09 percent.

These findings may have implications for transit agencies in the matter of resource allocation. The correlation values show how reactionary riders are to fuel price, but the empirical relationships indicate the magnitude of that reaction.

Chapter 5 commences the forecasting model building, based in part on the findings from the research presented in this chapter.

Chapter 5: Data Used in Ridership Modeling and Issues in Time Series Analysis

5.1 OVERVIEW

The remainder of this work comprises the research, data treatments, and modeling conducted in developing a transferable short-term transit ridership forecasting methodology, incorporating, among other variables, a means of measuring the effect of fuel price on transit demand.

Time series data from the period January 2002 to December 2007 were employed to build and calibrate the forecasting model. These data included ridership information as well as time series data pertaining to system operating characteristics, among other data types. This chapter describes the data available for analysis and how the data were obtained. As will be discussed further in Chapter 9, model validation was performed following model development using the same time series data types for the six-month period from January through June of 2008.

Special issues inherent in analyses of time series data are also addressed in this chapter, including collinearity, non-stationarity, and heteroscedasticity, and the means by which the dependent variable was transformed to offset these issues. The reasons for exclusion of some public transportation systems from treatment and evaluation are also outlined.

5.2 DATA SOURCES

In compliance with the forecasting concerns highlighted in Chapter 3, particularly that regarding accessibility to and availability of modeling input, all data used in this proposed model are readily available to transit planners, either internally from the agency itself or directly from federal internet databases.

Data for the model were obtained from several sources, including the Federal Transit Administration's National Transit Database (NTD), personal correspondence with the American Public Transportation Association (APTA) for fare histories, and the Bureau of Labor Statistics (BLS) for monthly Consumer Price Indices (CPI) and fuel price.

5.2.1 Data and Variables Available in the National Transit Database

Using the sources listed, a variety of data were available, particularly from the NTD. Brief descriptions of these data follow.

5.2.1.1 Unlinked Passenger Trips (UPT)

The monthly unlinked passenger trip (UPT) counts for each evaluated system make up the dependent variable of the model, to be predicted in the forecasts developed herein. An unlinked passenger trip is defined as one segment of a transit passenger's total trip and does not include transfers between vehicles or modes. For instance, if a passenger caught a bus near one endpoint of his or her journey, transferred to a second bus, and then transferred to a rail system to reach the final destination, such a sequence would consist of three unlinked passenger trips.

No public transportation agencies currently gather data for linked trips or report statistics thereon, as the technology for collecting information on linked trips is not in place. What data exist regarding linked trips are generated through special network demand origin-destination studies and thus are synthetic, or artificial, data. Although it is conceivable that unlinked passenger trips could increase while the count of linked trips remained constant, it is extremely unlikely as travelers tend to view transfers (linkages) unfavorably and will make trips consisting of as few segments as possible. Thus unlinked passenger trips, as the only available patronage data type, are also well-suited for measuring growth in overall ridership.

5.2.1.2 TRS_ID

These four-digit identification numbers, assigned by the Federal Transit Administration, serve as an agency's unique identifier; the leading value of the number corresponds to the region of the country in which the agency is located. The ten regional assignments are as follows:

- Region 0: Pacific Northwest
 - Alaska, Idaho, Oregon, Washington
- Region 1: New England
 - Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
- Region 2: Northeast
 - New Jersey, New York
- Region 3: Mid-Atlantic
 - Delaware, District of Columbia, Maryland, Pennsylvania, Virginia, West Virginia
- Region 4: Southeast
 - Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, Puerto Rico, South Carolina, Tennessee
- Region 5: North Central
 - Illinois, Indiana, Michigan, Minnesota, Ohio, Wisconsin
- Region 6: South Central
 - Arkansas, Louisiana, New Mexico, Oklahoma, Texas
- Region 7: Mid-West
 - Iowa, Kansas, Missouri, Nebraska
- Region 8: Mountain West
 - Colorado, Montana, North Dakota, South Dakota, Utah, Wyoming
- Region 9: West
 - Arizona, California, Hawaii, Nevada

5.2.1.3 *Urbanized Area (UZA) and Urbanized Area (UZA) Name*

The UZA designations contained in the NTD correspond to the US Census Tracts in number and name. These values were used to match fuel prices with transit systems (see Section 5.2.2.1).

5.2.1.4 *MODE*

The NTD data supply information for numerous modes, including automated guideway (AG), cable car (CC), commuter rail (CR), demand response (DR), ferry boat (FB), heavy rail (HR), inclined plane (IP), light rail (LR), motor bus (MB), monorail (MO), trolley bus (TB), and van pool (VP).

In this report, the modes with widest implementation and heaviest usage were considered. Motor bus and trolley bus were combined into a “BUS” category, the difference between the two modes being their means of propulsion; motor buses are those involving some type of autonomous engine contained within the vehicle; trolley buses gain power from connection to an overhead electrical catenary. Also modeled were light rail (LR), heavy rail (HR) (subway), and commuter rail (CR) systems.

After accounting for systems with incomplete or inconsistent datasets, 215 bus systems (212 MB, 3 TB) were included in the final analysis, as were 17 light rail, 10 heavy rail, and 12 commuter rail systems, for a total of 254 public transportation systems.

5.2.1.5 *Type of Service (TOS)*

This information pertains to further differentiation of mode, representing how the systems are managed. In many cases, the transit systems are operated directly by the agencies themselves—these systems are designated “Directly Operated” (DO). In other cases, the system may be fully contracted out to a sub-contractor, or the agency may contract out a subset of their service; these systems are designated “Purchased Transportation” (PT). In many cases, the PT aspect of an otherwise DO system may indicate a special service operated for the benefit of some sub-section of the population, or comprise a group of such services.

5.2.1.6 *Vehicle Revenue Miles (VRM)*

Describing the amount of service offered, a vehicle revenue mile consists of one vehicle operating in revenue service for one mile. Vehicle revenue miles tend to meet with disfavor in measuring service when compared with the vehicle revenue hour (see Section 5.2.1.7), because the number of vehicle revenue miles served by an system depends in large part on the operating speed of the vehicles in service, which can vary significantly along the length of a route and by time of day.

5.2.1.7 *Vehicle Revenue Hours (VRH)*

Vehicle revenue hours are a secondary means of describing the quantity of service supplied. One vehicle revenue hour constitutes a single transit vehicle operating in revenue service for one hour. As mentioned in Section 5.2.1.6, the vehicle revenue hour is favored over the vehicle revenue mile for its consistency in measuring revenue service.

5.2.1.8 *Vehicles Operated in Maximum Service (VOMS)*

As demand for public transportation changes during the course of a day, more or fewer vehicles will be required in order to meet demand. The number of vehicles operated in maximum service gives a measure of fleet size by indicating the greatest number of vehicles deployed during maximum service (usually the peak morning and evening commuting hours) to meet demand.

5.2.2 Additional Data and Variables from Other Sources

Seeking additional information outside the NTD to supplement system-specific characteristics led to a variety of data from several sources.

5.2.2.1 *Fuel Price (FUEL)*

Fuel price data were obtained from the Bureau of Labor Statistics (BLS), which tracks average price data for numerous commodities. The values obtained from the BLS website represent the per-gallon prices for unleaded regular gasoline on several bases, which were applied as appropriate based on the UZA information supplied by the NTD (see Section 5.2.1.3).

There are 14 urbanized regions with specific price data in the BLS. When possible, fuel prices from these 14 regions were assigned to the evaluated systems. These regions include:

- New York-Northern New Jersey-Long Island, NY-NJ-CT-PA
- Philadelphia-Wilmington-Atlantic City, PA-NJ-DE-MD
- Boston-Brockton-Nashua, MA-NH-ME-CT
- Chicago-Gary-Kenosha, IL-IN-WI
- Detroit-Ann Arbor-Flint, MI
- Cleveland-Akron, OH
- Washington-Baltimore, DC-MD-VA-WV
- Dallas-Fort Worth, TX
- Houston-Galveston-Brazoria, TX
- Atlanta, GA
- Miami-Fort Lauderdale, FL
- Los Angeles-Riverside-Orange County, CA
- San Francisco-Oakland-San Jose, CA
- Seattle-Tacoma-Bremerton, WA

When a transit system did not fall into one of these 14 metropolises, it was still possible to assign fuel prices corresponding to city size and national region, as defined for the price data according to the BLS. Three population-based city sizes were available for four regions: Northeast, South, Midwest, and West. City size “A” indicates those cities having populations greater than 1,500,000; city size “B/C” corresponds to cities with populations between 50,000 and 1,500,000; and city size “D” represents cities with fewer than 50,000 inhabitants. Using Census population data and regional definitions as defined by the US Department of Labor, fuel prices were matched in the time series with the appropriate UZA and transit system data.

5.2.2.2 Consumer Price Index (CPI)

Inclusion of the CPI in analysis was intended as a measure to track changes in the national economy. The CPI is a free, easily-available data type corresponding to the national economic pulse and chosen for the reliability of its availability from and derivation by federal sources. Other measures of economic activity, such as the Consumer Sentiment Index or Consumer Confidence Index, were expensive to purchase. Within the data available for the CPI, the national series for “All Urban Consumers” was selected.

5.2.2.3 Weekdays per Month (WEEKDAYS)

Most trips made by public transportation occur on weekdays as work commute trips. Therefore, accounting for ridership variability stemming from differing numbers of weekdays in a month, the *WEEKDAYS* variable counts the number of weekdays in a given month, excepting the New Year’s Day, Thanksgiving, and Christmas holidays.

5.2.2.4 Fares (FARE)

Historically, changes to transit fares have brought on corresponding change in patronage. Increases in fares tend to bring about a decline in ridership. The magnitude of this relationship has been a subject of debate for many years (see Goodwin, 1992). In this research, measuring this relationship or elasticity was not the goal; the purpose of including a variable related to fare was merely to identify a potential stimulus for ridership change.

One year of fare data were purchased from the American Public Transportation Association (APTA), and remaining years’ data were obtained via personal correspondence. The only national agency found to record fares was APTA, which is comprised of member transit agencies and collects data only from these members. Hence, a drawback of these data was that not all systems in the FTA database had available fare information from APTA. In the end, 82 of a total 215 bus systems had reliable fare change information provided, as did 14 of 17 light rail, seven of ten heavy rail, and six of 12 commuter rail systems.

Due to discrepancies in reporting or recording errors, the usefulness of the fare data was minimized and ultimately led to inclusion of a binary variable indicating whether there had been a fare change or not. All fare changes implemented were increases to fare. Some fare increases were large compared to the previous fare; others were incrementally small. However, although some of the fare increases may have been as much as 200 percent, fares are nationally very low and therefore even such a doubling of fare does not equate to a large out-of-pocket cost (i.e. increasing fare from \$0.50 to \$1.00 or \$1.00 to \$2.00). The means by which this variable was assigned are described in further detail in Section 7.3.6.

5.3 RESOLVING STATISTICAL ISSUES IN RIDERSHIP DATA

Due to the nature of time series data, several inherent properties usually exist that introduce problems when attempting to model and forecast the data.

5.3.1 Collinearity

When using independent variables to predict a dependent variable, one must ascertain that the independent variables are, in fact, independent of each other, so that the effect of one independent variable is not masked by a secondary independent variable. When two independent variables vary together through time, those variables are said to be collinear.

In the data obtained for this analysis, vehicle revenue miles (*VRM*) and vehicle revenue hours (*VRH*) are collinear within each system. Dividing *VRM* by *VRH* produces a theoretical system operating speed, which will be essentially constant throughout the time series, and thus *VRM* is always proportional to *VRH* by the same ratio.

For this reason, it is necessary to eliminate one of these two variables from model building. *VRM* was selected for removal, so that *VRH* could be retained in the model. Vehicle revenue hours are generally considered a more reliable measure of service offered, since vehicle revenue miles are affected by operating speed, which can change during the course of a day, depending on roadway congestion and demand for service.

5.3.2 Non-stationarity and Heteroscedasticity

One of the primary problems with time series data is the necessity to verify (1) that as the data progress through time, values are stationary about the mean and (2) that the variance of the data does not change with time (the data are homoscedastic).

The most common means to deal with non-stationarity and heteroscedasticity is to transform the original data series in a way that yields a constant mean and variance. To deal with heteroscedasticity, an oft-used solution involves logarithmically transforming the data to achieve stability in the variance throughout the time series (Brockwell and Davis, 2002). An appropriate transformation to resolve non-stationarity is to difference the data series and use these differences rather than the original series to develop models and create projections (Makridakis *et al.*, 1998). These two transformations were combined to establish stationary, homoscedastic time series for all 254 transit ridership datasets.

5.3.3 Final Definition of Dependent Variable, *PDLOGUPT*

In following the appropriate treatments of the datasets to create suitable series for modeling, logarithms (base-10) were taken of each data point and first differences calculated of these logarithms, as in Equation 5.1.

$$PDLOGUPT_t = \frac{\log Y_t - \log Y_{t-1}}{\log Y_{t-1}} * 100\% \quad (5.1)$$

The models developed using these transformed data thus predict a change in the logarithm of ridership, which can easily be converted back to a comprehensible number of unlinked passenger trips. To facilitate comparison of trends among public transportation systems having vastly

different ridership magnitudes, the differences were further transformed to reflect percent changes in logarithmic values of unlinked passenger trips.

As a graphical example, consider the time series of ridership for the University of Michigan bus system in Ann Arbor, Michigan (MB 5158 DO), depicted in Figure 5.1. These data exhibit both non-stationarity in the mean and heteroscedasticity. The mean climbs as the series progresses through time and the seasonal fluctuations become more extreme as the magnitude of the series increases.

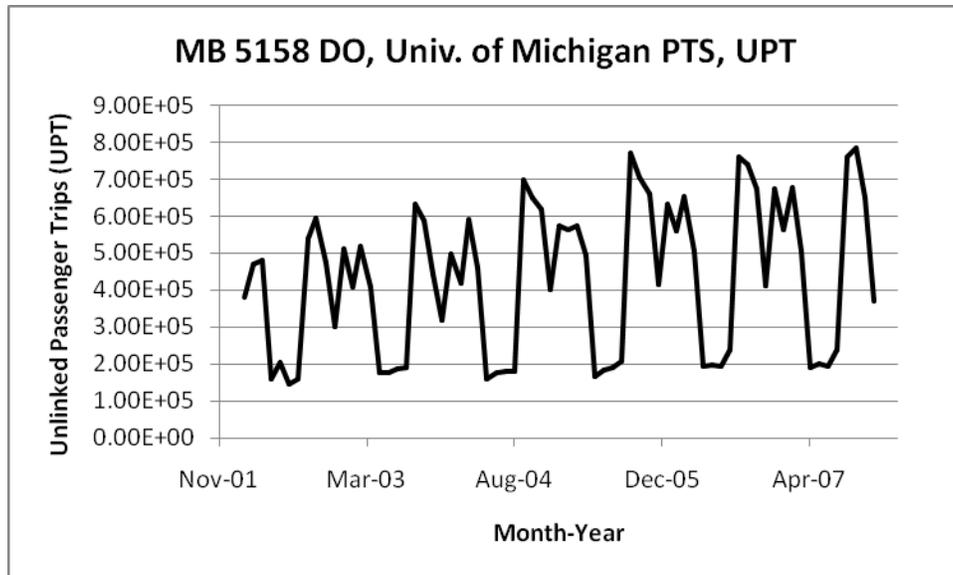


Figure 5.1 Time Series of Unlinked Passenger Trips (UPT), MB 5158 DO

However, transforming the original UPT time series logarithmically and differencing these log values produces the time series in Figure 5.2. As this figure shows, the transformed data series is now stationary with a mean of zero, and although seasonality is still apparent, the month-to-month fluctuations no longer grow with time or the changing magnitude of the series, providing homoscedasticity in the series.

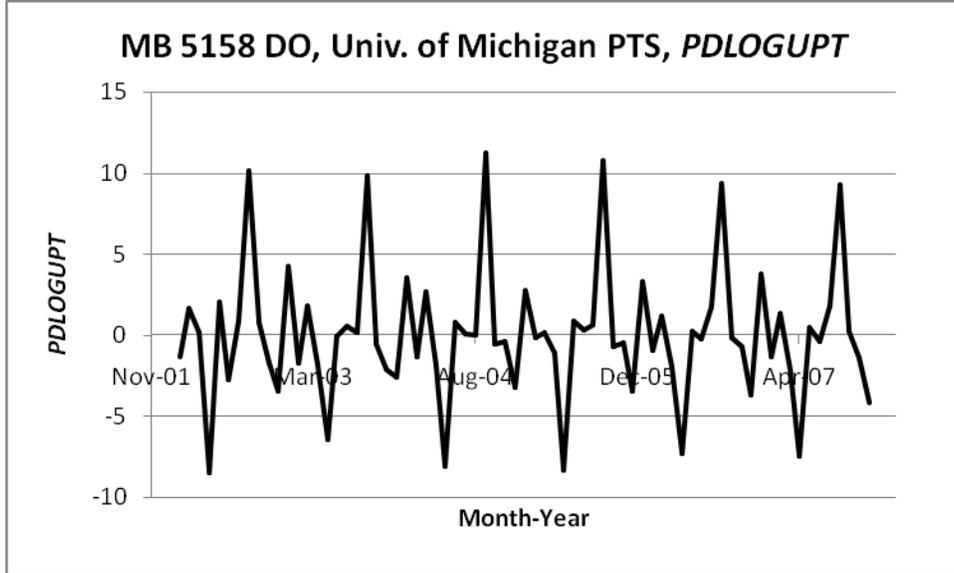


Figure 5.2 Transformed Time-Series of *PDLOGUPT*, MB 5158 DO

These transformations using logarithms and differencing were conducted on each of the final 254 transit systems included in this study.

While transforming the data in this way accomplished stationarity in the mean and variance, conditions necessary for successful time series forecasting, it makes direct interpretation of later analyses difficult. Working backwards from the transformation in Equation 5.1 yields the expressions in Equations 5.2 and 5.3:

$$PDLOGUPT_t = \frac{\log Y_t - \log Y_{t-1}}{\log Y_{t-1}} = \frac{\log Y_t}{\log Y_{t-1}} - 1 = (\log_{Y_{t-1}} Y_t) - 1 \quad (5.2)$$

$$PDLOGUPT_t = (\log_{Y_{t-1}} Y_t) - 1 \quad (5.3)$$

Based on these equations, we see that the final value derived for $PDLOGUPT_t$, in addition to representing the percent change in the logarithm of ridership, also equates to one less than the base- Y_{t-1} logarithm of Y_t . As such, it makes straightforward calculation of elasticities or similar evaluations challenging. However, understanding the directional effects of calculated parameters is still possible and the analyses in following chapters make use of this property.

5.3.4 Data Reporting Issues

In several cases, although the NTD supplied data for a particular system, further investigation of that system may have warranted its exclusion from continued analysis. Occasional omissions of a single data point were tolerated, but some systems were missing multiple data points and were thus removed from the analysis set.

Other reporting errors were obvious upon observation when transforming the data; recording no change in ridership from one month to the next or repeatedly adding and subtracting the same value for a period of several months—these types of data problems introduced skepticism and reduced confidence in the data and thus required elimination of the entire transit system.

Inspection of each individual transit system in this manner reduced the number of systems included in the final analysis set to 215 motor and trolley bus systems from an original 646 included in the full NTD database, as well as 17 of 33 original light rail, ten of 15 heavy rail, and 12 of 26 commuter rail systems, for a total of 254 transit systems. Notably, for the problematic concerns regarding data reliability described here, the New York City Metropolitan Transportation Authority bus and heavy rail systems were among the eliminated systems.

Figure 5.3 provides a graphical representation of the national distribution of systems included in the analysis.

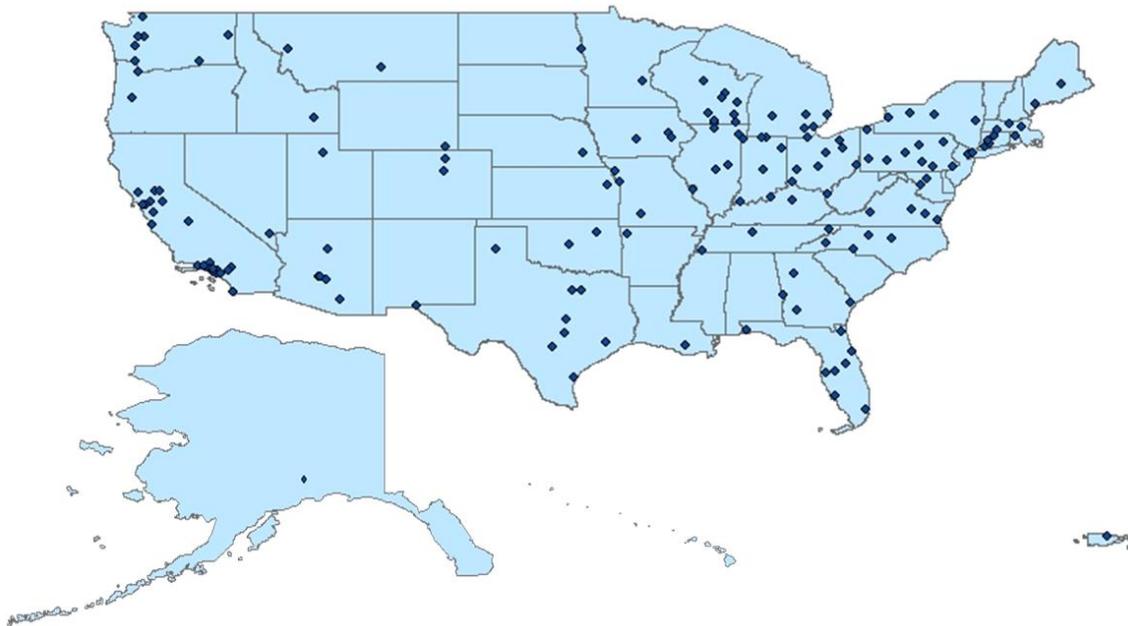


Figure 5.3 National Distribution of Evaluated Public Transportation Systems

5.4 SUMMARY

This chapter described the data collected for model building and calibration, as well as issues inherent in time series analysis. The problems of non-stationarity and heteroscedasticity in the dependent ridership variable were resolved by differencing the logarithmically transformed data series. Chapter 6 explains the process by which seasonal variability was removed from the 254 ridership time series datasets using seasonal decomposition.

Chapter 6: Dealing with Seasonality in Ridership Data

6.1 OVERVIEW: ADJUSTING FOR SEASONAL VARIATION

Public transportation ridership data are highly subject to seasonal variation. As depicted in Chapter 4, when averaging ridership across the nation, ridership tends to be higher in the more temperate spring and fall seasons and lower in the summer and winter months. These climatic patterns are further exacerbated by seasonal demands resulting from school or university populations, and seasonal migrations of transit riders (and others) from northern climates to southern.

However, given the variety of seasonal patterns experienced throughout the US, these seasonal transit ridership fluctuations are not standard from one area to the next. In the Northeast, the four distinct seasons produce different patterns than those in Florida with little seasonal variability. Even transit systems within a few hundred miles of each other can see marked differences in seasonal patterns; San Francisco, with a temperate climate year-round, has a markedly different seasonality than neighboring smaller cities with large university populations following academic schedules.

A useful tool for uncovering underlying seasonality is the autocorrelation function, or ACF. By calculating and plotting the ACF for a transit system's ridership, seasonality trends emerge and can be verified. Figure 6.1 presents an example correlogram for the Capital Metro bus system in Austin, Texas (MB 6048 DO). In this plot, extreme values can be seen at 12-month intervals, indicating an annual seasonal trend to the time series. Another extreme autocorrelation value is shown at the one-month lag, indicating that ridership observations are not independent from one time period to the next.

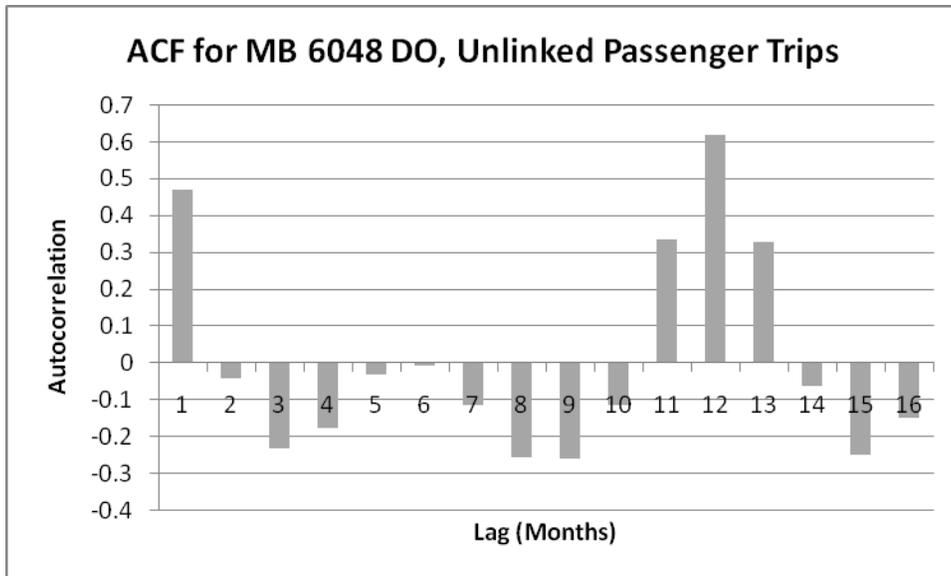


Figure 6.1 Autocorrelation Function of UPT Series for System MB 6048 DO

After transforming the UPT data by the method described in Chapter 5, the seasonal pattern is retained in the transformed series, *PDLOGUPT*, as shown in Figure 6.2, again presenting data for the Austin Capital Metro bus system. In this plot, logarithmically transforming the data and differencing the series leads to a more stable ACF plot and removes much of the autocorrelation with the one-month-lagged series, indicating greater independence of observations.

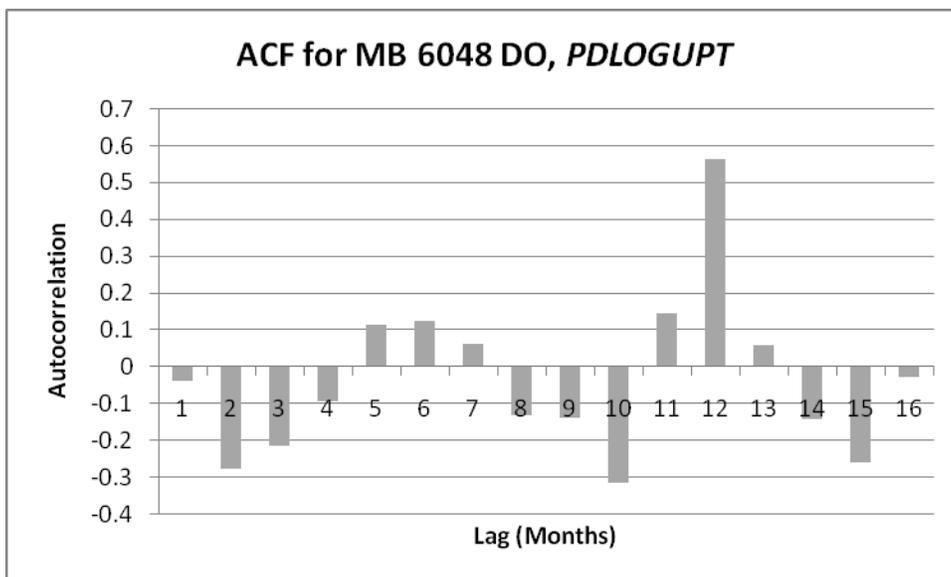


Figure 6.2 Autocorrelation Function for Transformed *PDLOGUPT* Series for System MB 6048 DO

The plots in Figures 6.1 and 6.2 depict one selected system from the 215 bus systems (in addition to light, heavy, and commuter rail systems) analyzed. Due to the unique nature of seasonal fluctuations for a given system and the varied causes of these patterns, the ACF figures shown

are not representative of all transit systems, although they show similarities with many. These seasonal fluctuations are veritable “fingerprints”, uniquely describing the seasonal pattern of a particular system.

6.2 SEASONAL DECOMPOSITION

Any time series, particularly those known to exhibit seasonality, can be broken into various components. This process, known as “seasonal decomposition” (among other names), uses standardized procedures to break each time series data point into three components: a seasonal adjustment factor, a trend-cycle factor, and an error term.

The seasonal adjustment factor obtained through decomposition describes how, in each year of a multi-year series, a particular time period varies with respect to other time periods. In the case of the research contained herein, the seasonal time period was a single month of the year. Thus, following seasonal decomposition of the six-year model-building period (2002-2007), 12 seasonal adjustment factors are obtained, all 12 of which are repeated each year when creating or validating the seasonal model. In the work done here, these seasonal adjustment factors are denoted “*SAF*”, to be consistent with the notation used in the SPSS software used for modeling.

The trend-cycle series derived through seasonal decomposition describe the underlying growth or decline of the original time series once seasonality has been removed. The trend-cycle series in these analyses are labeled “*STC*”, again for consistency with SPSS.

An error term, e , reflecting what the model interprets as random noise, is also created in the course of seasonal decomposition. This term represents differing aspects of the seasonal model, depending on the type of decomposition performed.

6.3 METHODS USED

Seasonal decomposition can take two forms: additive (classical) and multiplicative. The primary difference in these two model forms lies in the underlying assumptions about the nature of the seasonal adjustment factors.

6.3.1 Additive Form (Classical Decomposition)

The additive form of seasonal decomposition, also known as “classical decomposition”, assumes that seasonal components do not vary with the magnitude of the series. Because the ridership data in the analyses of this report have been logarithmically transformed and differenced to create homoscedasticity and stationarity about the mean, it may be generalized that such an assumption applies to the 254 transit systems evaluated.

The mathematical form of this additive model at time t is:

$$Y_t = SAF_t + STC_t + e_t \quad (6.1)$$

The error term, “ e ”, produced through seasonal decomposition, represents the remaining variability or random noise in the original time series than cannot be explained by seasonality or the trend-cycle component. Variability in the error component is produced through other processes external to the seasonal fluctuations and growth or decline in the underlying series.

Assumptions associated with this model form when estimating SAF_t and STC_t terms include (Brockwell and Davis, 2002):

$E(e_t) = 0$ The error or random noise components are initially estimated to be zero for all time periods

$SAF_{t+d} = SAF_t$ Seasonal adjustment factors are equal for each like period, where d represents the periodicity of the series

$\sum_{j=1}^d SAF_j = 0$ The sum of the seasonal adjustment factors over d periods is zero

For the ridership time series analyzed here, the periodicity d of the data is 12 months.

The additive decomposition algorithm works by (1) calculating moving averages, which then become the trend-cycle series, (2) subtracting the smoothed moving averages from the original series, and then (3) calculating average values for each like month to determine the seasonal factors.

The first of the three models created for each transit system consisted of an additive seasonal decomposition calculated using the logarithmically-transformed and differenced UPT series. The portion of this research using multivariate regression involved analyses of the error terms from the additive seasonal decomposition of $PDLOGUPT$, further explaining additional variation in the original series brought on by operational and external factors. The regression procedure, parameters considered in the regression, and resulting analysis are elaborated upon in Chapter 7.

6.3.2 Multiplicative Form

In the multiplicative form of seasonal decomposition, it is assumed that the seasonal factors vary proportionally with the magnitude of the time series (Makridakis, 1998). As the series grows or declines, the seasonal adjustment factor for a particular period will always be the same percentage of the series.

The multiplicative model for a data point at time t has the mathematical form:

$$Y_t = SAF_t * STC_t * e_t \tag{6.2}$$

Ridership data typically follow a multiplicative seasonal form, where seasonal fluctuations increase as the overall magnitude of ridership grows. However, the data used in this analysis

have been transformed to minimize the effects of non-stationarity and heteroscedasticity, as described in Chapter 5. In so doing, the series characteristics that normally lend themselves to the multiplicative form have been stabilized and lessen the suitability of this model form. To verify this assumption, though, the second of three models created for each transit system used the multiplicative form on the transformed ridership datasets, *PDLOGUPT*. The third model derived in this research was a multiplicative model based on differencing the original UPT time series. These models will be discussed in more detail in Section 6.3.3.

In this multiplicative case, the error term, e , is a multiplicative factor required to bring the product of *SAF* and *STC* back to the original series. As such, it is inappropriate to assign any alternative practical meaning to this term.

6.3.3 Models Created

For each of the 254 transit systems evaluated, three seasonal decomposition modeling procedures were performed.

The first decomposition performed on each system was an additive model of the *PDLOGUPT* variable. Because the transformations performed to create the *PDLOGUPT* variable served to remove the influence of proportionally-distributed seasonal factors associated with the multiplicative decomposition form, this additive form was expected to perform best.

The second model was a multiplicative decomposition on the variable *PDLOGUPT*. Due to the transformations already performed on the original UPT series to obtain the *PDLOGUPT* variable, this model did not perform well and was eliminated from further analysis.

The third and final decomposition model performed on each transit system consisted of a multiplicative model of *PDUPT*, the percentage-differenced original ridership series. Because these series had not been logarithmically transformed, the data points were neither homoscedastic nor stationary in the mean. This model did not perform well and was omitted from further consideration.

6.4 METHOD SELECTED: ADDITIVE DECOMPOSITION ON *PDLOGUPT*

After running the three prescribed seasonal decomposition models on each transit system, the first model, the additive decomposition of *PDLOGUPT*, performed best overall, as expected.

Following decomposition of the 254 transit ridership time series datasets, the monthly seasonal adjustment factors (*SAF*) were tabulated. These may be located in Appendix A for each of the four modes: bus (listed by region), light rail, heavy rail, and commuter rail. As indicated in Section 6.1, the seasonal adjustment factors and trend-cycle values are unique to the individual systems and vary depending on geographic, climatic, socio-demographic, cultural, and developmental characteristics of the service area of the transit system. The need to determine and apply these system-specific factors can inhibit the transferability of a ridership forecasting model. However, by determining these components prior to further analysis, the transferability of a model can be enhanced by removing seasonal fluctuations before evaluating the ridership detail more closely.

Once SAF and STC values were determined for each transit system, it was desired to know what percentage of ridership variability could be attributed to seasonal fluctuation. To calculate these percentages, the least-squares definition for R^2 was applied to each system (see Equation 6.3).

$$R^2 = \frac{\sum(\hat{Y}_t - \bar{Y})^2}{\sum(Y_t - \bar{Y})^2} = \frac{\text{Sum of Squares due to Regression}}{\text{Sum of Squares about Mean}} \quad (6.3)$$

where Y_t = Observed values of $PDLOGUPT$

\hat{Y}_t = Estimated values of $PDLOGUPT$; $\hat{Y}_t = SAF_t + STC_t$

$\bar{Y} = (\sum Y_t)/n$

The calculated values of seasonal R^2 for each system are listed in Appendix B.

In addition to calculating values of SAF_t , STC_t , and e_t for each time period and each system, we can also derive a seasonality-adjusted time series, SAS_t , for each transit system, equivalent to subtracting the seasonal adjustment factor SAF_t from the original series of $PDLOGUPT_t$, as in Equation 6.4:

$$SAS_t = PDLOGUPT_t - SAF_t \quad (6.4)$$

To determine whether the decomposition process successfully removed the seasonality from the series, we can plot and examine autocorrelation functions for the seasonally-adjusted series SAS for the transit systems analyzed. Figure 6.3 provides such a correlogram for the Capital Metro bus system in Austin, as addressed in Figures 6.1 and 6.2.

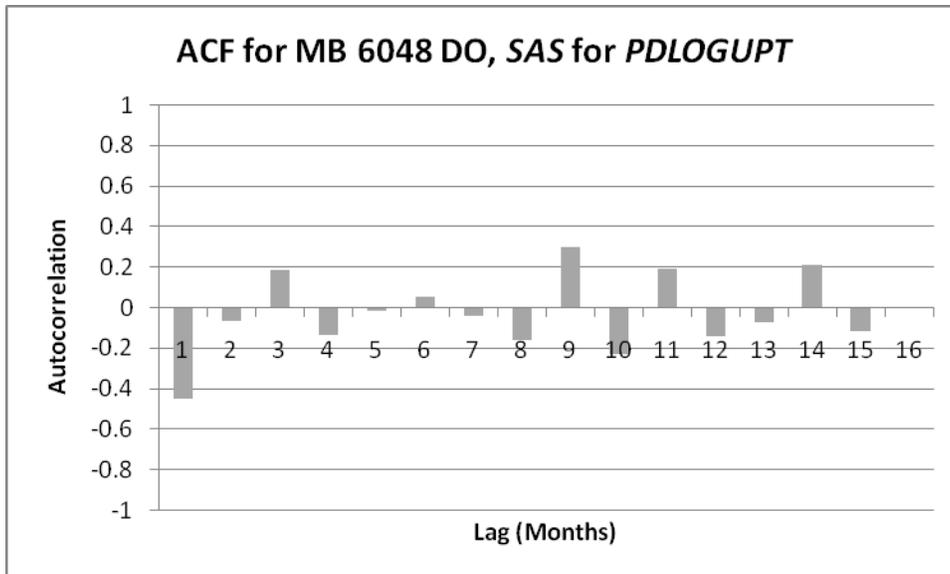


Figure 6.3 Autocorrelation Function for Seasonally-Adjusted Series for System MB 6048 DO

One can see from this ACF plot that the seasonality at the 12-month lag, very apparent in Figures 6.1 and 6.2, has all but vanished, leaving a seasonally-stable series in the wake of additive seasonal decomposition.

The value of R^2 represents the amount of variability in a particular dataset that can be explained by the applied model. In this case, the dataset is the original time series of *PDLOGUPT* and the model in question is that created by adding the appropriate *SAF* and *STC* values. The seasonal R^2 value for Austin’s Capital Metro system, portrayed in Figures 6.1, 6.2, and 6.3, describing the percentage of variation in the original *PDLOGUPT* series explained by seasonality, is 0.7714. Table 6.1 provides summary statistics of these R^2 values for each mode evaluated. Fully tabulated values of seasonal R^2 values are provided in Appendix B.

Table 6.1: Summary Statistics for Calculated R^2 Values, Explaining Seasonal Variation

Ridership Data Variability Attributable to Seasonality				
Summary Statistics				
	Mode			
	Bus	Light Rail	Heavy Rail	Commuter Rail
Minimum	0.1316	0.2377	0.1861	0.3951
Maximum	0.9645	0.8481	0.8773	0.9792
Average	0.6049	0.5268	0.6099	0.6262
Median	0.6009	0.4963	0.7025	0.5999
Std. Dev.	0.1661	0.2134	0.2382	0.1478

Table 6.1 indicates that, on average, in all four transit modes, seasonality accounts for more than half of the variability in ridership.

In inspecting the R^2 values calculated for the transit systems, some generalities can be made. Systems in larger cities with higher ridership tended to show lower seasonal variation, particularly systems with high numbers of passenger-miles serving New York City and Los Angeles. Systems serving student populations, particularly university-based systems, had the highest measureable seasonal fluctuations.

Table 6.2 provides average R^2 information for the analyzed bus systems on a regional basis. Region 2, covering New York and New Jersey (including the NYC metropolitan area), shows the least response to treatment of seasonality, with an average seasonal R^2 value of 0.487. Given the historically high level of public transportation usage and dependence in this area, it is not surprising that seasonality has a minimal effect on ridership in this region. Region 5, the North Central area, shows the greatest response to seasonal treatment, with an average seasonal R^2 value of 0.679; this section of the nation experiences arguably the most extreme weather patterns and it is intuitive that seasonality would show the greatest effect in this area. Also exhibiting high correlation with seasonal trends are Regions 0 and 7 (both with average $R^2 = 0.667$), the Pacific Northwest and Mid-west, two areas of the US having strong seasonal weather patterns.

Table 6.2 Regional Average R^2 Values for Seasonal Contribution to Variability

Region	Average Seasonal R^2
0	0.667
1	0.578
2	0.487
3	0.556
4	0.526
5	0.679
6	0.636
7	0.667
8	0.598
9	0.631

Figure 6.4 provides a histogram of seasonal R^2 values for the analyzed bus systems. This histogram, which had far more observations in the sample than the other three modes, reveals a rather normal distribution, perhaps somewhat skewed to the right.

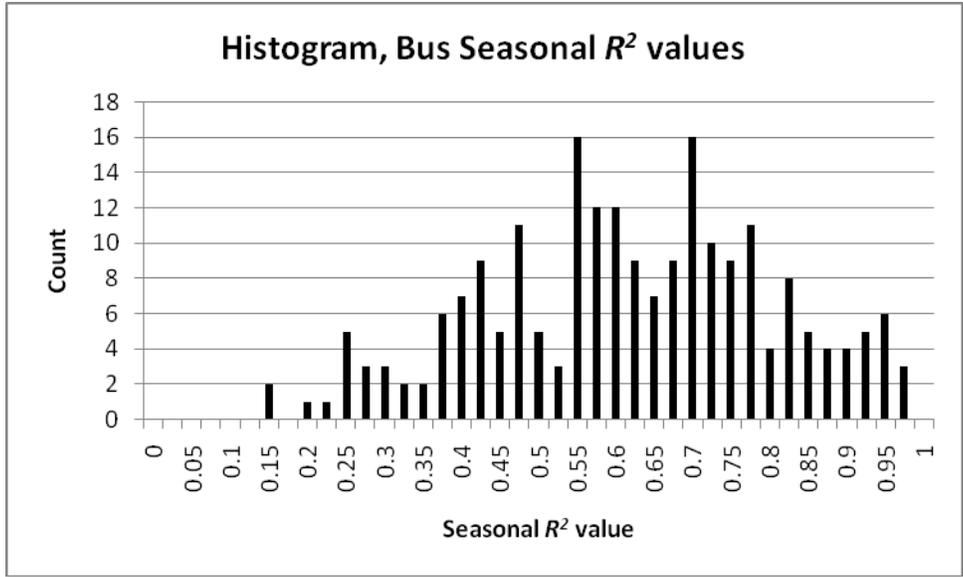


Figure 6.4 Histogram of Seasonal R^2 Values, Bus Systems

The comparable histogram for light rail seasonal R^2 values is given in Figure 6.5. In this figure, we see that the R^2 values tended to cluster lower on the R^2 range than for bus systems; while a few systems showed stronger response to seasonal treatment (five systems having seasonal R^2 values above 0.65), most light rail systems can attribute less than half of their ridership variability to seasonality.

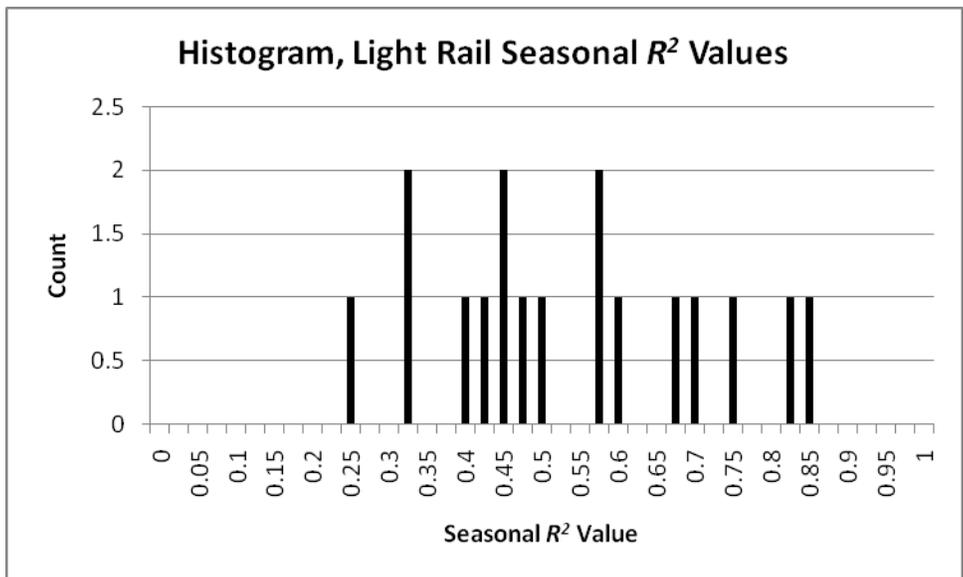


Figure 6.5 Histogram of Seasonal R^2 Values, Light Rail Systems

With only ten systems in the heavy rail sample, drawing any conclusions from the histogram in Figure 6.6 is difficult. Six of the ten systems show seasonal R^2 values above 0.65, while the

remaining four fall below 0.5. In four of the systems, seasonality explains more than 80 percent of the ridership variability.

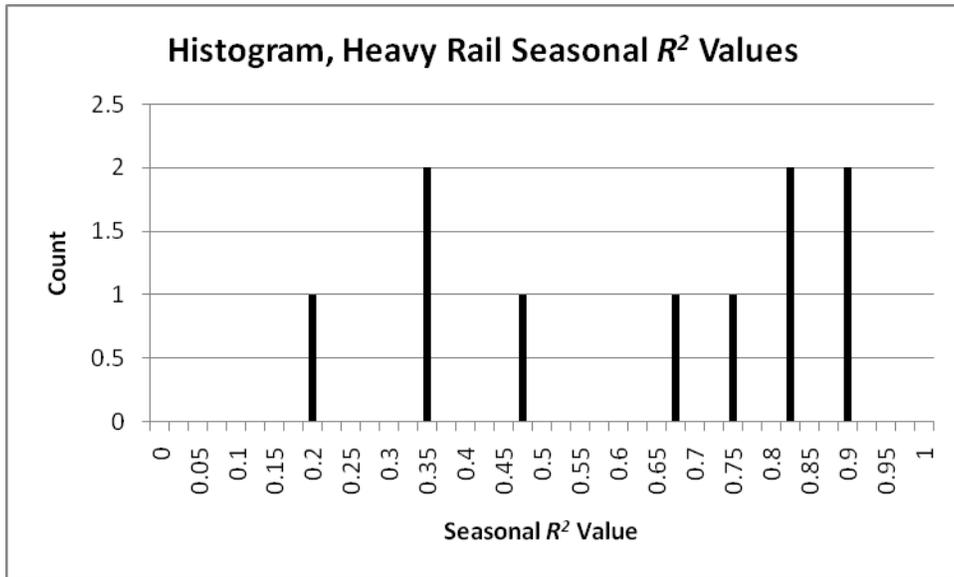


Figure 6.6 Histogram of Seasonal R^2 Values, Heavy Rail Systems

In Figure 6.7, we see that the distribution of seasonal R^2 values for commuter rail systems follows a roughly normal pattern. For five of the 12 systems, seasonal variability contributes to more than 65 percent of ridership fluctuations. In the remaining seven systems, seasonality accounts for between 40 to 65 percent of ridership variability.

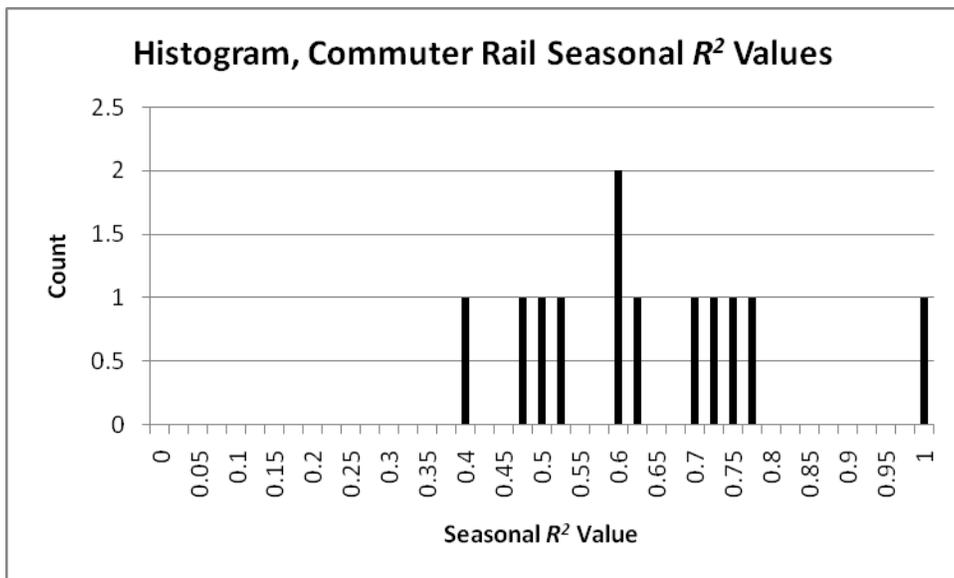


Figure 6.7 Histogram of Seasonal R^2 Values, Commuter Rail Systems

6.5 SUMMARY

Seasonality plays a large part in the annual fluctuations in ridership seen on public transportation systems. Before uncovering the roles played in ridership change by operating characteristics or external factors such as fuel price, it is necessary to remove the seasonal trends from the analyzed time series. For this research, this removal was accomplished through additive seasonal decomposition, which reduces the original series to seasonal factors, an underlying trend-cycle series, and error terms which represent the non-seasonal components of ridership.

In Chapter 7, these non-seasonal components are evaluated using multivariate regression to further explain variability in transit ridership.

Chapter 7: Examining Non-Seasonal Variability

7.1 OVERVIEW

Having removed seasonal variability from the *PDLOGUPT* series of the 254 evaluated transit systems, the task now stands to address the systems' time series of decomposition error terms representing the non-seasonal components of ridership. Using independent variables and multivariate regression, this portion of the model attempts to explain as much of the non-seasonal variability as possible and thus minimize remaining error.

7.2 MULTIVARIATE REGRESSION ON DECOMPOSITION ERROR TERMS

After performing seasonal decomposition using the additive model form and deriving seasonal adjustment terms (*SAF*) and trend-cycle values (*STC*), we were left with error terms, representing the share of the original *PDLOGUPT* series that could not be explained by seasonal variability (see Equation 6.1). These non-seasonal components form their own time series, and yet are related to the time series of the independent variables, including system operations elements and external factors such as fuel price.

Treating these error terms now as dependent variables, multivariate regression was employed for each of the 254 systems in order to determine the relationships between the gathered independent variables and the non-seasonal components of ridership, and thus calibrate the non-seasonal model (see Section 7.7).

7.3 VARIABLES INCORPORATED INTO REGRESSION MODEL

Because the original transformed variable, *PDLOGUPT*, included the percent-change transformation to facilitate comparisons between systems having varying ridership magnitudes, the error components against which the multivariate regressions were run necessarily also contained the percent-change element and could thus be viewed as the percent change in the logarithm of UPT that was attributable to forces other than seasonality. Therefore, many of the dependent variables were also transformed to reflect a percent change from the previous month's value. Those variables following this change are indicated where appropriate in the following sub-sections.

In all decisions to include a particular variable, the primary intent was to account for fluctuations in the non-seasonal component of ridership in an explanatory manner.

7.3.1 Vehicle Revenue Hours (*PDVRH*)

The original series for VRH was transformed to reflect the percent change in VRH from one month to the next. Vehicle revenue hours are a measure of the quantity of transit service provided—with a decline in service offered, one would expect a corresponding decrease in transit patronage as headways are lengthened, operating hours are reduced, or routes are curtailed.

Significant efforts were made to collect information about transit labor strikes, including contact with numerous federal agencies, transit union organizations, and news media article searches. However, obtaining comprehensive information about strike start dates, durations, and the amount of service affected by a strike proved impossible. Work strikes, while occasionally used as threats by transit labor unions, are rare events in occurrence. Additionally, in many documented cases of transit work strikes, skeleton crews comprised of regular transit agency employees and non-unionized labor managed to maintain some semblance of service during strikes, often constituting a large percentage of regular service, and usually eliminating fares during the reduced service period to retain disgruntled riders.

The *PDVRH* variable was thus selected for its ability to incorporate the effects of service reductions due to strikes and other disruptions, as well as its capacity to measure transit system growth in terms of new routes and service extensions.

7.3.2 Vehicles Operated in Maximum Service (*PDVOMS*)

Although fleet size is a variable closely related to ridership magnitude, the variable *PDVOMS* was created to again measure changes to the transit system. The addition of vehicles to service during the busiest times of day reflects a growing system with increasing carrying capacity and perhaps shorter headways.

7.3.3 Fuel Price (*PDFUEL*)

As the primary variable of political interest, fuel price has been hypothesized by many to play a great role in encouraging use of public transportation. This effect differs by city and mode type, as discussed in Chapters 2 and 4.

It was further hypothesized in designing this modeling procedure that travelers are more sensitive to small nominal changes in price when they occur in the upper range of fuel prices. For instance, when fuel price reached four dollars per gallon in late 2008, a ten-cent increase in price was perceived as more burdensome to gasoline consumers than a ten-cent increase when fuel cost two dollars or less per gallon at other times.

For this reason, two regression analyses were calculated for each transit system. The first analysis used the percent change in fuel price from the previous month (*PDFUEL*), while the second replaced the *PDFUEL* variable with *PDFUEL_2*, a variable representing the percent change from the previous month in the squared values of fuel price. With these differing variable definitions, detecting heightened sensitivity to price was attempted.

7.3.4 Consumer Price Index (*PDCPI*)

While fuel price can reflect changes in the national economy, it often has little to do with economic laws of supply and demand. The national value of the consumer price index (CPI) was included as a means of tracking general economic activity and its accompanying effects on transit patronage. In this case, the variable was transformed to represent the percent change in CPI from the previous month.

7.3.5 Weekdays (*WEEKDAYS*)

As discussed in Chapter 5, the number of weekdays can have an effect on public transportation ridership since most transit usage occurs as part of workday commuting. This variable comprised a straight count of the number of weekdays in a month, excepting the New Year's Day, Thanksgiving, and Christmas holidays.

7.3.6 Fare (*DFARE*)

Not all systems could be represented with this variable since fare information was limited in its availability. Of 215 total bus systems, 82 had fare data applied to the analyses. Additionally, 14 of 17 light rail, seven of ten heavy rail, and six of 12 commuter rail systems had fare data applied to the regression models.

Chapter 5 elaborated the logic behind inclusion of a binary variable for *DFARE*, indicating whether a fare change had occurred in the month in question. The available fare data provided dates of fare changes, and determining which month to represent with the affirmative fare change required consulting this date. If the fare change occurred prior to the fifteenth day of the month, the fare change was assigned to that month. If the fare change took place on the fifteenth day or later, the fare change was associated with the following month, ascribing it to the month when the fare change might show its greatest impact on ridership.

7.4 ADDITIONAL VARIABILITY EXPLAINED BY REGRESSION

Provided with the SPSS regression output for each of 508 models (two fuel-price-variable models calculated for 254 systems), standard and adjusted R^2 values indicating the percent of variation described by the regression models were tabulated. These are provided in Appendix B for both the *PDFUEL* and *PDFUEL_2* models. Overall, the squared fuel price term did not significantly or universally improve the explanatory power of the model and thus the model based on the simpler non-squared fuel price variable was selected for further evaluation.

It is important to point out that because the ridership, fuel price, and other data used to build the model covered a six-year period, the results of the regression are likely to represent long-term behavior shifts for all variables, rather than short-term reactions to stimuli such as fuel price change. Short-term trends are likely to be more acute than those found here and warrant future investigation, particularly with regard to fuel price change and heightened sensitivity to extreme prices.

Table 7.1 Summary Statistics for Adjusted R^2 Values from Regression, All Modes

Adjusted R^2 Statistics from Regression, All Modes

	Mode			
	Bus	Light Rail	Heavy Rail	Commuter Rail
Minimum	-0.075	-0.066	0.001	-0.065
Maximum	0.596	0.540	0.543	0.422
Average	0.205	0.107	0.196	0.252
Median	0.201	0.098	0.164	0.309

Table 7.1 provides multi-modal summary statistics for the adjusted R^2 values resulting from the regression. In general, the regression performed equally well for each mode; light rail (which, as a categorical definition, tends to include systems having disparate operating characteristics and serving a variety of purposes) tended to comply more poorly than other modes (average $R^2 = 0.107$), while commuter rail systems (which have more consistent operating characteristics within the modal definition) were more explicable using the parameters in the model (average $R^2 = 0.252$).

Figure 7.1 shows a histogram of the distribution of adjusted R^2 values from the multiple regression for the 215 bus systems included in the analysis. When standard R^2 values were adjusted for sample size, a few of the values in three of the modes became negative; this trend is reflected in Table 7.1 and in the other modal histogram plots. The plot shows that the R^2 values are fairly normally distributed between zero and 0.40, with eight systems attaining 0.48 or better.

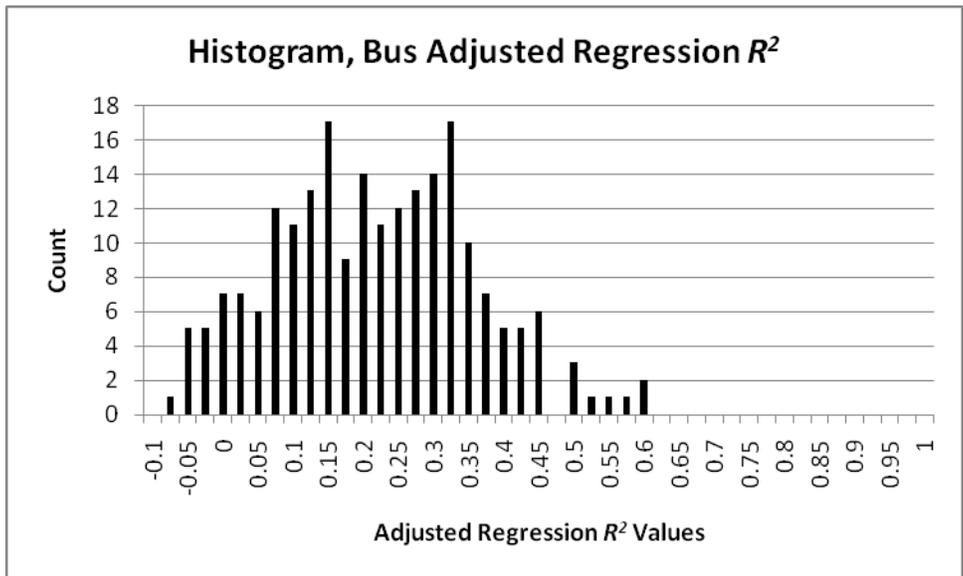


Figure 7.1 Histogram of Regression-Derived Adjusted R^2 Values for Bus Systems

A similar plot for the 17 light rail systems is given in Figure 7.2 and comparable depictions are shown for the heavy and commuter rail systems in Figures 7.3 and 7.4, respectively. The light

rail plot shows that adjusted R^2 values were fairly well distributed between zero and 0.20, with one system (Los Angeles County Metropolitan Transportation Authority) yielding an R^2 value of 0.540.

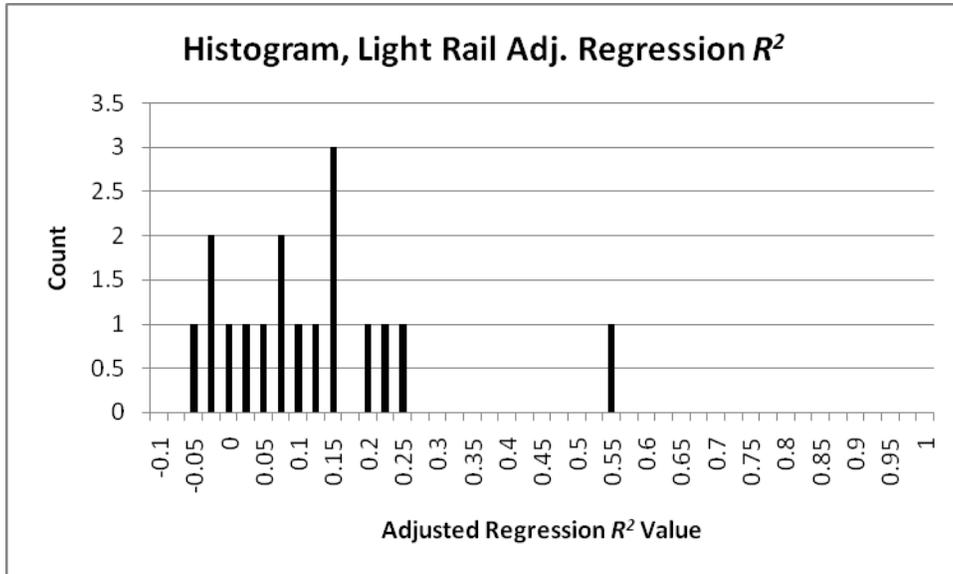


Figure 7.2 Histogram of Regression-Derived Adjusted R^2 Values for Light Rail Systems

The histogram for the ten heavy rail regressions, Figure 7.3, shows that adjusted R^2 values tended to be lower through the first half of the systems, climbing to more than 0.50 through the end of the dataset.

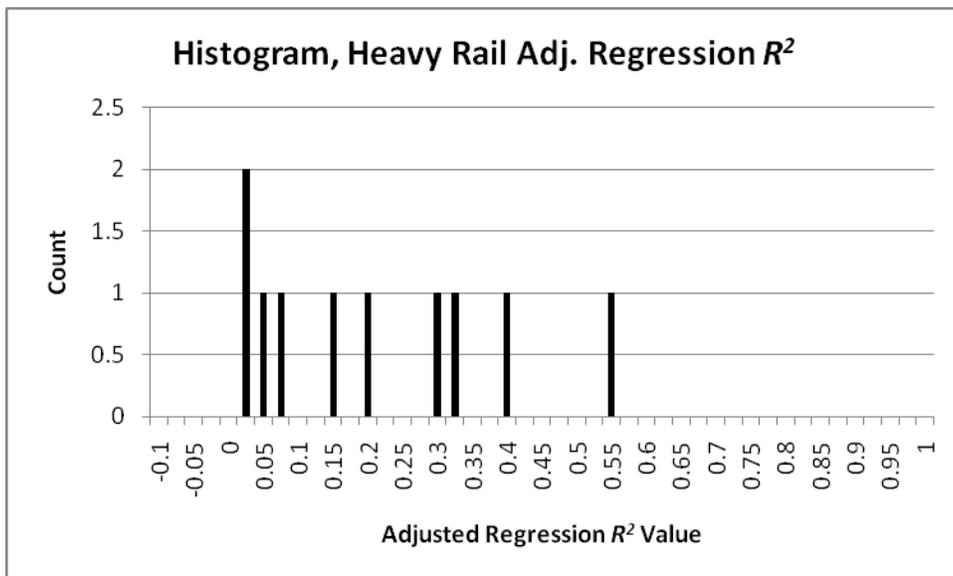


Figure 7.3 Histogram of Regression-Derived Adjusted R^2 values for Heavy Rail systems

The commuter rail regressions, reflected in the histogram in Figure 7.4, show much more consistency in their applicability to the regression model; 75 percent of the commuter rail systems had R^2 values above 0.19 and 50 percent of the systems reached R^2 values above 0.30.

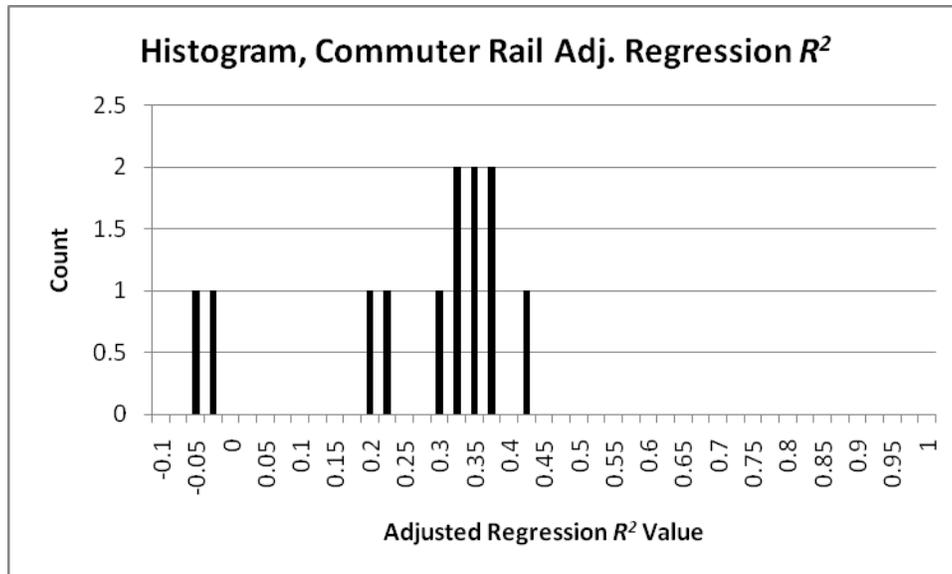


Figure 7.4 Histogram of Regression-Derived Adjusted R^2 Values for Commuter Rail Systems

7.5 REGIONAL DIFFERENCES IN REGRESSION COEFFICIENTS FOR BUS SYSTEMS

The parameter coefficients calculated in the multivariate regression are tabulated in Appendix C.

As noted in Chapter 5, the bus systems are divided, per FTA assignment, into ten regions, determined by the first digit of the systems' four-digit identification numbers. These regions are as follows:

- Region 0: Pacific Northwest
 - Alaska, Idaho, Oregon, Washington
- Region 1: New England
 - Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
- Region 2: Northeast
 - New Jersey, New York
- Region 3: Mid-Atlantic
 - Delaware, District of Columbia, Maryland, Pennsylvania, Virginia, West Virginia
- Region 4: Southeast
 - Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, Puerto Rico, South Carolina, Tennessee
- Region 5: North Central
 - Illinois, Indiana, Michigan, Minnesota, Ohio, Wisconsin
- Region 6: South Central

- Arkansas, Louisiana, New Mexico, Oklahoma, Texas
- Region 7: Mid-West
 - Iowa, Kansas, Missouri, Nebraska
- Region 8: Mountain West
 - Colorado, Montana, North Dakota, South Dakota, Utah, Wyoming
- Region 9: West
 - Arizona, California, Hawaii, Nevada

Upon conclusion of the regression modeling for the 215 bus systems, the constant terms and six variables for each model were evaluated on the basis of region to discern trends among the regression parameters. Although these coefficients appeared to fall into similar ranges, it was desired to know which regions showed similar values and thus behaviors in responding to operational or external stimuli.

These regional comparisons among the bus systems were accomplished using one-way ANOVA testing and the associated F -test, followed by multiple range tests to group regions according to their parameter values (Devore, 2004; Garson, 2009).

Conducting multiple range tests involves three distinct preparatory steps. First, the data must be analyzed to determine whether the variances of the data in each region are equal. The condition of variance equality or inequality determines the type of range test to be conducted—some tests assume equal variances of the grouped data, while others are needed if the variances are unequal or cannot be known. The test used to determine the likelihood of variance equality or inequality is known as the Levene test.

The Levene statistic tests for inequality of variances of a variable X between any two groups i and j . The Levene test statistic, W , is defined as follows (NIST, 2009):

$$W = \frac{(N - k) \sum_{i=1}^k N_i (\bar{Z}_i - \bar{Z}_{..})^2}{(k - 1) \sum_{i=1}^k \sum_{j=1}^{N_i} (Z_{ij} - \bar{Z}_i)^2} \quad (7.1)$$

where

N is the total sample size, divided into k groups, and

N_i is the sample size of the i^{th} group.

Z_{ij} as used in the analysis here is defined as:

$$Z_{ij} = |X_{ij} - \bar{X}_i| \quad (7.2)$$

where \bar{X}_i is the mean of the i^{th} group.

Table 7.2 shows the results of using the Levene statistic to test the null hypothesis assumption of equality of variances for each parameter x across all ten regions of bus systems evaluated ($H_0: s_{x0} = s_{x1} = s_{x2} = s_{x3} = s_{x4} = s_{x5} = s_{x6} = s_{x7} = s_{x8} = s_{x9}$). The presence of unequal variances increases the odds of concluding later in the ANOVA F -test that a significant relationship exists between groups when in fact no relationship exists (Type I error).

Table 7.2 Levene Statistics and Multiple Range Tests Selected for Regional Bus Parameter Comparisons

Regression Parameter	Levene Statistic	Significance ($\alpha=0.05$)	Variances Equal?	Range Test
<i>CONSTANT</i>	3.222	0.001	No	Games-Howell
<i>PDVRH</i>	1.149	0.330	Yes	LSD; HSD; Ryan
<i>PDVOMS</i>	2.589	0.008	No	Games-Howell
<i>PDFUEL</i>	2.284	0.018	No	Games-Howell
<i>PDCPI</i>	1.355	0.211	Yes	LSD; HSD; Ryan
<i>WEEKDAYS</i>	3.156	0.001	No	Games-Howell
<i>DFARE</i>	1.294	0.255	Yes	LSD; HSD; Ryan

Having determined the equality or inequality of regional variances for each variable's coefficients, the second step in comparing the coefficient means for the ten different bus system regions is to compute F statistics for the one-way ANOVA analyses. With a null hypothesis that the parameter means of the variable x are equal for all regions ($H_0: \mu_{x0} = \mu_{x1} = \mu_{x2} = \mu_{x3} = \mu_{x4} = \mu_{x5} = \mu_{x6} = \mu_{x7} = \mu_{x8} = \mu_{x9}$), the F statistic allows one to reject the null hypothesis if the computed f value exceeds the tabulated F value; rejection of the null hypothesis implies that at least one of the means is unequal to the others. This procedure was repeated for the constant term and each of the six regression variables and the results are given in Table 7.3.

Table 7.3 Results of ANOVA F -test for Equality of Parameter Means for Bus Systems

Coefficient	Computed f	I	J	$\nu_1 = I-1$	$\nu_2 = I(J-1)$	Critical F_{α, ν_1, ν_2}	Sig. ($\alpha = 0.05$)	Conclusion	Means Equal?
<i>CONSTANT</i>	1.651	10	215	9	2140	1.884	0.103	Do not Reject H_0	Yes
<i>PDVRH</i>	1.809	10	215	9	2140	1.884	0.068	Do not Reject H_0	Yes
<i>PDVOMS</i>	0.838	10	202	9	2010	1.885	0.582	Do not Reject H_0	Yes
<i>PDFUEL</i>	3.874	10	215	9	2140	1.884	0.000	Reject H_0	No
<i>PDCPI</i>	7.281	10	215	9	2140	1.884	0.000	Reject H_0	No
<i>WEEKDAYS</i>	1.614	10	215	9	2140	1.884	0.113	Do not Reject H_0	Yes
<i>DFARE</i>	1.077	10	82	9	810	1.891	0.390	Do not Reject H_0	Yes

Following the ANOVA F -test methodology, only two variables caused the null hypothesis to be rejected; these were *PDFUEL* and *PDCPI*. In these two cases, the computed f -statistics were highly significant and the conclusion could be reached that the means were not equal across all ten regions; the appropriate range test was applied to the data as indicated in Table 7.2.

In the case of the *PDFUEL* variable, Levene's test found inequality among variances for the regional values of the models' fuel price parameters and therefore the Games-Howell range test was employed. Noted for its suitability in the case of unequal sample sizes among more than five groups (having ten regions or groups here), the Games-Howell test is designed for mean comparison experiments when variances are unequal or unknown and is conservative without being exceedingly so.

For the *PDCPI* variable where the variances were equal across the ten regions, the selected tests were the Least Significant Difference (LSD) test, Tukey's honestly significant difference (HSD) test, and the Ryan-Einot-Gabriel-Welsch-Q test (the Ryan test).

The first of these tests, the Least Significant Difference (LSD) test, is the most liberal post-hoc multiple range test available—it will tend to indicate differences in regions when no difference exists (encouraging rejection of H_0 and incurring Type I error). The second test, Tukey's honestly significant difference (HSD) test, is the most conservative post-hoc range test and can underestimate the presence of differences between regions (heightening the chance of making a Type II error, failing to reject H_0). (Since the sample sizes for the different regions were unequal, SPSS actually computes the Tukey-Kramer test using the harmonic mean rather than the standard HSD test.) The Ryan test (Ryan-Einot-Gabriel-Welsch-Q) is a compromise between the LSD and HSD tests in its conservatism (Garson, 2009). Both the Tukey and Ryan tests use the Studentized range distribution, or the Q statistic.

The following subsections discuss the parameter values in detail as well as the range tests conducted.

7.5.1 Constant Term (*CONSTANT*)

Descriptive statistics for the *CONSTANT* terms in the bus regressions are found in Table 7.4. From the previous analysis, the Levene statistic determined that variances among the ten regions were not equal, but the F -statistic for this parameter showed equality of the means for the groupings and thus performing further tests for similarities was unnecessary.

The mean value for the *CONSTANT* term in the regression model is -3.360 for all groups. The greatest deviation from this average value is -1.711 for the Northeast region. As anticipated from the findings of the Levene statistic, standard deviation values range from 1.596 to 5.718, supporting the conclusion that the variances of the groups are unequal.

Table 7.4 Descriptive Statistics for *CONSTANT* Terms in Regression Model, Bus Systems Only

CONSTANT Descriptives

Region	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0	17	-4.695	5.562	1.349	-7.555	-1.836	-25.209	-0.169
1	11	-3.464	1.848	0.557	-4.705	-2.223	-6.976	-0.815
2	20	-1.711	2.531	0.566	-2.896	-0.526	-6.765	3.607
3	27	-3.939	5.718	1.100	-6.201	-1.677	-24.065	6.317
4	28	-2.300	1.596	0.302	-2.919	-1.681	-5.422	2.769
5	43	-3.527	1.849	0.282	-4.096	-2.958	-8.42	2.205
6	17	-4.501	3.822	0.927	-6.466	-2.537	-11.063	-1.116
7	9	-4.261	2.427	0.809	-6.127	-2.396	-8.781	0.034
8	7	-2.865	2.323	0.878	-5.014	-0.717	-5.406	0.523
9	36	-3.134	2.240	0.373	-3.892	-2.376	-6.763	1.857
Total	215	-3.360	3.322	0.227	-3.806	-2.913	-25.209	6.317

The 95% confidence interval on the *CONSTANT* term is -3.806 to -2.913. For the national bus regression model, the cumulative average value (which also serves as a weighted average in this case) of -3.360 will be employed.

7.5.2 Vehicle Revenue Hours (*PDVRH*)

In the case of the percent change in vehicle revenue hours, summary statistics for which are shown in Table 7.5, the average effect was a positive one on ridership, as expected, with the national average for the coefficient falling at 0.009. Thus, a one percent increase in vehicle revenue hours results in a 0.009 percent increase in the logarithmically transformed value of ridership.

The 95% confidence interval on this parameter falls between 0.006 and 0.012. While all but one region had a minimum value below zero (the Mountain West region, which also had the smallest sample size at seven systems), all but one regional average is positive (the exception being the Pacific Northwest region, which also had the national minimum of -0.122, a relative outlier in this analysis and affecting the calculated average sufficiently to pull it below zero).

Table 7.5 Descriptive Statistics for *PDVRH* Values in Regression Model, Bus Systems Only

***PDVRH* Descriptives**

Region	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0	17	-0.004	0.033	0.008	-0.021	0.014	-0.122	0.042
1	11	0.010	0.008	0.002	0.005	0.015	-0.003	0.025
2	20	0.018	0.020	0.004	0.009	0.027	-0.005	0.076
3	27	0.008	0.022	0.004	0.000	0.017	-0.044	0.064
4	28	0.013	0.019	0.004	0.005	0.020	-0.030	0.057
5	43	0.008	0.013	0.002	0.004	0.012	-0.024	0.041
6	17	0.007	0.013	0.003	0.001	0.014	-0.023	0.033
7	9	0.010	0.019	0.006	-0.005	0.025	-0.011	0.055
8	7	0.019	0.020	0.008	0.001	0.038	0.003	0.054
9	36	0.006	0.018	0.003	0.000	0.012	-0.020	0.046
Total	215	0.009	0.019	0.001	0.006	0.012	-0.122	0.076

The Levene and *F*-tests concluded that the variances and means of the coefficient on this variable are equal for the ten regions, and so the average value of 0.009 (which again constitutes a weighted average in this case when considering the regional values) will be used for the national bus regression model.

7.5.3 Vehicles Operated in Maximum Service (*PDVOMS*)

The Levene statistic found that variances for the *PDVOMS* variable are not equal; however, the *F*-test determined that means across the regions are equal and thus no further grouping evaluation was needed.

Table 7.6 Descriptive Statistics for *PDVOMS* Values in Regression Model, Bus Systems Only

***PDVOMS* Descriptives**

Region	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0	16	0.005	0.025	0.006	-0.009	0.019	-0.034	0.055
1	10	0.024	0.063	0.020	-0.021	0.069	-0.067	0.145
2	17	-0.001	0.054	0.013	-0.029	0.026	-0.193	0.064
3	26	0.001	0.044	0.009	-0.017	0.018	-0.151	0.072
4	28	-0.013	0.057	0.011	-0.036	0.009	-0.240	0.048
5	42	0.004	0.018	0.003	-0.002	0.010	-0.060	0.056
6	15	-0.017	0.087	0.022	-0.065	0.031	-0.322	0.042
7	8	-0.022	0.049	0.017	-0.063	0.019	-0.119	0.038
8	6	-0.021	0.131	0.054	-0.158	0.117	-0.239	0.168
9	34	-0.001	0.054	0.009	-0.020	0.018	-0.169	0.150
Total	202	-0.002	0.053	0.004	-0.010	0.005	-0.322	0.168

It should be noted from Table 7.6 that the total sample size was smaller in this case, including 202 bus systems rather than the 215 comprising the full analysis dataset. This reduction occurred because, according to the NTD database, 13 of the analyzed systems had no change in the number of vehicles operated in maximum service conditions over the 2002-2007 calibration period. When the number of VOMS was constant over this six-year period, the parameter values for the percent change in VOMS were zero for each time period and the variable was thus eliminated from regression analysis.

Although it is far from intuitive, the average national value for this parameter is -0.002, indicating that a one percent increase in the number of vehicles operated in maximum service brings about a decrease of -0.002 percent in the logarithmic values of unlinked passenger trips. The 95% confidence interval on this parameter falls between -0.010 and 0.005. One would expect that as fleet size increases, ridership would increase, and that the findings here seem to indicate otherwise leads one to suspect there are more complex forces at play with regard to this variable; this non-intuitive conclusion may mask or accompany another effect. Alternatively, since the 95% confidence interval contains zero, there may be no effect of adding vehicles to maximum service. Nonetheless, the average value of -0.002 will be included in the national bus model.

7.5.4 Fuel Price (*PDFUEL*)

The Levene and ANOVA *F*-tests on *PDFUEL* found that neither the variances nor the means are equal across regions. Given the variation nationally in demographics, fuel transport means and availability, and resistance to or acceptance of public transportation, to name only a few factors affecting gasoline use, it is not surprising that fuel effects show varying relationships to transit patronage in different parts of the country.

It is important to note that because the regression model was built upon six years of data, the gas price effects here generally represent long-term shifts of behavior. Short-term reactions may be more acute, particularly at higher prices, as were seen towards the end of the model calibration period.

Table 7.7 Descriptive Statistics for *PDFUEL* Values in Regression Model, Bus Systems Only

<i>PDFUEL</i> Descriptives								
Region	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0	17	0.020	0.018	0.004	0.011	0.029	-0.001	0.071
1	11	0.012	0.013	0.004	0.004	0.021	-0.021	0.035
2	20	0.010	0.023	0.005	-0.001	0.021	-0.066	0.059
3	27	0.008	0.052	0.010	-0.013	0.028	-0.196	0.117
4	28	0.011	0.021	0.004	0.002	0.019	-0.031	0.083
5	43	-0.012	0.018	0.003	-0.018	-0.007	-0.064	0.028
6	17	0.002	0.036	0.009	-0.016	0.021	-0.098	0.055
7	9	-0.001	0.016	0.005	-0.013	0.011	-0.022	0.021
8	7	0.014	0.013	0.005	0.002	0.026	0.003	0.039
9	36	0.018	0.017	0.003	0.012	0.023	-0.008	0.070
Total	215	0.007	0.028	0.002	0.003	0.010	-0.196	0.117

Because the *F*-test determined that means are unequal, the next step is to use a multiple range test to identify and group those regions having similar mean values and then to calculate a parameter value that may be attributed to all regions within a particular group.

The Levene statistic, which evaluated the equality or inequality of variances, serves to dictate the multiple range test to be applied to a set of grouped data. Because the variances in this case are not equal, the Games-Howell test was used because of its suitability to comparisons among more than five groups when variances are unequal or unknown.

Table 7.8 shows the tabulated output from the Games-Howell test. Regions having means that were determined with an alpha value of 0.05 to be statistically different are indicated with an “X” in the appropriate cell. Region 5, the North Central portion of the US, shows the greatest dissimilarity from other regions.

PDFUEL Games-Howell test

Region	0	1	2	3	4	5	6	7	8	9
0	■					X				
1		■				X				
2			■			X				
3				■						
4					■	X				
5	X	X	X		X	■			X	X
6							■			
7								■		
8						X			■	
9						X				■

Table 7.8 Games-Howell Test Results for *PDFUEL* Parameter Means across Bus Systems Only

For this *PDFUEL* variable, the interpretation of the Games-Howell results is one that must be made with care. Region 5 is substantially different from Regions 0, 1, 2, 4, 8, and 9, but not substantially different from Regions 3 (Mid-Atlantic), 6 (South Central), and 7 (Mid-west). However, 3, 6, and 7 are not substantially different from 0, 1, 2, 4, 8, and 9.

When determining which regions to group together, it can be helpful to examine the summary statistics, found in Table 7.7. Ordering the means for the four regions with average values similar to Region 5, we get: $x_5 = -0.012$; $x_7 = -0.001$; $x_6 = 0.002$; and $x_3 = 0.008$. The first two of these means, those for Regions 5 and 7, are negative, while the values for Regions 6 and 3 are positive.

Deciding where to delineate groupings can be a judgment call in many cases. As a next step to finding a point of separation, consider the standard deviations and 95% confidence intervals as shown in Table 7.7. Regions 5 and 7, both with negative means, have similar standard deviations (0.018 and 0.016, respectively) while Region 6 shows a much larger deviation of 0.036. Additionally, the upper bound on the 95% confidence interval for Region 6, at 0.021, falls in a range comparable with the other regions (excluding Regions 5 and 7).

Following this logic, the break point for grouping regions in terms of their parameter values on the *PDFUEL* variable was chosen to be between Region 7 and Region 6. Thus, Regions 5 and 7 will be assigned to one group and the remaining eight regions will belong to a second group.

It remains to determine the final values to be assigned to the two *PDFUEL* regional groupings. Using the regional mean values and group sample sizes, weighted averages are calculated. For the first group consisting of Regions 5 and 7, the weighted average is:

$$\frac{43(-0.012) + 9(-0.001)}{52} = -0.010$$

For the remaining eight regions, the same procedure is employed to calculate a weighted average corresponding to these groups; this computed value is 0.012.

The implication behind the summary statistics in Table 7.7 is that in all but the North Central and Mid-west regions of the US, a one percent increase in fuel price tends to produce a 0.012 percent increase in the logarithm of transit ridership. This conclusion is consistent with anecdotal evidence from public transportation operators, who reported surges in demand as fuel prices climbed. However, in the North Central and Mid-west sections, the effect appears to be opposite—a one percent increase in fuel price has generally brought on a 0.010 percent decline in the logarithm of ridership.

One potential explanation for such a difference in the directions of these relationships concerns the consumption of alternative fuels. Table 7.9 tabulates the consumption of ethanol fuel in each FTA region between 2000 and 2006 in millions of gallons (National Priorities Project Database, 2009; Oak Ridge National Laboratory, 2008). It is clear from these values that Region 5 has consistently shown the highest ethanol use in the US, many times greater than other regions, particularly in earlier years. Region 7 has had the third-highest ethanol use. (Region 9 should also be noted for its higher ethanol use; most of this consumption has occurred in California since 2003.)

Table 7.9 US Ethanol Consumption by FTA Region, Mgal of Ethanol (NPPD, 2009; ORNL, 2008)

Ethanol Fuel Consumption by FTA Region, Mgal Ethanol/Year

Region	2000	2001	2002	2003	2004	2005	2006	2000-2006 Total	
0	55	54	122	109	63	69	116	588	2.7%
1	5	1	5	25	191	201	224	652	3.0%
2	28	19	6	27	335	373	827	1614	7.4%
3	60	65	131	118	218	256	536	1384	6.4%
4	49	84	117	181	197	261	391	1280	5.9%
5	862	882	995	1098	1112	1311	1558	7817	35.9%
6	103	84	83	87	93	112	547	1109	5.1%
7	176	172	255	310	279	363	355	1910	8.8%
8	114	144	126	140	132	167	140	964	4.4%
9	126	165	178	737	1037	1097	1101	4440	20.4%
Sum	1579	1670	2018	2831	3655	4210	5796	21759	100.0%

Based on the higher consumption of ethanol, it is logical to hypothesize that as gasoline prices rise, ethanol becomes a natural alternative for those to whom it is available. Ethanol sells at a lower price point than gasoline, encouraging its use in the face of higher gasoline prices. It should be noted, though, that ethanol and gasoline are not equivalent in terms of their energy content; a gallon of regular unleaded gasoline comprises roughly 115,000 Btu, whereas a gallon of ethanol holds only about 75,700 Btu. Therefore, ethanol could conceivably cost more per Btu than gasoline if the price ratio of ethanol to gasoline were to exceed 0.66, which it frequently does.

Although ethanol, or ethyl alcohol, is present in most regular gasoline blends in some low percentage in order to make it cleaner-burning and raise octane levels, the most widely recognized ethanol blend from a commercial standpoint is E85, which is composed of 85 percent ethanol and 15 percent gasoline. “Flex-fuel” vehicles are uniquely built to function with gasoline, E85, or combinations thereof (Flexible Fuel Vehicle Club of America, 2008). It is of particular note that, in support of the region’s higher ethanol use, most E85 service stations are located in the states making up FTA Region 5, as shown in Figure 7.5 (USDOE Energy Efficiency and Renewable Energy AFDC, 2009).

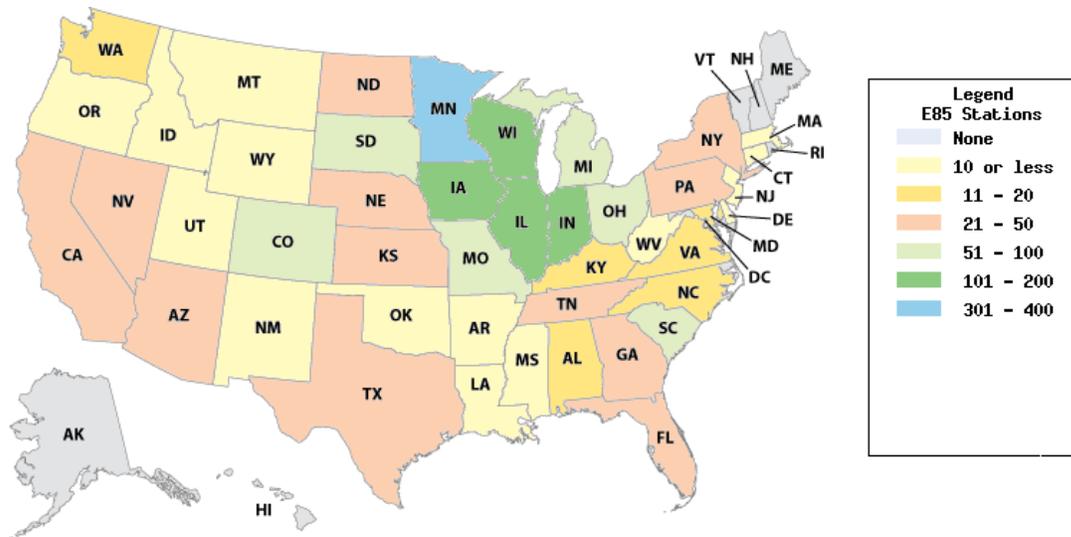


Figure 7.5 Availability of E85 Fueling Stations (from USDOE Energy Efficiency and Renewable Energy AFDC, 2009)

Because availability and acceptance of ethanol pervades the North Central and, to a lesser extent, Mid-west regions, it provides a ready alternative for travelers struggling with rising fuel prices. As ethanol use doubled between 2000 and 2006 in both of these atypical regions, transit use in these areas may have suffered or simply continued on a prior downward trend, whereas other regions of the nation were seeing ridership climb in association with gasoline price and lack of alternative fuel sources.

Table 7.10 provides similar statistics to those in Table 7.9 for regular formulation gasoline. Comparing the two fuel consumption tables reveals that while Region 5 accounted for 35.9 percent of US ethanol use between 2000 and 2006, it made up only 16.1 percent of national gasoline sales.

Table 7.10 US Gasoline Consumption by FTA Region, Mgal of Gasoline (US Department of Energy)

Regular Gasoline Consumption by FTA Region, Mgal Gasoline/Year

Region	2000	2001	2002	2003	2004	2005	2006	2000-2006 Total	
0	4224	4355	4370	4293	4321	4601	4732	30897	4.1%
1	4665	4960	5282	5509	5665	5702	5658	37441	5.0%
2	6548	6993	7302	7524	7655	8206	8286	52515	7.0%
3	8915	9358	9550	9718	10169	10694	10860	69264	9.3%
4	19972	21123	22056	22824	23791	24241	24948	158954	21.3%
5	16578	16681	16836	17107	17682	17515	17784	120183	16.1%
6	14150	14628	15035	15632	16192	17147	17003	109787	14.7%
7	5749	5878	5782	5817	5737	5297	5189	39447	5.3%
8	3549	3552	3413	3400	3633	3893	3981	25421	3.4%
9	13524	13975	14149	14417	14368	15776	16369	102579	13.7%
Sum	97874	101503	103776	106241	109213	113071	114811	746488	100.0%

7.5.5 Consumer Price Index (*PDCPI*)

As a measure of economic function, one would expect the effect of the CPI to differ across the nation. This suspicion is confirmed by the *F*-statistic calculated earlier, which found that means for this parameter are unequal. The Levene statistic, however, concluded that variances were equal from region to region, and thus the multiple range tests used are those necessitating equality of variance; namely, the Least Significant Difference (LSD) test, Tukey's Honestly Significant Difference (HSD) test (Tukey-Kramer test due to unequal group sizes), and the Ryan-Einot-Gabriel-Welsch-Q (Ryan) test.

Table 7.11 yields summary statistics for the *PDCPI* variable for the ten regions. Conversely to the *PDFUEL* analysis, where Regions 5 and 7 were negative outliers in an otherwise positive trend, Regions 5 and 7 are, in the case of *PDCPI*, positive outliers in an otherwise negatively trended result set. These seemingly conflicting findings may indicate that the effects of *PDFUEL* and *PDCPI*, as calculated through regression analysis, are complementary and, when modeled simultaneously, produce a cumulative effect. Even under this logic, however, it is still appropriate to retain both variables in the model and allow this cumulative effect to play out in final modeling.

Table 7.11 Descriptive Statistics for *PDCPI* Values in Regression Model, Bus Systems Only

***PDCPI* Descriptives**

Region	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0	17	-0.258	0.294	0.071	-0.409	-0.106	-0.909	0.370
1	11	-0.216	0.212	0.064	-0.359	-0.074	-0.620	0.262
2	20	-0.276	0.312	0.070	-0.422	-0.130	-1.050	0.529
3	27	-0.141	0.310	0.060	-0.263	-0.018	-0.842	0.658
4	28	-0.130	0.336	0.064	-0.260	0.001	-1.089	0.569
5	43	0.207	0.349	0.053	0.099	0.314	-1.269	0.871
6	17	-0.049	0.548	0.133	-0.331	0.232	-0.890	1.433
7	9	0.077	0.206	0.069	-0.082	0.235	-0.240	0.345
8	7	-0.264	0.219	0.083	-0.467	-0.062	-0.676	0.006
9	36	-0.302	0.292	0.049	-0.401	-0.204	-1.078	0.158
Total	215	-0.110	0.375	0.026	-0.161	-0.060	-1.269	1.433

One potential explanation for the negative parameter values in the majority of areas may involve less overall travel being made as prices rise, including travel by public transportation. The conflicting regional results may involve influences from differences in property values and costs of living. Future work may include use of regional CPI values, as done in the case of assigning appropriate fuel prices (see Section 5.2.2.1), and/or adjusting fuel prices by the CPI to reflect constant monetary values. Unfortunately, regional and city-specific values of the consumer price index cannot be used to compare costs of living between regions or cities in the US. According to the Bureau of Labor Statistics (2009):

An individual area index measures how much prices have changed over a specific period in that particular area; it does not show whether prices or living costs are higher or lower in that area relative to another. In general, the composition of the market basket and the relative prices of goods and services in the market basket during the expenditure base period vary substantially across areas.

Tables 7.12 (a) and (b) (respectively) present the graphical representation of the LSD and HSD multiple range tests on the *PDCPI* parameter. The least significant difference (LSD) test, being the most liberal test in use, finds many more significant differences between regions (each “X” denoting a statistically significant difference at the 0.05 level). Tukey’s HSD test, the most conservative test available, finds far fewer regional differences.

Table 7.12 (a) LSD and (b) Tukey's HSD Test Results for PDCPI Parameter Means across Bus Systems Only

(a) PDCPI Least Sig. Difference (LSD) test

Region	0	1	2	3	4	5	6	7	8	9
0						X		X		
1						X				
2						X	X	X		
3						X				
4						X				X
5	X	X	X	X	X		X		X	X
6			X			X				X
7	X		X						X	X
8						X		X		
9					X	X	X	X		

(b) PDCPI Tukey's HSD test

Region	0	1	2	3	4	5	6	7	8	9
0						X				
1						X				
2						X				
3						X				
4						X				
5	X	X	X	X	X				X	X
6										
7										
8						X				
9						X				

Compromising between the very liberal LSD test and the very conservative HSD test, the Ryan test finds two statistically different groups similar to the Tukey HSD test. Comparative results from the Ryan and HSD test are shown in Table 7.13. While both tests conclude the presence of two groups, the break point between the two groups is not distinct in either test and particularly so in the HSD test, which indicates four regions that could belong to either subset.

Table 7.13 (a) Ryan and (b) Tukey's HSD Test Results for PDCPI Parameter Means across Bus Systems Only

PDCPI					
		(a) Ryan-Einot-Gabriel-Welsch Range		(b) Tukey's HSD*	
REGION	N	Subset for $\alpha = 0.05$		Subset for $\alpha = 0.05$	
		1	2	1	2
9	36	-0.302		-0.302	
2	20	-0.276		-0.276	
8	7	-0.264		-0.264	
0	17	-0.258		-0.258	
1	11	-0.216		-0.216	
3	27	-0.141		-0.141	-0.141
4	28	-0.130		-0.130	-0.130
6	17	-0.049	-0.049	-0.049	-0.049
7	9	0.077	0.077	0.077	0.077
5	43		0.207		0.207
Sig.		0.283	0.206	0.052	0.106

Means for groups in homogeneous subsets are displayed.

* Uses Harmonic Mean Sample Size = 15.716.

Following the Ryan test’s less conservative findings (as compared to the HSD test) and more defined break point, this test is chosen to further classify the regions into groups. As in the case of *PDFUEL*, the summary statistics are examined on the bases of standard deviation and 95% confidence intervals to determine where to divide the groups. It is clear from such an assessment that Region 6 finds itself on the brink of each group due to its relatively large standard deviation, which yields an upper bound in order with Regions 5 and 7, but a lower bound consistent with the remaining regions. Returning to the full listing of regression results in Appendix C, we find that a single outlier, 1.433 exists for one system in Region 6, as indicated in the summary statistics. By calculating the mean value for this region when omitting this outlier value, we achieve a new Region 6 mean of -0.142, comparable to the majority of systems outside the group formed by Regions 5 and 7. This new mean also yields a smaller variance and lands Region 6 within the larger group. For these reasons, the group break point is made between Regions 6 and 7.

Calculating weighted averages for both groups as in Section 7.5.4, we determine that the national bus model will contain two values for the coefficient on *PDCPI*. The first value corresponds to Regions 0, 1, 2, 3, 4, 6, 8, and 9, and is equal to -0.204. The weighted average for the remaining regions, 5 and 7, is 0.184. In the first set of regions, a one percent increase in the CPI brings about a -0.204 percent drop in the logarithm of unlinked passenger trips; for Regions 5 and 7, a comparable change in CPI induces a 0.184 percent increase in the dependent ridership variable. As with all variables included in the analysis, these conclusions are valid only when the other variables are present.

7.5.6 Weekdays (*WEEKDAYS*)

The summary statistics for the *WEEKDAYS* variable are given in Table 7.14. Although the Levene statistic concluded that the regional variances are not equal, the *F*-test found that the means are equivalent and therefore no regional grouping is necessary.

Table 7.14 Descriptive Statistics for *WEEKDAYS* Values in Regression Model, Bus Systems Only

<i>WEEKDAYS</i> Descriptives								
Region	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0	17	0.223	0.270	0.065	0.084	0.361	0.009	1.222
1	11	0.162	0.086	0.026	0.103	0.220	0.036	0.326
2	20	0.081	0.116	0.026	0.026	0.135	-0.161	0.309
3	27	0.183	0.266	0.051	0.078	0.289	-0.295	1.129
4	28	0.107	0.074	0.014	0.078	0.135	-0.131	0.253
5	43	0.161	0.085	0.013	0.135	0.188	-0.108	0.385
6	17	0.208	0.177	0.043	0.116	0.299	0.043	0.518
7	9	0.196	0.112	0.037	0.110	0.282	-0.001	0.405
8	7	0.134	0.109	0.041	0.034	0.235	-0.023	0.251
9	36	0.147	0.105	0.018	0.112	0.183	-0.088	0.316
Total	215	0.156	0.156	0.011	0.135	0.177	-0.295	1.222

As one would expect, the overall statistics for this parameter, including positive confidence intervals for all regions, show that transit ridership increases with the number of weekdays in a month. Since most public transportation use occurs as part of workday commuting, weekdays see the heaviest ridership; the results tabulated here substantiate this pattern.

Comparing the regional values, Region 2, the Northeast (including the New York City metropolitan area), yields the lowest mean value, indicating that the number of weekdays in a month plays the least role in this region. This finding agrees with an intuitive assumption: transit use in this area comprises roughly one-third of national use and one would intuit that with many more residents having no access to automobiles and such an ingrained culture of transit use, travelers in the Northeast region will use public transportation for weekend, as well as weekday, trip making.

Using the national average value of 0.156, we can conclude that an extra weekday in a particular month will bring on a 0.156 percent increase in the logarithmically transformed value of ridership, as compared to a month with one less weekday.

7.5.7 Fare (*DFARE*)

Table 7.15 presents the summary statistics for the binary *DFARE* variable. Generally, one would expect that a change in fare of any magnitude would induce a reduction in ridership. Although the sample sizes were much reduced in this case to 82 total systems by the availability and reliability of collected fare data, the assumption of negative fare elasticities appears to generally hold true, although the effect is mixed; regions with larger sample sizes tend to have unintuitive positive coefficient values.

Table 7.15 Descriptive Statistics for *DFARE* Values in Regression Model, Bus Systems Only

<i>DFARE</i> Descriptives								
Region	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
0	7	-0.120	0.209	0.079	-0.314	0.074	-0.503	0.141
1	3	-0.198	0.292	0.169	-0.924	0.528	-0.415	0.134
2	3	-0.277	0.426	0.246	-1.335	0.781	-0.666	0.178
3	11	-0.085	0.514	0.155	-0.430	0.261	-0.975	0.938
4	15	0.024	0.308	0.080	-0.147	0.194	-0.414	0.66
5	15	0.069	0.670	0.173	-0.302	0.440	-0.779	2.118
6	5	0.534	0.832	0.372	-0.499	1.568	-0.45	1.418
7	2	-0.129	0.397	0.281	-3.693	3.436	-0.409	0.152
8	2	0.121	0.095	0.068	-0.737	0.978	0.053	0.188
9	19	-0.169	0.534	0.123	-0.427	0.088	-1.65	0.744
Total	82	-0.029	0.518	0.057	-0.143	0.085	-1.65	2.118

Because the Levene and *F*-tests determined that the variances and means are statistically equal across regions, we can examine the national average of -0.029. This value indicates that a positive fare change is accompanied by a 0.029 percent decline in the logarithm of unlinked passenger trips.

While the magnitude of the national average value is small, it is worth noting that the computed confidence intervals for all regions contain zero; thus it is possible that fare has no sizeable effect, since the overall results are mixed positive and negative.

7.6 DIFFERENCES IN REGRESSION COEFFICIENTS ACROSS MODES

The procedure followed in Section 7.5 for the regional bus parameter analyses is repeated in this section for a multi-modal comparison of the regression coefficients calculated for all bus, light rail, heavy rail, and commuter rail systems.

Table 7.16 tabulates the results of the Levene test for the same seven model parameters, comparing this time among the four modes rather than across regions for a single mode.

Table 7.16 Levene Statistics and Multiple Range Tests Selected for Parameter Comparisons across All Four Modes

Regression Parameter	Levene Statistic	Significance ($\alpha=0.05$)	Variances Equal?	Range Test
<i>CONSTANT</i>	0.515	0.672	Yes	LSD; HSD; Ryan
<i>PDVRH</i>	2.245	0.084	Yes	LSD; HSD; Ryan
<i>PDVOMS</i>	4.777	0.003	No	Tamhane's T2
<i>PDFUEL</i>	1.167	0.323	Yes	LSD; HSD; Ryan
<i>PDCPI</i>	1.797	0.148	Yes	LSD; HSD; Ryan
<i>WEEKDAYS</i>	0.493	0.688	Yes	LSD; HSD; Ryan
<i>DFARE</i>	5.975	0.001	No	Tamhane's T2

In the regional comparisons for the bus systems, the Games-Howell test, appropriate for comparisons of more than five groups, was employed as necessary when variances were determined to be unequal. However, in this condition of comparing across modes, Tamhane's T2 test, a conservative test, is used because there are only four groups rather than ten as in the regional bus comparison case when the Games-Howell was better suited (Garson, 2009).

Table 7.17 provides the results of *F*-tests conducted to examine the equality of means across the four modes. In this comparison, three parameters were found to have unequal means: the *CONSTANT* term, *PDVOMS*, and *WEEKDAYS*. The following sections detail the conclusions drawn from the multiple range tests conducted on these parameters.

The analysis contained in this section is performed to find similarities between modes. However, due to the very different operational characteristics and functional environments of bus, light rail, heavy rail, and commuter rail systems, the conclusions drawn herein will not be used to establish

a universal transit equation; for the mode-specific equations outlined in Section 7.7, each mode retains its individual mean values for parameter coefficients.

Table 7.17 Results of ANOVA *F*-test for Equality of Parameter Means across All Modes

Coefficient	Computed <i>f</i>	<i>I</i>	<i>J</i>	$\nu_1 = I-1$	$\nu_2 = I(J-1)$	Critical F_{α, ν_1, ν_2}	Sig. ($\alpha = 0.05$)	Conclusion	Means Equal?
CONSTANT	2.808	4	254	3	1012	2.614	0.040	Reject H_0	No
PDVRH	0.572	4	254	3	1012	2.614	0.634	Do not Reject H_0	Yes
PDVOMS	2.876	4	240	3	956	2.614	0.037	Reject H_0	No
PDFUEL	0.415	4	254	3	1012	2.614	0.742	Do not Reject H_0	Yes
PDCPI	1.249	4	254	3	1012	2.614	0.292	Do not Reject H_0	Yes
WEEKDAYS	2.848	4	254	3	1012	2.614	0.038	Reject H_0	No
DFARE	1.116	4	109	3	432	2.626	0.346	Do not Reject H_0	Yes

7.6.1 Constant Term (CONSTANT)

Summary statistics for the *CONSTANT* term across the four modes are given in Table 7.18. Although the variances were determined to be equal using the Levene statistic, the ANOVA *F*-test found that the means are not equal.

Table 7.18 Descriptive Statistics for *CONSTANT* Terms in Regression Model, All Modes

CONSTANT Descriptives - All Modes

Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
BUS	215	-3.36	3.32	0.23	-3.81	-2.91	-25.21	6.32
LR	17	-1.22	2.95	0.72	-2.74	0.30	-4.03	6.93
HR	10	-2.23	1.60	0.51	-3.37	-1.08	-5.70	0.03
CR	12	-3.87	2.33	0.67	-5.35	-2.39	-7.87	0.25
Total	254	-3.20	3.25	0.20	-3.60	-2.79	-25.21	6.93

The appropriate range tests for this parameter are the LSD, HSD, and Ryan test, as indicated in Table 7.16.

The liberal LSD test found when evaluating these data that light rail differs from bus and commuter rail. Tukey’s HSD test, the most conservative test, also concluded that light rail and bus are different. The Ryan test, compromising between the LSD and HSD tests in conservativeness, found no differences between any of the modes.

Again, for the mode-specific equations, the modal mean values will be used, regardless of similarities found in these sections.

7.6.2 Vehicle Revenue Hours (*PDVRH*)

The Levene and ANOVA *F*-tests concluded that the variances and means for the *PDVRH* variable are equal across the four modes. Summary statistics for this parameter are given in Table 7.19. Generally, a percent change in vehicle revenue miles of service for bus produce the strongest change in ridership (0.009), while reactions for commuter and heavy rail are weakest (0.004 and 0.003, respectively).

Table 7.19 Descriptive Statistics for *PDVRH* Values in Regression Model, All Modes
***PDVRH* Descriptives - All Modes**

Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
BUS	215	0.009	0.019	0.001	0.006	0.012	-0.122	0.076
LR	17	0.007	0.011	0.003	0.001	0.012	-0.009	0.033
HR	10	0.003	0.012	0.004	-0.005	0.012	-0.008	0.034
CR	12	0.004	0.006	0.002	0.001	0.008	-0.003	0.016
Total	254	0.008	0.018	0.001	0.006	0.011	-0.122	0.076

7.6.3 Vehicles Operated in Maximum Service (*PDVOMS*)

As in the regional bus analysis, some bus and heavy rail systems included in the analysis had no change in the number of vehicles operated in maximum service during the 2002-2007 calibration period. For this reason, the sample sizes for this parameter are reduced from the full sample of 254 systems to 240. Summary statistics for *PDVOMS* are provided in Table 7.20.

For the *PDVOMS* variable, variances and means were both found to be unequal across modes. This conclusion dictates that Tamhane's T2 test be conducted to compare the means for the four modes. Tamhane's T2 test is appropriate to use when variances are not equal or are unknown and comparisons are made among fewer than five groups.

Table 7.20 Descriptive Statistics for *PDVOMS* Values in Regression Model, All Modes

***PDVOMS* Descriptives - All Modes**

Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
BUS	202	-0.002	0.053	0.004	-0.010	0.005	-0.322	0.168
LR	17	0.008	0.046	0.011	-0.015	0.032	-0.100	0.138
HR	9	0.050	0.126	0.042	-0.047	0.146	-0.052	0.355
CR	12	-0.015	0.040	0.012	-0.040	0.010	-0.107	0.030
Total	240	0.000	0.057	0.004	-0.007	0.007	-0.322	0.355

A caveat to the accuracy of the *F*-test when comparing means occurs when sample sizes are unequal, as in all the cases evaluated in this chapter. When sample sizes are unequal, the chances of making a Type I error increase, that is, concluding that a difference exists between parameter means when in actuality there is no difference. The significance of the *F*-statistic for *PDVOMS* (shown in Table 7.17) is 0.037, only slightly below the 0.05 significance threshold.

Despite the ANOVA *F*-test's indication that the parameter means are unequal, Tamhane's T2 test of these data reveals no similar groupings between modes. This finding is consistent with the likelihood of making a Type I error due to differing sample sizes as discussed. Although the *F*-statistic implied that the means were not equal, further range testing was unable to substantiate this conclusion. Thus, we infer that the means are essentially equal. Although the modal means indicate differing directions for the effect of changing the number of vehicles in maximum service, the average effect across all modes is nil.

7.6.4 Fuel Price (*PDFUEL*)

The effect of changing fuel price was determined through the *F*-test to be the same across all modes. Interestingly, the summary statistics in Table 7.21 show a much smaller effect for light rail systems (no effect, on average) than for the other three modes. This conclusion may be consistent with the various roles played in communities by light rail systems, oftentimes serving more as tourist attractions than true commuting solutions. There are, of course, several exceptions to this generalization, as indicated by the higher standard deviation in the mean of the light rail mode calculations.

Table 7.21 Descriptive Statistics for *PDFUEL* Values in Regression Model, All Modes

***PDFUEL* Descriptives - All Modes**

Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
BUS	215	0.007	0.028	0.002	0.003	0.010	-0.196	0.117
LR	17	0.000	0.030	0.007	-0.016	0.015	-0.094	0.030
HR	10	0.008	0.014	0.004	-0.002	0.018	-0.023	0.021
CR	12	0.010	0.011	0.003	0.003	0.017	-0.010	0.024
Total	254	0.006	0.027	0.002	0.003	0.010	-0.196	0.117

In Chapter 4, high correlation was calculated between light rail ridership and fuel price. The two light rail systems included in the Chapter 4 analysis were exceptional systems, those serving Dallas and Los Angeles. The findings here, reflecting the analyses of 17 light rail systems, are at once different and yet consistent with those in Chapter 4, as revealed in the high standard deviation of the *PDFUEL* parameter mean.

Also intriguing are the confidence intervals calculated for the modes. While the light rail and heavy rail confidence intervals include zero (although barely so for heavy rail), leaving open the possibility that fuel price exerts no effect on ridership, both the bus and commuter rail systems

have confidence intervals that include only positive values. These ranges imply that decidedly positive relationships exist between rising fuel price and ridership for these two modes.

Intuitively, this finding is reasonable; bus systems are the most prolific type of transit offered in the US and thus provide the greatest opportunity for public transportation use, while commuter rail systems tend to carry longer-haul trips and frequently serve as substitutes for airline travel. Longer trips on commuter rail systems, whether for commuting purposes or as alternatives to flying, can represent financial savings for travelers who would otherwise have paid substantially for fuel to make the same trip by auto.

7.6.5 Consumer Price Index (*PDCPI*)

Summary statistics for the *PDCPI* variable are shown in Table 7.22. Overall, the mean values for the *PDCPI* parameter indicate that as the CPI grows and the buying power of a dollar decreases, fewer travelers use transit. This effect is felt most strongly in commuter rail systems (with a mean of -0.166), which can have much higher fares than the other modes. Bus systems, having a mean value of -0.110, see the second-strongest impact on ridership by the CPI. The effect of the CPI on ridership may counter, to some extent, the effect of rising fuel prices on encouraging transit use, as suggested by the multi-modal PDFUEL analysis in Section 7.6.4 and similar to the regional bus results in Sections 7.5.4 and 7.5.5.

Table 7.22 Descriptive Statistics for *PDCPI* Values in Regression Model, All Modes

Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
BUS	215	-0.110	0.375	0.026	-0.161	-0.060	-1.269	1.433
LR	17	0.066	0.578	0.140	-0.231	0.364	-0.793	1.646
HR	10	-0.084	0.266	0.084	-0.275	0.106	-0.382	0.485
CR	12	-0.166	0.218	0.063	-0.305	-0.028	-0.534	0.226
Total	254	-0.100	0.383	0.024	-0.147	-0.053	-1.269	1.646

7.6.6 Weekdays (*WEEKDAYS*)

The Levene statistic for the modal comparisons of the *WEEKDAYS* parameter found that although variances are equal, means for this variable are not. See Table 7.23 for *WEEKDAYS* summary statistics. As with the regional bus analysis, all mean values are positive, agreeing with the intuitive relationship between monthly weekdays and ridership. Similarly to the *CONSTANT* term range analysis, the LSD test found that light rail differs from bus and commuter rail, while the HSD test determined that differences exist between light rail and bus; the Ryan test found no differences among the modes.

Table 7.23 Descriptive Statistics for *WEEKDAYS* Values in Regression Model, All Modes

***WEEKDAYS* Descriptives - All Modes**

Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
BUS	215	0.156	0.156	0.011	0.135	0.177	-0.295	1.222
LR	17	0.055	0.141	0.034	-0.018	0.127	-0.344	0.188
HR	10	0.103	0.076	0.024	0.049	0.157	-0.002	0.268
CR	12	0.180	0.109	0.031	0.111	0.249	-0.011	0.367
Total	254	0.148	0.153	0.010	0.130	0.167	-0.344	1.222

7.6.7 Fare (*DFARE*)

Due to the data limitations discussed previously, the total sample size for *DFARE* was restricted to 109 of the total 254 systems available for analysis. Final sample sizes and summary statistics for this variable are given in Table 7.24.

Table 7.24 Descriptive Statistics for *DFARE* Values in Regression Model, All Modes

***DFARE* Descriptives - All Modes**

Mode	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
BUS	82	-0.029	0.518	0.057	-0.143	0.085	-1.650	2.118
LR	14	-0.110	1.098	0.293	-0.744	0.524	-2.034	2.092
HR	7	-0.472	0.785	0.297	-1.198	0.254	-1.741	0.586
CR	6	-0.007	0.195	0.079	-0.211	0.198	-0.195	0.317
Total	109	-0.066	0.628	0.060	-0.186	0.053	-2.034	2.118

Although the 95% confidence intervals for the four modes contain zero and thus leave open the possibility that no effect on ridership occurs by increasing fares, the mean values indicate that a reduction in ridership is achieved with a positive change in fare, which is consistent with historical literature on the subject of fare elasticities of demand for public transportation (see Goodwin, 1992).

The ANOVA *F*-test found that the means across the four modes are equal, while the Levene statistic concluded that variances are unequal. Despite the findings of these tests, it is interesting to look more closely at the modal mean values. The least negative effect on ridership is shown with the commuter rail mode (-0.007), which usually has the highest fares of any evaluated mode. This value may reflect the willingness of riders to pay for the convenience afforded them by the fast, direct service offered by commuter rail.

The second-least negative effect is seen on bus systems (-0.029). Such an effect could be attributable both to the widespread use of bus systems and to the very low magnitude of bus fares, both before and after a fare change. Most systems have fares set at two dollars or less, and when a fare change is implemented, it typically amounts to less than an additional dollar. Bus systems also tend to have a higher proportion of “captive” riders, who are less responsive to fare changes, having few alternatives to transit use.

The higher magnitude of the heavy rail mean value could be indicative of a reduction in non-essential or discretionary trips as fares increase, since heavy rail fares tend to be higher than bus fares, yet the two systems serve similar types of trips.

7.7 GENERALIZED REGRESSION EQUATIONS

Ideally, it is more appropriate and accurate to use the parameter coefficients calibrated specifically for a particular system. However, in the event that general equations describing behavior on bus systems within a selected region or on a particular mode are desired, this section builds on the calculations in Sections 7.5 and 7.6 to develop region-specific equations for bus systems and mode-specific equations for the most generalized forecasts. Modal equations are the most general model forms developed here; given the different operating characteristics of the four modes and disparities between the types of trips served by each, creating a general equation to indiscriminately address all modes is neither practical nor realistic. It should be noted that these regression equations must be combined with the appropriate seasonal model (discussed more in Chapter 8) to determine the full forecast values.

7.7.1 Unique System Equations

Since coefficient values have been calculated for each parameter x in each of the 254 transit systems analyzed here (tabulated in Appendix C), the most accurate way to forecast ridership for an individual system n is to use its unique coefficient values in the non-seasonal portion of the model. In so doing, we can represent this forecasting system in the following manner:

$$\hat{Y}_n = X_n b_n \quad (7.3)$$

where

\hat{Y}_n is the vector of estimated *PDLOGUPT* for the non-seasonal regression model in each time period t for which a forecast is sought (and which must be combined with the seasonal model for period t),

X_n is the matrix of independent variables for the forecast period, and

b_n is the vector of parameters corresponding to system n .

Also stated,

$$\hat{Y}_n = \begin{bmatrix} Y_{1n} \\ Y_{2n} \\ \vdots \\ Y_{tn} \end{bmatrix} \quad X_n = \begin{bmatrix} 1 & X_{11n} & X_{12n} & \cdots & X_{1pn} \\ 1 & X_{21n} & X_{22n} & \cdots & X_{2pn} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{t1n} & X_{t2n} & \cdots & X_{tpn} \end{bmatrix} \quad b_n = \begin{bmatrix} b_{0n} \\ b_{1n} \\ \vdots \\ b_{pn} \end{bmatrix} \quad (7.4)$$

where the first subscript 1 through t represents the time period (month) for which the forecast is sought, the second subscript 0 through p indicates the parameter (the models here consist of a constant b_0 and six independent variables), and the final subscript n specifies the transit system under consideration.

The b_n vector may also be defined for each system n :

$$b_n = \begin{bmatrix} \text{CONSTANT}_n \\ \text{PDVRH}_n \\ \text{PDVOMS}_n \\ \text{PDFUEL}_n \\ \text{PDCPL}_n \\ \text{WEEKDAYS}_n \\ \text{DFARE}_n \end{bmatrix} \quad (7.5)$$

Following this procedure produces forecasts for t time periods representing a percent change in the logarithm of UPT, which must then be combined with the seasonal model and used to calculate the nominal change in ridership from the last observed or forecasted point.

7.7.2 Regional Bus Equations

While the unique system equations in Section 7.7.1 allow specific treatment of individual transit systems, we can also use the more general regional parameter values for exploration of bus system trends. For region r , analyzed across t time periods, we can define the forecasting system as follows:

$$\hat{Y}_r = X_r b_r \quad (7.6)$$

where

$$\hat{Y}_r = \begin{bmatrix} \hat{Y}_{1r} \\ \hat{Y}_{2r} \\ \vdots \\ \hat{Y}_{tr} \end{bmatrix} \quad X_r = \begin{bmatrix} 1 & X_{11r} & X_{12r} & \dots & X_{1pr} \\ 1 & X_{21r} & X_{22r} & \dots & X_{2pr} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{t1r} & X_{t2r} & \dots & X_{tpr} \end{bmatrix} \quad b_r = \begin{bmatrix} b_{0r} \\ b_{1r} \\ \vdots \\ b_{pr} \end{bmatrix} \quad (7.7)$$

In these expressions,

t represents the time period (month) for which the forecast is sought,

r indicates the bus region (0 through 9) undergoing forecasting, and

p specifies the regression parameter (which ranges from 0 to 6 in these cases and corresponds with Equation 7.5).

The b_r vectors may be further defined per the analyses in Section 7.5, using the regional values or those determined through multiple range testing. Using the regional averages, the seven b_r vectors for the ten regions are as follows, respectively:

$$b_0^T = [-4.695 \quad -0.004 \quad 0.005 \quad 0.020 \quad -0.258 \quad 0.223 \quad -0.120]$$

$$b_1^T = [-3.464 \quad 0.010 \quad 0.024 \quad 0.012 \quad -0.216 \quad 0.162 \quad -0.198]$$

$$b_2^T = [-1.711 \quad 0.018 \quad -0.001 \quad 0.010 \quad -0.276 \quad 0.081 \quad -0.277]$$

$$b_3^T = [-3.939 \quad 0.008 \quad 0.001 \quad 0.008 \quad -0.141 \quad 0.183 \quad -0.085]$$

$$b_4^T = [-2.300 \quad 0.013 \quad -0.013 \quad 0.011 \quad -0.130 \quad 0.107 \quad 0.024]$$

$$b_5^T = [-3.527 \quad 0.008 \quad 0.004 \quad -0.012 \quad 0.207 \quad 0.161 \quad 0.069]$$

$$b_6^T = [-4.501 \quad 0.007 \quad -0.017 \quad 0.002 \quad -0.049 \quad 0.208 \quad 0.534]$$

$$b_7^T = [-4.261 \quad 0.010 \quad -0.022 \quad -0.001 \quad 0.077 \quad 0.196 \quad -0.129]$$

$$b_8^T = [-2.865 \quad 0.019 \quad -0.021 \quad 0.014 \quad -0.264 \quad 0.134 \quad 0.121]$$

$$b_9^T = [-3.134 \quad 0.006 \quad -0.001 \quad 0.018 \quad -0.302 \quad 0.147 \quad -0.169]$$

Using the results of the multiple range tests instead, we find b_r vectors equal to:

$$\begin{aligned}
b_0^T &= [-3.360 \quad 0.009 \quad -0.002 \quad 0.012 \quad -0.204 \quad 0.156 \quad -0.029] \\
b_1^T &= [-3.360 \quad 0.009 \quad -0.002 \quad 0.012 \quad -0.204 \quad 0.156 \quad -0.029] \\
b_2^T &= [-3.360 \quad 0.009 \quad -0.002 \quad 0.012 \quad -0.204 \quad 0.156 \quad -0.029] \\
b_3^T &= [-3.360 \quad 0.009 \quad -0.002 \quad 0.012 \quad -0.204 \quad 0.156 \quad -0.029] \\
b_4^T &= [-3.360 \quad 0.009 \quad -0.002 \quad 0.012 \quad -0.204 \quad 0.156 \quad -0.029] \\
b_5^T &= [-3.360 \quad 0.009 \quad -0.002 \quad -0.010 \quad 0.184 \quad 0.156 \quad -0.029] \\
b_6^T &= [-3.360 \quad 0.009 \quad -0.002 \quad 0.012 \quad -0.204 \quad 0.156 \quad -0.029] \\
b_7^T &= [-3.360 \quad 0.009 \quad -0.002 \quad -0.010 \quad 0.184 \quad 0.156 \quad -0.029] \\
b_8^T &= [-3.360 \quad 0.009 \quad -0.002 \quad 0.012 \quad -0.204 \quad 0.156 \quad -0.029] \\
b_9^T &= [-3.360 \quad 0.009 \quad -0.002 \quad 0.012 \quad -0.204 \quad 0.156 \quad -0.029]
\end{aligned}$$

7.7.3 Mode-Specific Equations

As for the mode-specific equations, we can represent the model for the non-seasonal portion of the forecasts:

$$\hat{Y}_m = X_m b_m \quad (7.8)$$

where

$$\hat{Y}_m = \begin{bmatrix} \hat{Y}_{1m} \\ \hat{Y}_{2m} \\ \vdots \\ \hat{Y}_{tm} \end{bmatrix} \quad X_m = \begin{bmatrix} 1 & X_{11m} & X_{12m} & \cdots & X_{1pm} \\ 1 & X_{21m} & X_{22m} & \cdots & X_{2pm} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & X_{t1m} & X_{t2m} & \cdots & X_{tpm} \end{bmatrix} \quad b_m = \begin{bmatrix} b_{0m} \\ b_{1m} \\ \vdots \\ b_{pm} \end{bmatrix} \quad (7.9)$$

Using this notation,

t represents the time period (month) for which the forecast is sought,

m indicates the mode (bus = 1, light rail = 2, heavy rail = 3, or commuter rail = 4) undergoing forecasting, and

p specifies the regression parameter (which ranges from 0 to 6 in these cases and corresponds with Equation 7.5).

With b_n vectors comprising the seven parameters (the constant term and six independent variables) specified as in Equation 7.5, we create the following transposed b_m vectors for the four modes:

$$\begin{aligned} b_1^T &= [-3.36 & 0.009 & -0.002 & 0.007 & -0.110 & 0.156 & -0.029] \\ b_2^T &= [-1.22 & 0.007 & 0.008 & 0.000 & 0.066 & 0.055 & -0.110] \\ b_3^T &= [-2.23 & 0.003 & 0.050 & 0.008 & -0.084 & 0.103 & -0.472] \\ b_4^T &= [-3.87 & 0.004 & -0.015 & 0.010 & -0.166 & 0.180 & -0.007] \end{aligned}$$

7.8 SENSITIVITY ANALYSIS

Of the variables included in the regression analysis, most are determined in-house prior to, or in conjunction with, conducting forecasts. Parameters such as scheduled vehicle revenue hours, the number of vehicles in peak service, and/or whether a fare change is pending are already known prior to developing ridership projections. The counts of weekdays in the coming months are also known ahead of time. However, the consumer price index cannot be known beforehand, although estimates may produce an approximate value. Of the parameters used in this research, fuel price presents the greatest hurdle in anticipating input values for the models; the context and procedures for forecasting fuel prices constitute a continuing challenge for econometricians and are far beyond the scope of the work contained herein.

This sensitivity analysis investigates how deviations from the true value of an external unknown input (fuel price or CPI) affect the accuracy of the forecast prior to combining the regression model with the seasonal model for a transit system. Because many of the independent variables in the model already consist of a percent change in the parameter of concern, interpretation of the regression results in sensitivity terms is straightforward.

7.8.1 Fuel Price (PDFUEL) and Consumer Price Index (CPI)

With the fuel price and CPI variables transformed to reflect the percent change from the previous month's price or index, the units on these parameters in the final model definition also represent percent changes. Thus, sensitivity analysis reveals that determining the effect of wrongly estimated fuel prices or indices is as simple as consulting the parameter value associated with the *PDFUEL* or *PDCPI* variable. For specific systems, these effects are listed in Appendix C. For the broader regional values for bus, the mean values tabulated in Tables 7.7 and 7.11 for *PDFUEL* or *PDCPI*, as appropriate, are valid.

In the case of determining the sensitivity to inaccurate fuel price estimates of non-seasonal ridership in the four different modes, the mean values in Table 7.21 serve here demonstratively. For bus systems as a whole, one percent overestimates in the percent change in fuel price result in an error of +0.007 percent in the non-seasonal component of *PDLOGUPT*. The final error on the estimate will depend on the seasonal parameters for the system in question, as determined and tabulated in Chapter 6. Similarly, the non-seasonal components of *PDLOGUPT* for light rail will be essentially nil, while for heavy and commuter rail systems, the non-seasonal portions of

the estimate will suffer +0.008 and +0.010 percent errors, respectively. This logic and interpretation of parameters pertains to the regional or system-specific PDFUEL coefficient values as well. Again, the final estimate of *PDLOGUPT* will depend on the seasonal factors, which vary too widely between regions and systems to define modally.

Modal sensitivity analyses of inaccurate CPI estimates rely on Table 7.22. Using modal mean values for *PDCPI*, we see that a one percent overestimate of the percent change in the monthly CPI value brings about errors in the non-seasonal portion of *PDLOGUPT* equivalent to -0.110, +0.066, -0.084, and -0.166 percent, respectively, for bus, light rail, heavy rail, and commuter rail systems. The ultimate error in the final forecast of *PDLOGUPT* will depend on the seasonal *SAF* and *STC* values used in the projection.

7.9 SUMMARY

The non-seasonal error terms from the seasonal decomposition in Chapter 6 were analyzed in this chapter using multivariate regression to explain additional ridership variability due to operational and external factors. The regression results showed differences between modes and in the case of bus systems, differences in behavior between regions. The greatest differences are shown when comparing the effects of fuel price and consumer price index in the North Central and Mid-west sections of the US with the remainder of the nation.

Non-seasonal model specifications were developed on system-, region-, and mode-specific bases, and sensitivity analyses for the external parameters were conducted. In the next chapter, the seasonal and non-seasonal models are combined to form the final composite transit ridership forecasting model.

Chapter 8: Composite Ridership Forecasting Model

8.1 OVERVIEW

Chapter 6 outlined the process by which seasonality was removed from the transformed *PDLOGUPT* time-series for each of 254 evaluated transit systems. The *SAF* and *STC* values derived for each system make up the seasonal portion of the forecasting models.

Chapter 7 described the multivariate regression analysis conducted on the error terms e_t from the additive seasonal decomposition and the calibration results from the regressions, formulating matrices used in defining the model elements describing the effects of non-seasonal factors on ridership.

To create the final ridership forecasts, the two model types must be additively combined to arrive at a final model definition comprised of both seasonal and non-seasonal components. This chapter discusses the composite model and the performance of this final model designation in terms of how well it explains variability within the dataset used for model construction and calibration. The next chapter, Chapter 9, describes model validation procedures and statistical implementation outcomes.

8.2 VARIABILITY EXPLAINED BY COMPOSITE MODEL

From the R^2 value associated with the seasonality model and the adjusted R^2 derived from the multivariate regression, a composite R^2 value was calculated for each system, to determine the total percent of variation explained in the original series when combining the seasonal decomposition model and non-seasonal regression model.

To calculate this value, the percent of variation described by the seasonal model (seasonal R^2) was subtracted from one to determine what percentage of variability was not explained by seasonality. This percentage was multiplied by the R^2 resulting from the regression, to find the percent of non-seasonal variation that could be described by the operational and external factors included in the regression. Finally, the R^2 for seasonality was added to this non-seasonal value to calculate the total percentage of variation explained by the combined seasonal and regression models. These calculations are included in Appendix B.

In a few cases, adjusting the regression R^2 value to account for sample size led the value to become negative; in these instances, the R^2 value associated with the regression was omitted from the final calculation, giving all explanatory power to the seasonal model.

Table 8.1 presents summary statistics for composite R^2 values across the four modes. With the exception of light rail systems, the final combined model explains an average of 70 percent of the total variation in the original ridership time-series. The maxima of these combined R^2 values exceed 85 percent in all cases and 96 percent for bus and commuter rail systems.

Table 8.1: Total Variation (R^2) Explained by Composite Forecasting Model, Summary Statistics

Total Variation Explained by Composite Forecasting Model
Summary Statistics

	Mode			
	Bus	Light Rail	Heavy Rail	Commuter Rail
Minimum	0.1316	0.2377	0.2024	0.3951
Maximum	0.9645	0.8564	0.9017	0.9792
Average	0.6896	0.5901	0.6879	0.7253
Median	0.7120	0.5721	0.7953	0.7221
Std. Dev.	0.1643	0.1584	0.2382	0.1478

Figures 8.1 through 8.4 provide histograms for the R^2 values derived from the composite system-specific models for bus, light rail, heavy rail, and commuter rail, respectively.

In the case of bus systems (Figure 8.1), only 11 percent of bus systems have composite R^2 values below 0.5. Thus, 89 percent of bus systems have 50 percent or more of their ridership variability explained by the composite forecasting model. In addition, for 38 percent of bus systems, more than 75 percent of total variability is explained by the model.

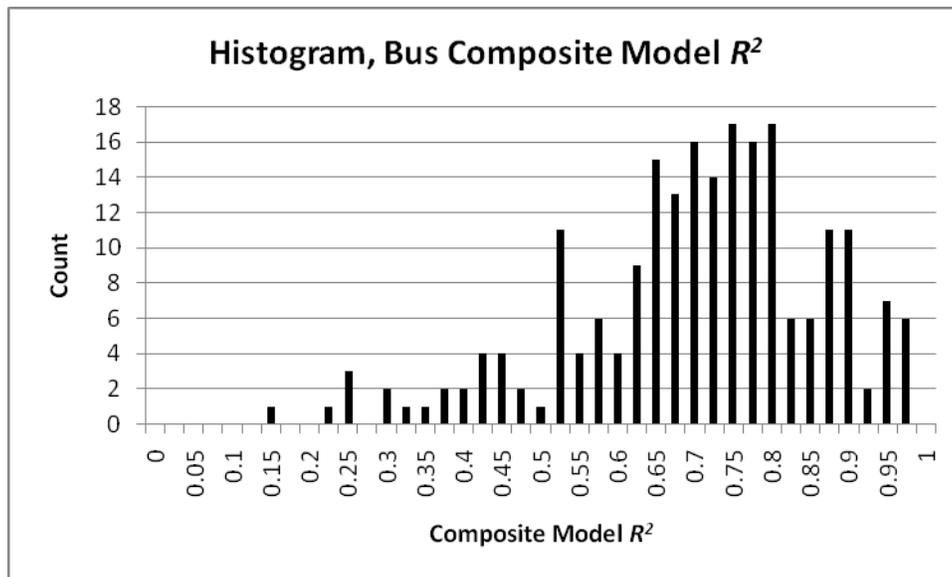


Figure 8.1 Histogram of Composite R^2 Values for Bus Systems

For the light rail systems in Figure 8.2, 71 percent of systems have R^2 values above 0.5; in 18 percent of systems (three of 17), the composite model serves to explain more than 75 percent of ridership variability.

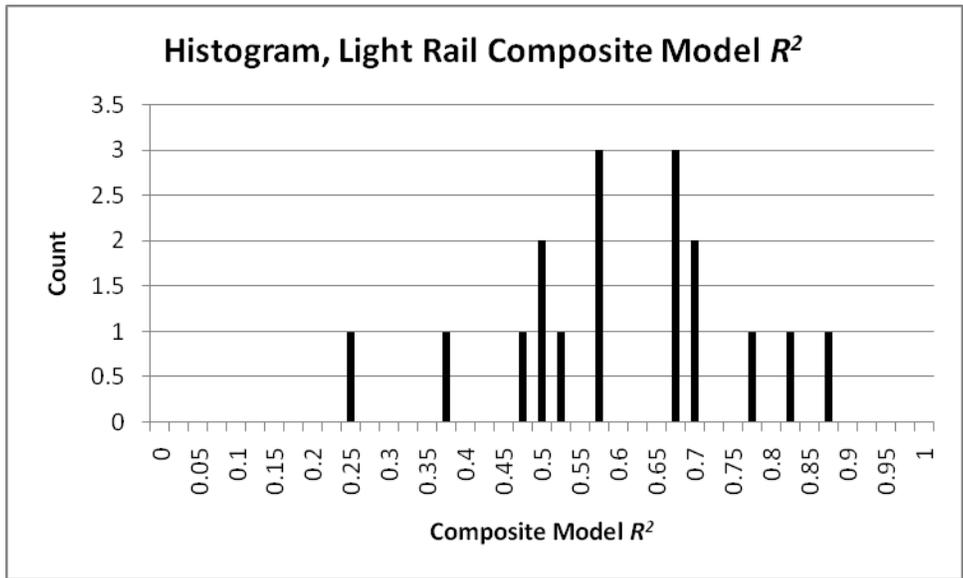


Figure 8.2 Histogram of Composite R^2 Values for Light Rail Systems

Figure 8.3 shows the histogram of R^2 values for heavy rail. For this mode, 50 percent of variability is described by the model in 80 percent of systems, and in half of the heavy rail systems, 75 percent or more of ridership fluctuations are explained by the composite model. The R^2 values tend to cluster near the top of the possible range.

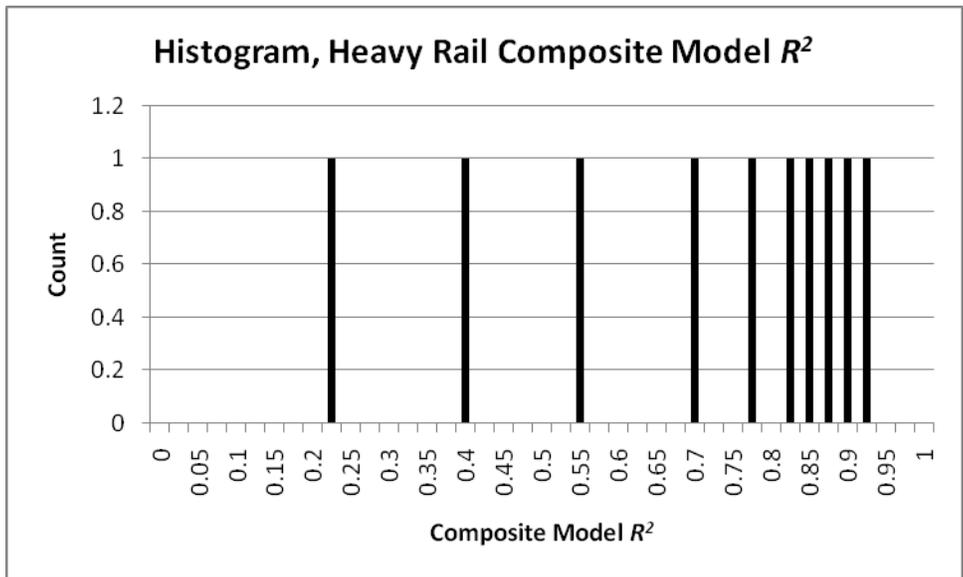


Figure 8.3 Histogram of Composite R^2 Values for Heavy Rail Systems

In evaluating the composite model for commuter rail systems (Figure 8.4), only one system (eight percent) had an R^2 value below 0.5. The remaining 92 percent of R^2 values were 0.6 or

greater. Additionally, in two-thirds of commuter rail systems (eight of 12), 75 percent or more of ridership variability could be explained by the composite model.

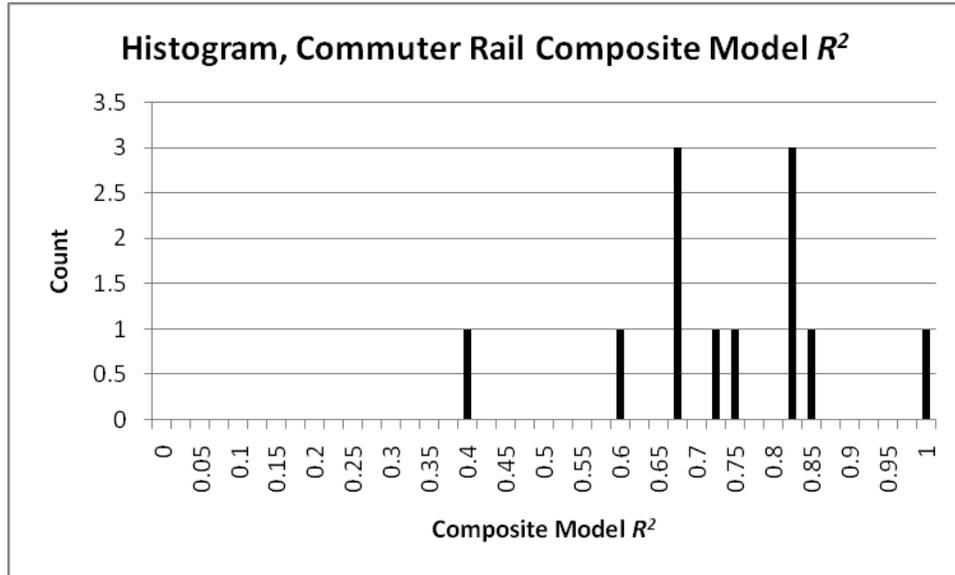


Figure 8.4 Histogram of Composite R^2 Values for Commuter Rail Systems

8.3 FINAL COMPOSITE MODEL FORM

In combining the seasonal model and non-seasonal regression model to form the final composite model, the calculation is additive and takes the general form:

$$PDLOGUPT = [SEASONAL MODEL] + [REGRESSION MODEL] + \{error\} \quad (8.1)$$

Combining the seasonal and non-seasonal models mathematically to establish the final model form produces a theoretical expression as given in Equation 8.2, which assumes that all variability is captured in the model:

$$Y_t = SAF_n I + STC_n I + X_t b_t \quad (8.2)$$

where

Y_t is the vector of accurate $PDLOGUPT$ values over n time periods,

t indicates the subscript n , r , or m , for the system, region, or mode under consideration,

I is the t by t identity matrix,

SAF_n is the vector of seasonal adjustment factors for system n ,

STC_n is the vector of trend-cycle factors for system n ,

\mathbf{X}_n is the matrix of independent variables as defined in Chapter 7, and

\mathbf{b}_n is the vector of parameters as defined in Chapter 7.

In actuality, the forecasts each have an additive error term associated with the expression, yielding a model form as follows:

$$\hat{\mathbf{Y}}_n = \mathbf{Y}_n + \mathbf{e} = \mathbf{SAF}_n \mathbf{I} + \mathbf{STC}_n \mathbf{I} + \mathbf{X}_n \mathbf{b}_n + \mathbf{e} \quad (8.3)$$

where

$\hat{\mathbf{Y}}_n$ is the vector of estimated forecasts over n time periods, and

\mathbf{e} represents the error vector associated with each of n forecasts.

The contribution of this error term \mathbf{e} to the forecasts is discussed more in Chapter 9.

Although non-seasonal models were developed in Chapter 7 for regional and modal comparisons, comparable seasonal factors (SAF and STC) have not been developed on these bases. In addressing the seasonal patterns when regional or modal models are employed, it is suggested that one of the following methods be used to determine seasonal factors:

- When the system of interest is included in the analyses and appendices here, values may be drawn directly from the appropriate appendix.
- If a particular system is of interest and not included in the analyses and appendices here, seasonal decomposition may again be used to calculate unique seasonal factors.
- For general regional values of SAF and STC , average or median values may be calculated for the appropriate region as provided in the appendices.
- When evaluating a particular mode, the region of the US where the modal system resides must be known. Then SAF and STC values for a comparable system may be used, or regional average or median values may be found.

8.4 SUMMARY

This chapter described the additive procedure by which the seasonal and non-seasonal models are combined to produce the composite forecasting model. Most of the evaluated transit systems respond well to this approach, achieving composite R^2 values around 0.7.

The following chapter uses data from the first six months of 2008 to validate the composite model and assess its performance.

Chapter 9: Model Validation

9.1 OVERVIEW

In Chapter 8, the composite model describing seasonal and non-seasonal patterns was explained and formulated. Using R^2 values to compare the formulated model to the time series data upon which the model was created, the total variability explained by the model was explored for each of four modes.

In this chapter, we use the system-specific composite model for each transit system to forecast ridership in the first six months of 2008. Two types of forecasts are made; the first set consists of single-month forecasts based on actual observations from the previous month. Because the dependent variable in the model, *PDLOGUPT*, represents a percent change from the previous month, this forecast type is more accurate because it builds upon a confirmed ridership value.

The second type of forecast created here uses the last observation point in December 2007 to project six months into the future with no input from actual ridership counts between December 2007 and the final forecast month. This method is less accurate than the single-month projections due to the nature of the dependent variable because projections are based on the preceding forecast and thus errors tend to grow with time.

For both types of forecasts, error analyses are conducted to explore the reliability of the composite model in developing ridership projections. Describing the outcome and accuracy of a forecast cannot be readily accomplished through the use of a single statistic and therefore several are used here, including the mean forecast percentage error (MFPE), root mean squared error (RMSE), mean absolute percentage deviation (MAPD), and tracking signal, formulae for each of which are described in turn in Section 9.3. Tables of cumulative percentages of systems below given error levels are also included.

9.2 FORECASTING *STC* VALUES

In the seasonal portion of the model, two parameters, SAF_t and STC_t , are used to determine the seasonal component of ridership at time t . SAF values are constant through time for the month to which they pertain. However, STC values, representing the slow, underlying change of ridership over time, need to be projected before continuing with the final forecasts.

Several options exist for creating the STC projections for the first six months of 2008. For the purposes here, simple three-month moving averages were used to forecast STC values. As such, this approach required that STC values for April, May and June 2008 were based solely on the estimated STC values earlier in 2008. Given the small magnitude and contribution of STC values to the overall ridership forecasts, the method by which to calculate the estimated STC trend was deemed trivial to the forecasts. Other methods that might have been effectively employed include replication of the last six months' values, moving averages of varying lengths, and weighted averages having greater reliance on observed values and giving less power to projected values.

9.3 ACCURACY MEASURES APPLIED TO FORECASTS

The following subsections describe mathematically the definitions of the accuracy measurements used in this chapter and the reasons for utilizing them in quantifying how well the forecasts performed.

9.3.1 Percentage Error

Percentage error measures the deviation of the forecast at time t from the actual UPT count as a proportion of the observed ridership. Based on the definition in Equation 9.1, positive percentage errors indicate an overestimate, while an underestimate yields negative values.

$$e_t = \frac{Y_t - Y_t}{Y_t} * 100\% \quad (9.1)$$

9.3.2 Mean Forecast Percentage Error (MFPE)

As a measure of forecast bias (SCRC, 2006), the mean forecast percentage error (Equation 9.2) is the average percentage error incurred over the entire forecast period. MFPE can also be calculated at intermediate periods prior to the end of the forecast period by adjusting n accordingly.

$$MFPE = \bar{e} = \frac{\sum_{t=1}^n e_t}{n} \quad (9.2)$$

9.3.3 Root Mean Squared Error (RMSE)

Root mean squared error is the square root of MSE, or mean squared error, calculated by subtracting the average monthly error over the validation period, \bar{e} (or MFPE), from the individual monthly errors, squaring and summing these differences, dividing by the n forecast periods, and taking the square root (Equation 9.3). Here, the errors e used in the calculations are percentage errors.

$$RMSE = \sqrt{\frac{\sum_{t=1}^n (e_t - \bar{e})^2}{n}} \quad (9.3)$$

9.3.4 Mean Absolute Percentage Deviation (MAPD)

The mean absolute percentage deviation measures the absolute deviation of the forecasts from the observed ridership values (Equation 9.4). By summing the absolute values of the percentage errors and dividing by n , we determine the average absolute deviation from the real values. MAPD may also be calculated at intermediate points during the forecast period.

$$MAPD = \frac{\sum_{t=1}^n |e_t|}{n} \quad (9.4)$$

9.3.5 Tracking Signal (TS)

The tracking signal is a method of easily discerning which forecasts should be adjusted (SCRC, 2006). By summing the errors over n periods and dividing by the mean absolute percentage deviation (MAPD) as in Equation 9.5, we calculate a positive or negative value indicating whether the model tends to over- or underestimate the true UPT count. The tracking signal has an acceptable range between -4.0 and +4.0; values falling outside this range indicate that the model could perform better.

$$TS = \frac{\sum_{t=1}^n e_t}{MAPD} \quad (9.5)$$

9.4 PERFORMANCE: SINGLE-MONTH PROJECTIONS

Tables of statistics concerning the outcomes of single-month forecasts for the January 2008 to June 2008 validation period may be found in Appendix D for each transit system, including month-by-month percentage error values, mean forecast percentage error (MFPE) and root mean squared error (RMSE) over the six-month period, as well as mean absolute percentage deviation (MAPD) and tracking signal values for each monthly forecast. Tracking signal values outside the acceptable range are highlighted in the appendix. It should be noted that transit ridership became rather volatile during 2008 as economic factors began to play an unexpectedly greater role in travel patterns.

The interpretation of MAPD and tracking signal values for these single-month forecasts is somewhat different from the multi-month forecasts, addressed in Section 9.5. Whereas for the multi-month forecasts, calculated values and errors build upon previous projection values, the single-month forecasts are based solely on the actual ridership value for the preceding month. Thus, percentage errors are lower because accuracy is dependent only on the model itself, rather than the precision of previous estimates. Values of RMSE, MAPD, and tracking signal are also smaller because errors are not propagated through the forecast series.

Table 9.1 displays the median values of root mean squared percentage error (RMSE) and mean forecast percentage error (MFPE) for each of the ten bus regions, as analyzed previously. Median values are used here to eliminate the influence of outliers resulting from a handful of extremely poorly-performing systems. While some regions, such as Regions 3 and 5, show higher RMSE (9.0 and 9.1 percent, respectively), their median MFPE values over the six-month validation period are very low (0.3 and -0.6 percent, respectively); this indicates that although the MFPE tends to hover around zero, the error values contained in the sample fall into a wide range. Seven of the ten regions yield median MFPE within two percent of the true ridership value over the six-month validation period. Overall, the composite model tends to underestimate ridership.

Table 9.1 Regional Median Values of RMSE and MFPE, Single-Month Forecasts, Bus Systems Only

Region	Median 6-month RMSE (%)	Median 6-month MFPE (%)
0	6.9	-1.9
1	5.7	-2.8
2	7.0	-0.5
3	9.0	0.3
4	6.9	-1.0
5	9.1	-0.6
6	9.5	-1.0
7	7.0	-2.9
8	6.7	-3.9
9	6.5	-1.5

Regional bus statistics for median MAPD and tracking signal values are provided in Table 9.2. Examining the MAPD values laterally through the table shows that, since each month's forecast is based upon the actual UPT count from the preceding month, the errors are generally stable throughout the validation series. In fact, Regions 0 and 1 show that errors decreased with time, as month-to-month ridership variability decreased. With one exception in May 2008 for Region 7, median tracking signal values for the ten regions fall within the acceptable range (-4.0 < TS < +4.0), indicating that the composite model works well in predicting ridership on a single-month basis. The profusion of negative tracking signal values substantiates the conclusion that the composite model tends to underestimate ridership.

Table 9.2 Regional Median Values of MAPD and Tracking Signal, Single-Month Forecasts, Bus Systems Only

Region	Median MAPD (%)						Median Tracking Signal (TS)					
	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08
0	8.8	7.8	8.7	8.1	7.0	6.2	-1.0	-2.0	-0.3	-1.4	-1.3	-2.3
1	10.3	8.0	7.7	7.7	6.7	6.3	-1.0	-2.0	-0.9	-2.1	-2.2	-2.5
2	8.2	6.7	7.4	7.2	6.7	6.3	-1.0	-1.7	0.1	-1.0	-0.1	-0.6
3	9.7	7.5	7.9	8.5	8.8	7.6	-1.0	-2.0	0.1	-1.0	-0.2	0.3
4	3.1	5.6	6.9	7.4	6.4	6.1	-1.0	-1.8	0.3	-0.4	-0.5	-1.3
5	6.3	5.3	7.5	8.5	8.4	8.0	-1.0	-1.8	0.4	-1.4	-0.6	-0.6
6	3.4	8.8	8.2	9.8	9.1	8.7	-1.0	-1.7	0.4	-0.2	0.2	-0.6
7	8.8	7.1	7.6	7.5	6.6	7.0	-1.0	-2.0	-3.0	-4.0	-4.5	-2.7
8	6.7	7.5	8.9	8.0	6.6	6.7	-1.0	-2.0	-1.2	-2.4	-2.4	-3.0
9	3.7	6.1	6.7	6.7	6.3	5.8	-1.0	-2.0	-0.3	-1.4	-0.5	-1.7

Regarding the median RMSE and MFPE results for all four modes, given in Table 9.3, bus systems as a whole had a median RMSE value of about 7.3 percent and a median MFPE of -1.1 percent. The rail modes, with much smaller sample sizes, had slightly higher overall errors; median MFPE values for light, heavy, and commuter rail modes were -3.3, -2.2, and -2.3 percent, respectively. However, heavy and commuter rail, with higher mean percentage error, showed lower RMSE values, indicating less spread about the mean error values, compared to bus and light rail system statistics.

Table 9.3 Modal Median Values of RMSE and MFPE, Single-Month Forecasts

Mode	Median 6-month RMSE (%)	Median 6-month MFPE (%)
Bus	7.3	-1.1
Light Rail	8.2	-3.3
Heavy Rail	5.8	-2.2
Commuter Rail	6.0	-2.3

Generally, those systems with higher composite R^2 values tended to have lower error, as shown in Figure 9.4, which includes information for all four evaluated transit modes. (One extreme outlier point with very high positive MFPE and low composite R^2 has been omitted from this figure for display purposes.) In Figure 9.1, it can be seen that MFPE values tend to cluster closer to the zero percent error line as R^2 increases. This observation implies that the composite model was suitable for explaining variability in both the 2002-2007 calibration series and in the validation series.

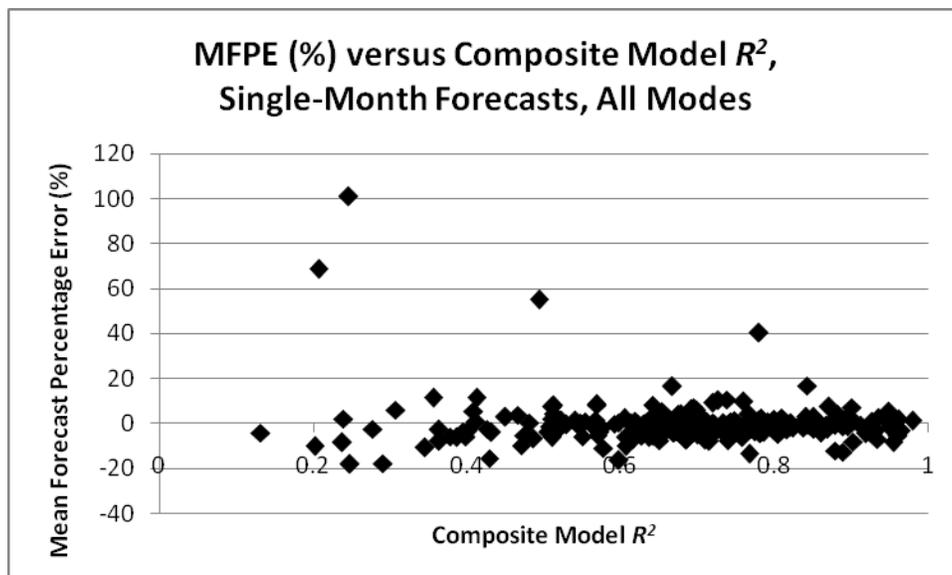


Figure 9.1 Mean Forecast Percentage Error (%) versus Composite Model R^2 , Single-Month Forecasts, All Modes

A cursory perusal of Appendix D and Tables 9.1 through 9.3 reveals that the forecasting model tended to underestimate ridership, as most of the individual monthly percentage error values are negative. One issue that arises from this result is the question of whether underestimates or overestimates of ridership are potentially more harmful. Underestimates could mean higher occupancies on vehicles and extreme underestimates could be detrimental to public perceptions when insufficient capacity is provided. Overestimates could lead to underutilization of vehicles and unnecessary expenditure of resources to provide for unmet ridership expectations.

Part of what may have contributed to this tendency to underestimate ridership resides in the development of the model. Because the regression model was built upon six years of data (2002 to 2007), the effects of included non-seasonal components tend to represent long-term behavior shifts since results are averaged over the six-year period. Utilizing this longer period for model calibration means that the regression results could be less capable of capturing short-term, immediate shifts of behavior. Especially in the validation period, the question of long-term versus short-term shifts is of great concern since the national economic environment was undergoing rapid change at this point (and was felt even more acutely in the latter part of 2008). Unprecedented increases in transit ridership during 2008 may have contributed to greater forecasting error in this model validation than would have been seen in a more typical year.

Table 9.4 provides the statistics for the cumulative percentage of bus systems with error in each validation month within a given error range (positive or negative percent error). In these results, more than 75 percent of the 215 systems evaluated fell within 15 percent of the actual ridership over the entire validation period. Comparing values laterally across the table, one can see that each month performed equally as well as the one preceding it, which agrees with the conclusions reached using Table 9.2. Looking vertically, it is clear that increasingly more systems fell within each next-higher hit range.

Table 9.4 Cumulative Percentages of Systems (%) with Percent Error within Given Range – Single-Month Forecasts: Bus Mode

**Cumulative Percentages of Systems (%) Below Given Percent Error
Single-Month Forecasts: BUS MODE**

Mode	Percent						
	Error	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08
Bus (215 systems)	1%	11.2	9.3	6.5	3.7	12.1	16.7
	5%	43.3	45.6	27.4	19.1	53.5	51.6
	10%	65.1	80.0	63.3	58.1	80.0	78.1
	15%	77.2	90.2	83.7	86.0	92.1	86.5
	20%	87.4	94.9	90.7	94.9	96.3	92.6
	25%	91.2	97.2	94.4	97.2	97.2	94.9

Hit statistics for rail systems, which had considerably fewer modal observations, are given in Table 9.5. Heavy and commuter rail systems, which had the lowest median RMSE values of 5.8 and 6.0 percent, respectively, also show good response to the model; all ten heavy rail systems had monthly errors within 15 percent of the actual values and all twelve commuter rail systems

had monthly errors within 20 percent of the observed ridership counts. Light rail, with the highest median RMSE of 8.2 percent, performed worst of the four modes, with 75 percent of its 17 systems seeing forecasting errors within 20 percent of the real values.

Table 9.5 Cumulative Percentages of Systems (%) with Percent Error within Given Range – Single-Month Forecasts: Rail Modes

**Cumulative Percentages of Systems (%) Below Given Percent Error
Single-Month Forecasts: RAIL MODES**

Mode	Percent Error						
	1%	5%	10%	15%	20%	25%	
Light Rail (17 systems)	1%	17.6	11.8	0.0	0.0	5.9	17.6
	5%	47.1	41.2	29.4	35.3	47.1	47.1
	10%	52.9	52.9	70.6	52.9	64.7	64.7
	15%	76.5	58.8	88.2	76.5	82.4	76.5
	20%	82.4	76.5	94.1	82.4	88.2	76.5
	25%	94.1	88.2	100.0	88.2	88.2	82.4
Heavy Rail (10 systems)	1%	70.0	90.0	20.0	90.0	20.0	70.0
	5%	100.0	90.0	40.0	100.0	80.0	100.0
	10%	100.0	90.0	80.0	100.0	90.0	100.0
	15%	100.0	100.0	100.0	100.0	100.0	100.0
	20%	100.0	100.0	100.0	100.0	100.0	100.0
	25%	100.0	100.0	100.0	100.0	100.0	100.0
Commuter Rail (12 systems)	1%	16.7	8.3	8.3	0.0	41.7	8.3
	5%	66.7	66.7	33.3	33.3	91.7	50.0
	10%	75.0	83.3	66.7	66.7	91.7	91.7
	15%	100.0	91.7	91.7	91.7	100.0	100.0
	20%	100.0	100.0	100.0	100.0	100.0	100.0
	25%	100.0	100.0	100.0	100.0	100.0	100.0

As can be seen from Tables 9.4 and 9.5, error ranges for the single-month projections tended to be similar across the six months of the validation period, once more indicating that forecasting accuracy did not decline with time, since each previous month's actual UPT count was used as the base for the following month's forecast.

9.5 PERFORMANCE: MULTI-MONTH PROJECTIONS

In Appendix E are located tables of monthly percentage errors, as well as mean forecast percentage errors (MFPE), root mean square errors (RMSE), mean absolute percentage deviations (MAPD), and tracking signal values on monthly bases for the multi-month forecasts during the validation period. These multi-month errors tend to be higher than those for the single-month forecasts because due to the nature of the dependent variable, which represents a percent change from the previous observation or projection, forecasts and errors build on each

other throughout the forecast period. Thus, each month is predisposed to have a higher error than its predecessor.

Concerning the model validation for the bus systems evaluated, Table 9.6 displays median values of RMSE and MFPE for each of the ten regions. Regions 6, 3, and 4 achieve the most accurate forecasts (five percent mean error or less), while Regions 1 and 7 have the greatest average errors. A side-by-side comparison of this table with Table 9.1 shows that although RMSE values were lower for the multi-month projections than for the single-month forecasts (showing less variability around the mean regional error values, MFPE), the median MFPE values are substantially greater than for the single-month cases. These results indicate that throughout the validation period, errors were consistently higher, though similar in magnitude from month to month. As in the single-month forecasts, the MFPE values in Table 9.6 indicate that the model projections tend to fall short of the actual ridership counts in all regions.

Table 9.6 Regional Median Values of RMSE and MFPE, Multi-Month Forecasts, Bus Systems Only

Region	Median 6-month RMSE (%)	Median 6-month MFPE (%)
0	4.2	-7.3
1	3.4	-14.6
2	4.8	-5.4
3	7.2	-4.5
4	6.3	-4.8
5	6.0	-6.0
6	7.9	-2.3
7	7.8	-18.8
8	5.6	-12.2
9	5.3	-6.2

Multi-month regional bus statistics for median MAPD and median tracking signal values are provided in Table 9.7. This table shows that, as expected, MAPD values increase as the forecast period progresses. In the single-month cases in Table 9.2, MAPD values were essentially stable throughout the six-month validation period. The progressively increasing MAPD values here illustrate how the errors in each month's forecast are greater than the preceding month's because projections build upon the estimate and any error incurred in the previous month. The proliferation of negative values in the tracking signals indicates again that the model generally underestimates ridership. Many of the tracking signal values in the last two forecast periods fall outside the acceptable range. These underestimates may have been exacerbated by the unprecedented growth in transit ridership in 2008 resulting from economic and other forces, and the longer-term trends captured by the regression model, as opposed to short-term behavior shifts.

Table 9.7 Regional Median Values of MAPD and Tracking Signal, Multi-Month Forecasts, Bus Systems Only

Region	Median MAPD (%)						Median Tracking Signal (TS)					
	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08	Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08
0	8.8	10.6	10.9	12.5	13.7	13.4	-1.0	-2.0	-3.0	-4.0	-5.0	-6.0
1	10.3	11.3	11.7	13.6	17.3	20.5	-1.0	-2.0	-3.0	-4.0	-5.0	-6.0
2	8.2	10.9	9.6	11.3	11.9	12.8	-1.0	-2.0	-2.9	-3.9	-4.7	-5.6
3	9.7	11.8	9.4	10.0	11.7	13.8	-1.0	-2.0	-3.0	-4.0	-4.0	-4.5
4	3.1	5.6	6.4	8.3	9.2	10.1	-1.0	-2.0	-2.5	-3.6	-4.6	-5.7
5	6.3	7.6	9.4	9.6	9.9	10.1	-1.0	-2.0	-2.1	-3.4	-4.5	-5.7
6	3.4	9.4	11.9	11.6	9.8	11.0	-1.0	-1.9	-0.6	-2.0	-0.4	-2.1
7	8.8	10.3	13.0	15.5	18.7	19.6	-1.0	-2.0	-3.0	-4.0	-5.0	-6.0
8	6.7	10.9	10.8	12.5	13.5	15.1	-1.0	-2.0	-3.0	-4.0	-5.0	-6.0

The modal statistics in Table 9.8 show that, with negative MFPE values, the model underestimates ridership for all four modes. Compared with the single-month forecasts, based on the preceding month's UPT count, the multi-month forecast errors are greater, building from month to month as forecasts differ from real ridership. While the median RMSE value for light rail systems did not change from the single-month forecasting case, the values for bus, heavy rail, and commuter rail modes dropped, showing smaller variability about the mean percentage error (MFPE) values; thus, although the MFPE values are higher for the multi-month projections, the error magnitude is similar from month to month.

Table 9.8 Modal Median Values of RMSE and MFPE, Multi-Month Forecasts

Mode	Median 6-month RMSE (%)	Median 6-month MFPE (%)
Bus	5.7	-6.3
Light Rail	8.2	-14.4
Heavy Rail	4.0	-8.3
Commuter Rail	5.2	-7.3

Comparing MFPE for the multi-month validation with composite model R^2 values for all 254 systems results in the plot given in Figure 9.2. (Four data points with MFPE greater than 150 percent and low composite R^2 have been removed from this figure for visual clarity.) This plot, like that in Figure 9.1 for the single-month errors, indicates that MFPE tends to cluster closer to zero error as R^2 increases, although much greater variation is present in this plot, compared to the single-month plot. We can again conclude that the R^2 values associated with the 2002-2007 calibration series are representative of the relative variability explained in the multi-month forecasts of the validation period, although to a lesser extent than in the single-month projections.

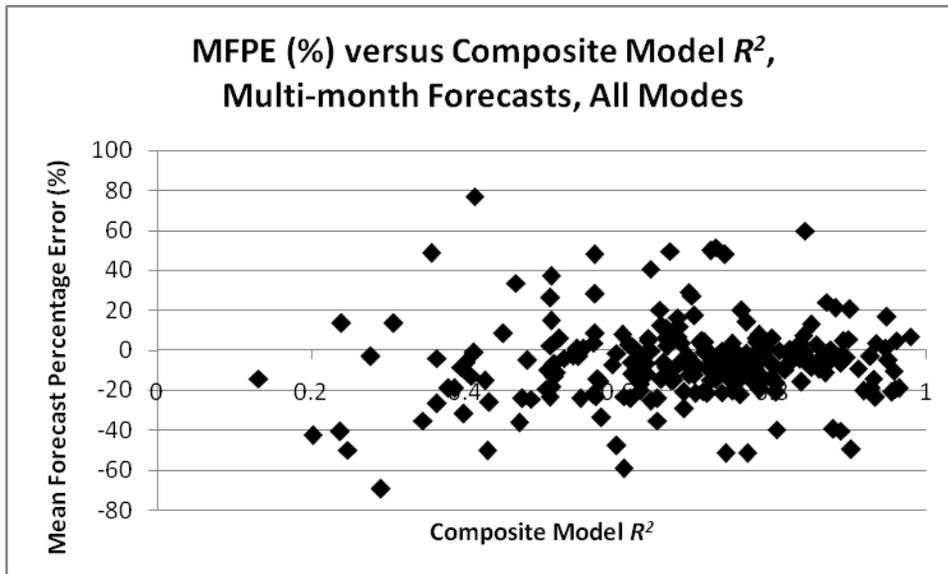


Figure 9.2 Mean Forecast Percentage Error (%) versus Composite Model R^2 , Multi-Month Forecasts, All Modes

Table 9.9 presents the cumulative statistics for the percentage of bus systems achieving accuracy within a given percent error range. Examining the table laterally, we see that as the forecast period progresses, fewer systems attain the given accuracy. This finding is consistent with the propagation of error with time through the validation period, as noted previously.

Table 9.9 Cumulative Percentages of Systems (%) with Percent Error within Given Range – Multi-Month Forecasts: Bus Mode

**Cumulative Percentages of Systems (%) Below Given Percent Error
Multi-Month Forecasts: BUS MODE**

Mode	Percent Error	Percent					
		Jan-08	Feb-08	Mar-08	Apr-08	May-08	Jun-08
Bus (215 systems)	1%	11.2	3.3	7.9	3.7	4.2	4.2
	5%	43.3	21.4	30.7	18.1	18.1	18.6
	10%	65.1	48.8	52.1	39.5	43.7	34.0
	15%	77.2	67.4	65.1	53.0	58.1	47.9
	20%	87.4	82.3	76.3	67.4	68.8	59.5
	25%	91.2	87.0	83.3	79.1	77.7	71.2

The same statistics of accuracy for the three rail modes with much smaller sample sizes are shown in Table 9.10. This table also indicates reduced prediction accuracy as forecasts grow further in time from the last observed period.

**Table 9.10 Cumulative Percentages of Systems (%) with
Percent Error within Given Range – Multi-Month Forecasts: Rail Modes**

**Cumulative Percentages of Systems (%) Below Given Percent Error
Multi-Month Forecasts: RAIL MODES**

Mode	Percent Error						
	1%	5%	10%	15%	20%	25%	
Light Rail (17 systems)	1%	17.6	11.8	0.0	5.9	0.0	0.0
	5%	47.1	29.4	17.6	11.8	17.6	5.9
	10%	52.9	35.3	41.2	29.4	23.5	23.5
	15%	76.5	47.1	52.9	35.3	35.3	35.3
	20%	82.4	58.8	64.7	35.3	47.1	41.2
	25%	94.1	70.6	76.5	52.9	52.9	47.1
Heavy Rail (10 systems)	1%	0.0	10.0	0.0	0.0	10.0	0.0
	5%	60.0	30.0	30.0	30.0	40.0	40.0
	10%	80.0	50.0	70.0	50.0	60.0	40.0
	15%	80.0	70.0	70.0	60.0	70.0	50.0
	20%	80.0	80.0	80.0	70.0	70.0	70.0
	25%	80.0	80.0	80.0	80.0	80.0	70.0
Commuter Rail (12 systems)	1%	16.7	0.0	8.3	16.7	0.0	8.3
	5%	66.7	25.0	58.3	25.0	16.7	8.3
	10%	75.0	66.7	83.3	58.3	50.0	33.3
	15%	100.0	83.3	91.7	66.7	66.7	41.7
	20%	100.0	100.0	91.7	100.0	91.7	66.7
	25%	100.0	100.0	100.0	100.0	100.0	100.0

Equations 9.6 through 9.9 describe mathematically the means by which errors are propagated through the multi-month forecasts:

$$\hat{F}_1 = F_1 + e_1 = C \left(\frac{F_1 - C}{C} \right) \quad (9.6)$$

$$\hat{F}_2 = \hat{F}_1 \left(\frac{F_2 - F_1}{F_1} \right) = (F_1 + e_1) \left(\frac{F_2 - F_1}{F_1} \right) = F_1 \left(\frac{F_2 - F_1}{F_1} \right) + e_1 \left(\frac{F_2 - F_1}{F_1} \right) \quad (9.7)$$

$$\begin{aligned}
\hat{F}_3 &= (F_2 + \varepsilon_2) \left(\frac{F_3 - F_2}{F_2} \right) = F_2 \left(\frac{F_3 - F_2}{F_2} \right) + \varepsilon_2 \left(\frac{F_3 - F_2}{F_2} \right) \\
&= \left[F_1 \left(\frac{F_2 - F_1}{F_1} \right) \left(\frac{F_3 - F_2}{F_2} \right) \right] + \left[\varepsilon_1 \left(\frac{F_2 - F_1}{F_1} \right) \left(\frac{F_3 - F_2}{F_2} \right) \right]
\end{aligned} \tag{9.8}$$

$$\hat{F}_t = F_1 \prod_{\tau=2}^t \left(\frac{F_\tau - F_{\tau-1}}{F_{\tau-1}} \right) + \varepsilon_1 \prod_{\tau=2}^t \left(\frac{F_\tau - F_{\tau-1}}{F_{\tau-1}} \right) \tag{9.9}$$

For these equations, C represents the last observed ridership data point before forecasting commences and T indicates the final time period for which a forecast is conducted. The single-month forecasts make use only of the first equation, 9.6. These forecasts thus contain only the error associated with the initial modeling error.

As the model is used to project beyond the first month and each consecutive forecast is based upon the preceding month's estimated value, the errors grow with time. Ultimately, as in Equation 9.9, the forecast at time t contains information regarding the product of all preceding ridership change estimates, combined both with the actual ridership values and the forecast errors, which cannot be known when creating the projections.

9.6 SUMMARY

The single- and multi-month model validation performed in this chapter revealed that while the model performs satisfactorily, it showed a tendency to underestimate ridership in the first half of 2008. The multi-month forecasts generally have greater error than the single-month predictions, due to error propagation through the series. Some of the error may be attributed to the unprecedented growth in transit ridership during 2008 which could not be anticipated by a model calibrated on historical data, and by the six-year calibration period of the model, which tends to produce estimates of longer-term behavior shifts, rather than immediate reactions to stimuli such as fuel price.

The final chapter, Chapter 10, reviews the process by which the forecasting model was established, discusses the academic and technical contributions of this research, and outlines future steps for the improvement of the transferable short-term transit ridership forecasting model developed herein.

Chapter 10: Conclusions and Future Steps

10.1 REVIEW

In the course of this research, a transferable short-term transit ridership forecasting model was developed, which includes, among other inputs, a parameter measuring the impact of fuel price change on ridership. The effect of gasoline price fluctuations on public transportation ridership varies by city, by region, and by transit mode and system, as do the relationships between ridership and the other included parameters.

Figure 10.1 presents a flow chart outlining the modeling procedure developed herein. Monthly ridership and other time series data were collected for the 2002-2007 period from various federal sources for 254 US transit systems, comprising 215 bus systems, as well as 17 light rail, 10 heavy rail, and 12 commuter rail systems. The modeling process included transformation of ridership data to achieve stability in the mean and variance, then decomposing the data to remove seasonal variability. Following the breaking of ridership data into seasonal components and non-seasonal residuals, multivariate regressions of the seasonally-adjusted ridership data were conducted. The results from the non-seasonal multivariate analyses were combined with the seasonal measures to create a composite model. To test the validity of the model, forecasting procedures, including projection of trend-cycle components, operational characteristics, and external factors, were applied via the composite model to estimate ridership counts for the first six months of 2008. The model produces values of the percent change in the logarithm of ridership, which must then be converted back into nominal ridership estimates.

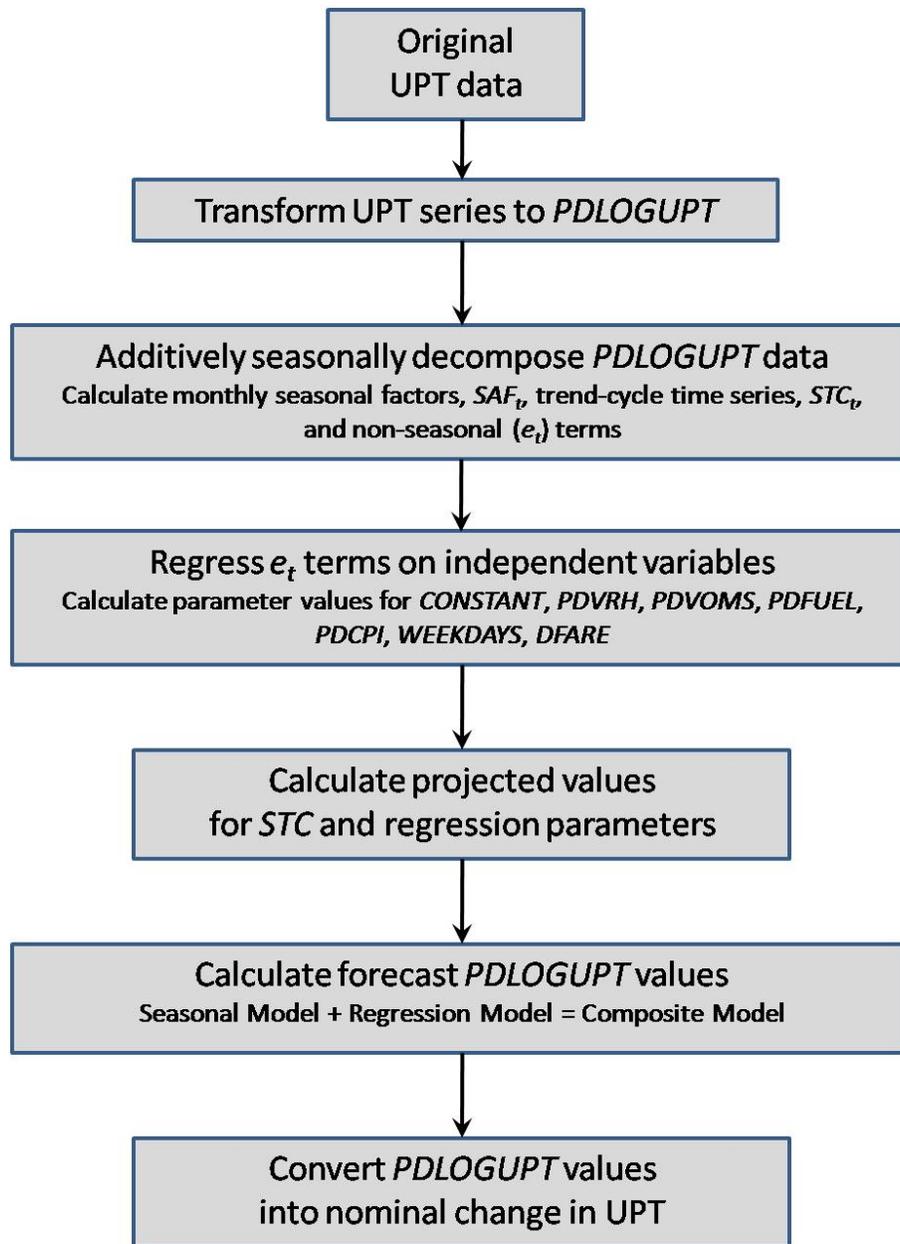


Figure 10.1 Flow Chart of Ridership Modeling Process

The model, as developed, performed satisfactorily, although it tended to underestimate ridership in 2008. These underestimates likely stem from the unprecedented growth in ridership during the validation period, in addition to the calibration period of the model, which encompassed a period of six years and thus may have led the model to contain longer-term behavior shifts from stimuli such as fuel price, rather than short-term, immediate reactions.

10.2 CONTRIBUTIONS

Academically, the research herein explores a topic which has received little attention, most transit agencies establishing their own forecasting methods in-house or within their local metropolitan planning organization. The procedures here are unique in that they combine established forecasting methodologies, such as data decomposition, with more advanced multivariate regression, in a complementary manner that leads to robust prediction abilities. By calibrating and examining each individual system within the evaluation set, transferability is achieved and comparisons are made across systems, regions, and modes, which, in the absence of comprehensive model-building, cannot otherwise be accomplished.

Technological contributions of this work include its transferability through individual system calibration of the seasonal and non-seasonal parameters. Additionally, the modeling procedure is straightforward, making use of commonly-available data, and readily adaptable to mathematical programming interfaces for unique system treatment.

10.3 FUTURE STEPS

Based on the work done here, several opportunities present themselves for improvement upon the methods utilized, and potential new directions for future innovations emerge.

In enhancing directly the research contained in this report, the first step should be two-fold. First, further exploration of the relationship between fuel price and the consumer price index is warranted. These variables may have some underlying relationship that leads to the contradictory or complementary effects seen in the multivariate regressions of Chapter 7. Simple analyses may begin with using the CPI to adjust fuel prices to a base year, to achieve constant dollar values throughout the calibration period. Additionally, if CPI is to be included in future models, it may prove useful to assign more disaggregate values to the systems evaluated, as was done with fuel price, rather than making use of the national CPI values.

The second step pertaining directly to this research would include re-calibrating the model using a shorter and more recent dataset, to compare and contrast longer-term behavior shifts (as captured here) with shorter-term, more reactionary shifts, especially with regard to fuel price.

Taking view of a more distant research horizon, augmenting the model developed here may be achieved using different model types. Some ideas include dynamic regression, which allow the effects of stimuli, such as fuel price, to be distributed over a longer time period, rather than the one-to-one correlation as included in the research of this report. This advantage could prove highly relevant to the forecasting of transit ridership, since it has already been shown in past research that reactions to fuel price are prolonged over several months in nearly all cases.

Another approach that could boost the estimation accuracy of this forecasting model involves state-space and structural time series models, which, among other advantages, allow for greater capture of random effects, particularly regarding seasonality.

10.4 SUMMARY

Although the methods presented here are straightforward, potential exists to enhance these techniques and develop more accurate transit ridership forecasting tools that can be applied nationwide. This work establishes a benchmark for future research into transferable transit ridership forecasting models that may aid public transportation system planners in an era when, due to fuel price concerns, global warming and green initiatives, and other impetuses, transit use is seeing a resurgence in popularity.

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