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16. Abstract

Highway relief routes may have a variety of both positive and negative impacts on small- and medium-size communities. The purpose of this research is to evaluate the impacts of relief routes on small- and medium-size communities in order to help the Texas Department of Transportation (TxDOT) better plan for both the positive and negative impacts of relief routes. One common concern is that the reduction in traffic through town, which has positive benefits for quality of life, may also have negative impacts on businesses in the community. This report describes the use of econometric models to test this hypothesis. The panel data set includes data from cites in Texas with and without relief routes for nine points in time. Models were developed for twelve economic indicators: per capita sales, numbers of establishments, and total sales in four highway-related sectors expected to be most impacted by changes in traffic levels. The models indicate both positive and negative impacts of relief routes, although for small cities the impacts are mostly negative. The magnitude of the shift in traffic to the relief route is the most significant characteristic of the relief route in explaining these impacts. The marginal influences of city demographics, location and traffic levels, and the regional trends on the local economy were also identified. It is important to note that the impact on the total economy was not assessed in the models and that the models do not fully explain the changes in the economic indicators.

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ECONOMIC EFFECTS OF HIGHWAY RELIEF ROUTES ON SMALL- AND MEDIUM-SIZE COMMUNITIES: AN ECONOMETRIC ANALYSIS

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CHAPTER 1. INTRODUCTION

Highway relief routes may have a variety of both positive and negative impacts on small- and medium-size communities. On the positive side, communities benefit from a reduction in traffic through the heart of the community and the negative impacts such traffic brings, including noise, emissions, and safety concerns. However, the reduction in through traffic may also have negative impacts on businesses in the community, particularly highway-oriented businesses located along the old route that are dependent on pass-by traffic. The negative impacts on local businesses may be partly offset by new development occurring along the highway relief route. How these impacts play out in a particular community depends the characteristics of the community and the new relief route, as well as larger economic and industry trends. The purpose of this study is to identify and understand the various factors that influence the economic impacts of highway relief routes on small- and medium-size communities in order to better plan for both the positive and negative impacts of relief routes.

Two approaches are used to explore the economic impacts of relief routes: econometric modeling, described in this report, and case studies, described in report 1843-3. Econometric modeling provides a powerful tool for quantifying the impacts of the relief route on the local economy, but it is limited in the range of impacts and explanatory factors it can assess by the availability of data. The case study approach does not generate statistically significant results, but it can provide important qualitative insights beyond what econometric modeling provides. The two techniques are thus complementary and together impart a richer understanding of the impacts of highway relief routes than could either one alone. Building on an extensive existing body of research, the econometric models presented here quantify the impacts of relief routes on the economies of communities in Texas over the past four decades and identify characteristics of the relief route and of the community that influence those impacts.

1.1 EXISTING EVIDENCE

There has been considerable research on the topic of relief route impacts. Some of the earliest studies date back to the 1950s. These and later studies have examined the economic impacts in terms of several indicator variables. Some of these include sales (Otto and Anderson 1995, Yeh et al. 1998, Burress 1996, Anderson et al. 1992, Whitehurst 1965); employment levels (Yeh et al. 1998, Burress 1996, Buffington and Burke 1991); land values (Whitehurst 1965, Holhouser 1960); and wages (Whitehurst 1965, Blackburn and Clay 1991). Other studies have also examined user benefits in terms of travel-time savings (Burress 1996) and safety (Otto and Anderson 1995), Yeh et al. 1998). A wide array of methodologies like the before-and-after studies (Whitehurst 1965, Blackburn and Clay 1991, Parolin and Garner 1996); case studies (Yeh et al. 1998, Anderson et al. 1992); and econometric modeling (Burress 1996, Anderson et al. 1992, Buffington and Burke 1991) have been employed. A more detailed discussion of these studies is provided in the earlier report (Handy et al. 2000).

Many of these studies have reported little evidence for adverse impacts due to highway relief routes alone. However, these studies used widely different methods and criteria to arrive at their results. The efforts together indicate that the net impacts of a relief route are not clear and that there are several factors that impact the local economy. The National Cooperative Highway Research Program (NCHRP) consolidated the state of knowledge in the area of relief-route impacts (NCHRP 1996). Based on a review of published literature and responses to survey questionnaires sent to state departments of transportation, the report concluded that there is no conclusive evidence of a loss of sales, even in vulnerable locations, due to the construction of the relief route alone. However, these findings do not preclude the possibility that relief routes can mean a loss in sales under certain conditions or, conversely, a gain in certain situations.

1.2 PROJECT OBJECTIVES AND REPORT OVERVIEW

In light of the inconclusive results found in previous studies, the purpose of this phase of the project was to quantify the impacts of relief routes specifically for Texas communities using more recent data and more sophisticated modeling techniques than have been used in previous studies. The analysis involves the identification of indicators of economic impact and a set of explanatory variables that determine those impacts. Econometric modeling is used to estimate the marginal effects of the explanatory variables, that is, the effect of each variable when controlling for the effects of the other variables. The models estimated in this study provide important insights into the significance of different variables in explaining the impacts of relief routes on the economies of these communities.

However, a number of caveats should be noted. First, the models provide a test of the hypothesis that relief routes negatively impact the local economy. As described in Chapter 2, this study focuses on those sectors of the economy likely to be most negatively impacted by the relief route and thus provides a worst-case assessment of the impacts. A rejection of this hypothesis for certain types of communities based on the statistical results doesn't mean that the impacts are necessarily positive. Second, the models test only those impacts and explanatory variables that can be quantified and for which data are available. Third, the models demonstrate statistically significant associations between impacts and explanatory factors but do not prove causation. Fourth, the models reflect the average impact of relief routes and other factors over a sample of communities where relief routes have been constructed some time in the past. They will not always provide an accurate prediction of the impact of a new relief route in a specific community.

The report is organized in the following manner: Chapter 2 summarizes the concerns of the communities and discusses the use of econometric modeling in this phase of the project. The development of the dataset is described in Chapter 3, and sample characteristics are provided. Chapter 4 describes the empirical modeling methodology, and the results are presented and discussed. Finally, the study findings are summarized in Chapter 5.

CHAPTER 2. ISSUES IDENTIFIED

Key issues from the perspective of the affected communities and the Texas Department of Transportation (TxDOT) were identified in the first phase of this research project. These issues are summarized below and in an earlier research report (Handy et al. 2000). This chapter also discusses the issues that can be addressed by econometric modeling and those that cannot. Finally, the approach adopted for modeling is briefly described.

2.1 COMMUNITY AND TXDOT CONCERNS

The concerns of communities about highway relief routes were identified based on interviews with officials of state and local organizations, TxDOT district engineers, and review of other studies. The hopes and concerns of residents vary within each community and from one community to the next. In general, residents seem to perceive the advantages of rerouting downtown traffic in terms of making the downtown a quieter and safer place. Some residents foresee the possibility that the relief route will attract new businesses and thus associate economic progress with a relief route. However, in many cases the business community is concerned about a potential net loss in tax base and the possibility of the closure of downtown establishments due to a reduction in pass-by traffic and possible competition from new establishments along the relief route.

The location of the relief route and the nature of access provided seem to be issues of specific concern to residents and community leaders. In the case of controlled access facilities, frontage roads along the relief routes are seen as necessary to stimulate businesses along the periphery of the town. If the relief route is far away from the city, then the cost of extending infrastructure to the vicinity of the relief route becomes of potential concern. The response of the community also depends on the strength of its tourism industry: those cities that have an established tourism industry tend to anticipate positive impacts from a relief route, while those that are trying to develop their tourism base tend to anticipate negative impacts (Handy et al. 2000).

TxDOT engineers and planners bring a wider regional and state-level perspective. Some relief routes in Texas are proposed as a part of the Texas Trunk System, a system that is intended to improve statewide mobility, in part by routing traffic around towns and thereby minimizing speed reductions. Safety is another concern expressed by TxDOT engineers, especially for Waste Isolation Plant Project (WIPP) routes. Also, compliance with National Environmental Protection Act (NEPA) is required in planning and designing relief routes. The choice of route and geometry that TxDOT prefers for a particular relief route may not be what the community prefers. The challenge, therefore, is to improve the mobility at a regional level by rerouting traffic around a community without adversely impacting the economy of the community.

2.2 SCOPE OF ECONOMETRIC MODELING

Econometric modeling provides a powerful analytical approach because of its ability to isolate the marginal influence of distinct explanatory variables. Estimation of these models, however, requires a large database and quantitative proxies for qualitative variables that might be difficult to derive at times. The definition of variables and the development of the data set are described in detail in Chapter 3, but several issues are important to note here in that they define the scope of the modeling effort.

The sample used in this study is drawn from the small- and medium-size cities in Texas where relief routes have been constructed. Selected control cities are also included to better account for factors not related to the relief routes. Because a loss in tax base has been identified as a significant community concern, sales in four different industrial sectors have been chosen as indicators of economic impact (i.e., as dependent variables in the models). These include total retail sales, sales at gasoline service stations, sales at eating and drinking places, and total service receipts. These industrial sectors are commonly assumed to be dependent on traffic levels and thus may be impacted by the construction of a relief route and the shift in traffic levels that results. Models for both total and per capita sales and for the number of local establishments in each industrial sector are estimated.

These indicators provide an important but limited measure of the impacts of the relief routes. Since the cities of interest are of small- and medium- size, much of the data is available only at the city level. Hence, the models capture the effects at an aggregate city level. Spatially disaggregate data (for example, data along specific corridors) is not readily available and thus the models do not account for spatial changes in the economy and the impacts along specific corridors. It is possible that even when the total sales levels in the city do not change, a significant impact on the local economy occurs in the form of business openings, closings, relocations, and so on. In addition, the industrial sectors chosen for analysis are those that are expected to have the most negative impacts. It is important to recognize that losses in one sector could be offset by developments in other sectors; hence, the overall economy may not suffer. The models here describe what should be a worst-case scenario. Finally, the relief route may also contribute to improvements in the quality of life in the community by diverting through traffic away from the city. These effects are more difficult to model quantitatively and therefore are addressed in the case studies rather than the models.

By isolating and quantifying the influence of the relief route on the economies of the cities, the estimated models contribute to an improved understanding of the impacts of relief routes and provide guidance on the planning and design of these facilities. In addition, the models could be used to forecast the economic impact of a new relief route in any small- and medium-size city in Texas. Such estimates could help in making the decision to construct a relief route or not. The marginal influences of the relief-route characteristics (such as the shift in traffic from the old route to the new route, the distance of the new route from the old, and the nature of access provided) could also be estimated. The results of this analysis could be useful in planning the relief route so as to minimize any adverse impact on the community. However, such forecasts should be used with extreme caution, if at all. These models are developed based on past experiences, and similar conditions may not prevail in the future. Each city has its own unique characteristics that cannot be fully captured in models.

CHAPTER 3. DATA

This chapter describes the data used for the econometric modeling. Identification of study cities is described first. The chosen indicators of impact on the local economy and the explanatory variables are then described. In each case, the sources of data are provided and sample characteristics presented.

3.1 IDENTIFICATION OF STUDY CITIES

A list of cities in Texas with populations between 2,500 and 50,000 was created, and traffic maps were reviewed to classify these into those that have relief routes and those that do not. The cities with relief routes were further classified into single relief route, multiple relief routes, multiple-city relief routes, loops, etc. Only cities with a single relief route were considered for the study. This is the simplest form, where the relief route splits from the old route at one side of the city and rejoins the same route on the other side. An example of this is the relief route around Littlefield, Texas (Figure 3.1).

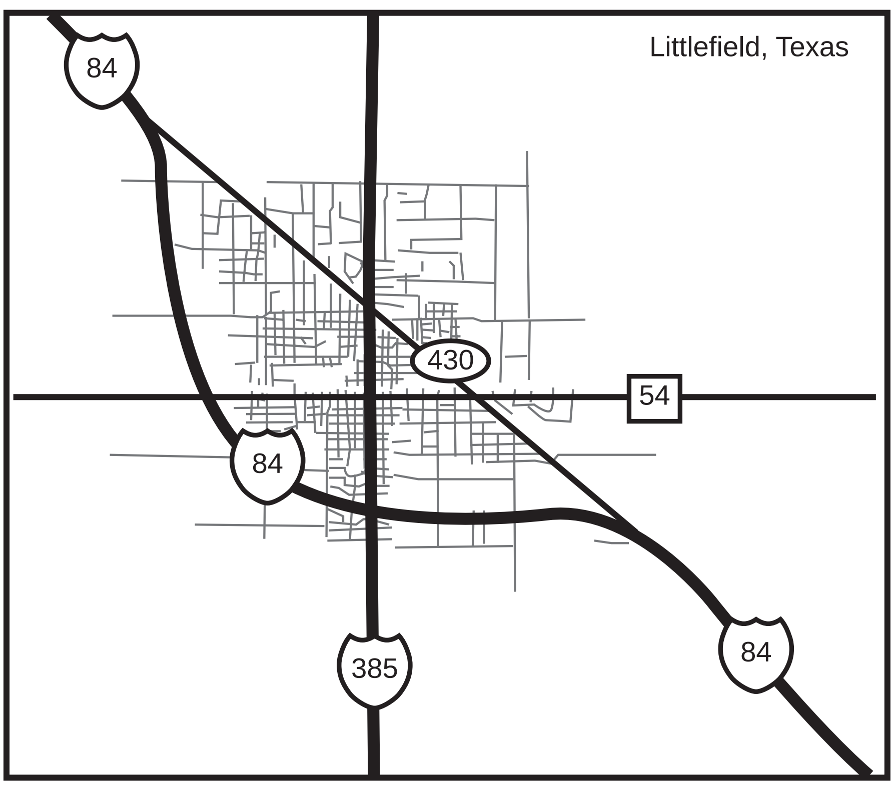

Figure 3.1 Relief Route (US 84) around Littlefield, Texas

Cities in which the relief routes were opened for traffic between1965 and 1990 were considered for analysis. After dropping cities for which adequate data were not available, twenty-three cities with relief routes remained available for analysis (Table 3.1). Nineteen other cities without relief routes were chosen as "control" cities (Table 3.2). For each of the total forty-two cities, nine years of data (in years falling between 1954 to 1992) were collected. These are the years for which the U.S. Economic Census data are available. Therefore, the sample has a total of 378 data points. The geographic location of the cities in Texas is also presented (Figure 3.2).

Table 3.1 Cities with Relief Route Used for Econometric Modeling

City	County	TxDOT District	Highway	Year of Relief Route
La Grange	Fayette	Yoakum	State 71	1990
Cleveland	Liberty	Beaumont	US 59	1988
Gatesville	Coryell	Waco	State 36	1986
Smithville	Bastrop	Austin	State 71	1984
Fort Stockton	Pecos	Odessa	US 290/IH 10	1983
Livingston	Polk	Lufkin	US 59	1981
Sinton	San Patricio	Corpus Christi	US 77	1981
Marlin	Falls	Waco	State 6	1980
Silsbee	Hardin	Beaumont	US 96	1979
Bowie	Montague	Wichita Falls	US 287	1978
Edna	Jackson	Yoakum	US 59	1974
Wharton	Wharton	Yoakum	US 59	1974
El Campo	Wharton	Yoakum	US 59	1973
Pearsall	Frio	San Antonio	US 81 / IH 35	1973
Henrietta	Clay	Wichita Falls	US 287	1972
Navasota	Grimes	Bryan	State 6	1972
Ranger	Eastland	Brownwood	US 80/IH 20	1971
Electra	Wichita	Wichita Falls	US 287	1969
Raymondville	Willacy	Pharr	US 77	1969
Coleman	Coleman	Brownwood	US 84	1968
Plainview	Hale	Lubbock	US 87 /IH 27	1967
Littlefield	Lamb	Lubbock	US 84	1966
Vernon	Wilbarger	Wichita Falls	US 287	1965

Table 3.2 Control Cities Used for Econometric Modeling

City	County	TxDOT District
Alice	Jim Wells	Corpus Christi
Bay City	Matagorda	Yoakum
Brady	McCulloch	Brownwood
Brownfield	Terry	Lubbock
Cameron	Milam	Bryan
Childress	Childress	Childress
Clarksville	Red River	Paris
Cleburne	Johnson	Fort Worth
Comanche	Comanche	Brownwood
Cuero	De Witt	Yoakum
Eagle Lake	Colorado	Yoakum
Giddings	Lee	Austin
Gilmer	Upshur	Atlanta
Graham	Young	Wichita Falls
Hearne	Robertson	Bryan
Liberty	Liberty	Beaumont
Lockhart	Caldwell	Austin
Nocona	Montague	Wichita Falls
Post	Garza	Lubbock

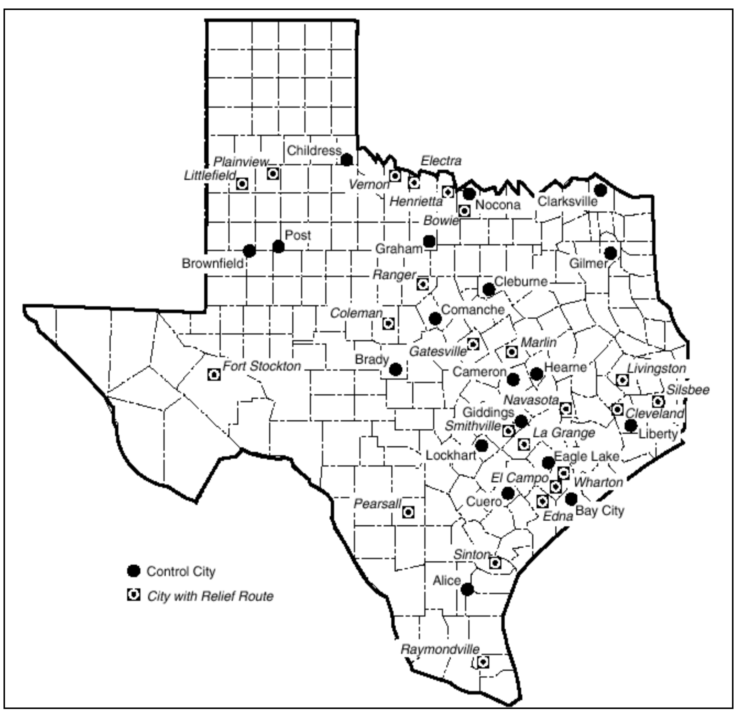

Figure 3.2 Location of Cities Used for Modeling

3.2 INDICATORS OF IMPACT

Per capita sales and the number of establishments in four different industrial sectors were identified as indicators of the local economy (Table 3.3). These industrial sectors can be expected to be most significantly impacted by a development like the opening of a relief route. Establishments that fall under this category may be significantly dependent on the highway traffic. Hence, a development like a relief route, which causes a spatial redistribution of traffic, can be expected to impact these sectors of the economy.

Table 3.3 Industrial Categories Chosen for Econometric Modeling

Industry	SIC code[1]	Description
Retail Trade	52 to 59	Establishments that primarily sell merchandise for personal or household consumption
Gasoline Service Stations	554	Establishments that primarily sell gasoline and automotive lubricants
Eating and Drinking Places	58	Establishments that primarily sell prepared food and beverages
Service Industries	70 to 89	Establishments that render a wide variety of services to individuals, businesses, government establishments, and other organizations

[1] SIC- Standard Industrial Classification

Data on the sales and the number of establishments for the Retail Trade, Gasoline Service Stations, and Eating and Drinking Places were obtained from the U.S Census of Retail Trade. Data on the sales and number of establishments for the Service Industries were obtained from the U.S. Census of Service Industries. All sales dollars were then corrected for inflation and converted to constant year-2000 dollars using the Consumer Price Index (University of Michigan 2000). Data were collected for nine distinct years over the period 1954 to 1992. The population data was collected from the U.S. Census of Population, available once each decade. The population data were linearly interpolated to obtain estimates for the data years corresponding to the Economic Census. Sales dollars corrected for inflation were then normalized by population to obtain estimates of per capita sales in the different industrial sectors. Sample characteristics of the sales levels and the number of establishments in the cites considered for modeling are presented below (Tables 3.4, 3.5, and 3.6). In general, data were available for all establishments. However, for the year 1982, data were available only for establishments with payrolls, thus leaving out family-run businesses without employees.

Table 3.4 Sample Characteristics for Per Capita Sales (in year-2000 $)

Year	Retail		Gasoline		Eat/Drink		Service	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1954	11,813	3,208	921	297	481	192	733	218
1958	10,578	2,214	1,010	292	431	160	764	241
1963	11,488	3,099	1,168	390	448	164	883	281
1967	12,077	3,146	1,266	550	540	232	910	289
1972	12,840	4,258	1,301	554	670	253	1,252	571
1977	14,398	5,906	1,339	812	780	377	1,601	760
1982[1]	13,478	5,806	1,041	826	716	367	2,354	1,514
1987	11,675	5,376	981	573	812	496	3,069	1,706
1992	12,026	6,088	990	614	945	504	3,641	2,085

[1] Data available only for establishments with payroll (except for retail industry)

Table 3.5 Sample Characteristics for Number of Establishments

Year	Retail		Gasoline		Eat/Drink		Service	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1954	127	52	17	6	18	10	53	29
1958	118	51	18	7	17	11	59	33
1963	123	54	20	8	18	10	63	31
1967	129	60	20	8	20	11	71	40
1972	135	62	21	9	21	11	89	49
1977	129	60	15	7	21	12	92	50
1982[1]	115	61	8	4	14	9	55	39
1987	125	69	11	6	22	13	213	138
1992	138	77	10	6	25	14	326	192

[1] Data available only for establishments with payroll (except for retail industry)

Table 3.6 Sample Characteristics for Total Sales[1] (in year-2000 $)

Year	Retail		Gasoline		Eat/Drink		Service	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1954	70,158	39,881	5,203	2,260	2,852	1,652	4,807	3,990
1958	67,432	39,852	6,140	2,945	2,792	1,789	5,182	3,987
1963	75,192	50,988	7,296	4,079	2,904	1,765	6,212	5,278
1967	79,284	53,578	7,633	3,799	3,477	2,261	6,307	5,208
1972	86,422	58,370	8,045	4,234	4,439	2,989	8,930	7,664
1977	105,074	72,338	8,878	5,689	5,792	4,545	12,460	11,976
1982	101,639	70,905	7,072	5,356	5,763	5,078	19,834	25,282
1987	88,361	65,699	6,932	4,786	6,531	6,233	25,462	26,106
1992	90,898	71,519	6,827	4,951	7,300	6,231	29,243	29,972

[1] in 1000 of Dollars

[2] Data available only for establishments with payroll (except for retail industry)

3.3 EXPLANATORY VARIABLES

Several variables were identified that are expected to impact the sales and the number of establishments in the city. These could be broadly classified into city demographics, traffic levels and the location of the city, relief-route characteristics, and regional trends (Table 3.7). More information on the source of these data and the procedure for deriving estimates wherever applicable is described below.

Data on city demographics — population, unemployment, and elderly populations — were obtained from the U.S. Census of Population. This census also provided data on median household income and average household size. These were used to derive an estimate of income per capita, as the ratio of median household income to the average household size, and incomes were converted to year-2000 dollars. All data from the census of population were obtained for the years 1950, 1960, 1970, 1980, and 1990. These data were then linearly interpolated for the required data years.

The influence of the strategic location of the city is captured in terms of its proximity to a large city. A "large city" was defined as the central city of a metropolitan statistical area (MSA) as defined by the U.S. Census Bureau in 1990. The nearest large city was identified for each city in the sample, and distances to these cities were obtained from the Texas Mileage Guide (Texas 1999). The populations of these large cities were also obtained from the U.S Census of Population and linearly interpolated for the required data years. The above-discussed variables are common to both cities with relief route and control cities (Table 3.8).

It was possible to infer from the Texas Department of Transportation (TxDOT) district traffic maps the year when traffic first appeared on the relief route. This was used to determine the opening year of the relief route, and hence the number of years since it was constructed for each data year. Estimates of traffic volumes (total and on the relief route) were obtained from the district traffic maps by averaging traffic counts at the reported points along the respective routes. Only counts on state, U.S., and interstate highways were used in this estimation. The traffic split variable was defined as the ratio of the traffic volume on the relief route to the total traffic approaching the city on all state, U.S., and interstate highways.

Table 3.7 Explanatory Variables Used in Econometric Modeling

Variable Name	Units	Description
Regional Trends		
STATE SALES	1000 Dollars	Sales at the state level in the respective industrial sectors
STATE NUM EST	Number	Number of establishments at the state level in the respective industrial sectors
STATE PERCAP SALES	Dollars/ person	Per capita sales at the state level in the respective industrial sectors
YEAR	Number	Data year
YEAR 1982	Binary	1 if the data year is 1982, 0 otherwise
City Demographics		
POPLTN	Number	Population of the city
ELDERLY	Percent	Fraction of the population above 65 years of age
UNEMP RATE	Percent	Unemployment Rate
INCOME PERCAP	Dollars/ person	Per capita income
Location and Traffic		
LARGECITY POP/DIST	Persons/ mile	Ratio of the population of the nearest large city to its distance from the city under study
TOT TRAFFIC	AADT	Total traffic approaching the city
TOT TRAFFIC PERCAP	AADT/ person	Traffic per capita approaching the city
Relief Route Characteristics		
RELIEF ROUTE	Binary	1 once the relief route opens in the city, 0 otherwise
NUM YEARS	Number	Number of years since the relief route was opened to traffic
TRAFFIC SPLIT	Fraction	Ratio of the traffic on the relief route to the total traffic approaching the city
DIST OLD	Miles	Distance along the old route
DIST RATIO	Fraction	Ratio of the distance along the old route to the distance along the relief route
ACCESS CONTROL	Binary	1 if the relief route has controlled access, 0 otherwise
RR*POPLTN	Number	Population of the city once the relief route opens, 0 otherwise
RR*TOT TRAFFIC	AADT	Total traffic approaching city once the relief route opens, 0 otherwise
RR*TOT TRAFFIC PERCAP	AADT/ person	Per capita traffic of the city once the relief route opens, 0 otherwise

Distances along the old and the new routes were obtained from county maps. The distances were measured from the point where the relief route branches off the old route to the point where it rejoins the old route. This variable can be either greater or less than one, depending on the orientation of the two routes. If the original route continues in the same direction through town, then the relief route is generally longer than the original. If the original route changes direction as it passes through town, turning to the right or the left, then the relief route may provide a shortcut. The county maps also provided information on the presence of frontage roads along the relief route. All these variables are specific to the cities with relief routes only (Table 3.9).

Regional trends in the respective industrial sectors can be expected to influence the trends at the city level. Hence, sales and number of establishments at the state level were introduced as explanatory variables (Table 3.10). The data year was also chosen as an explanatory variable to possibly capture time trends not captured by other variables.

Table 3.8 Mean Values of Variables Specific to all Cities

Year	POPLTN	ELDERLY	UNEMP RATE	INCOME PERCAP	LARGECITY POP/DIST	TOT TRAFFIC
1954	6,117	10.3%	4.9%	$ 6,363	4,196	5,608
1958	6,458	11.7%	4.9%	$ 6,982	4,907	5,941
1963	6,613	13.6%	4.6%	$ 7,627	5,722	6,415
1967	6,592	15.1%	4.3%	$ 8,074	6,181	7,651
1972	6,777	16.6%	4.0%	$ 8,652	6,999	9,520
1977	7,278	17.6%	4.0%	$ 9,259	7,588	12,012
1982	7,566	18.2%	4.9%	$ 9,437	8,124	13,717
1987	7,533	18.3%	7.2%	$ 9,120	8,366	15,021
1992	7,500	18.4%	9.6%	$ 8,760	8,608	17,855

Table 3.9 Mean Values of Variables Specific to Cities with Relief Routes

YEAR	# CASES	TRAFFIC SPLIT[1]	DIST OLD	DIST RATIO
1967	3	0.32	6.17	1.04
1972	9	0.46	5.67	0.98
1977	13	0.49	5.44	1.01
1982	18	0.48	5.29	0.99
1987	21	0.48	5.19	0.97
1992	23	0.47	5.11	0.97

[1] Values are fractions

Table 3.10 State Level Variables

Year	Retail	Gasoline	Eat/Drink	Service
Per Capita Sales				
1954	6,800	484	382	756
1958	6,937	565	382	892
1963	7,059	568	403	1,043
1967	7,868	641	490	1,321
1972	8,972	694	619	1,971
1977	9,736	732	782	2,423
1982	9,847	790	874	3,834
1987	9,426	688	945	5,422
1992	9,380	642	961	6,589
Number of Establishments				
1954	91,293	11,992	15,834	5,241,788
1958	99,093	14,902	17,124	6,732,513
1963	96,406	15,069	17,092	8,607,047
1967	110,085	16,632	19,582	11,596,599
1972	122,898	17,118	20,849	19,068,524
1977	120,595	12,747	22,246	26,457,157
1982	134,815	8,234	19,755	46,455,719
1987	173,677	10,666	33,456	71,822,768
1992	189,297	8,834	37,359	94,721,217
Total Sales[1]				
1954	57,521,751	4,095,512	3,234,873	6,394,982
1958	63,859,572	5,205,493	3,519,100	8,213,666
1963	71,048,435	5,717,948	4,054,580	10,500,598
1967	84,282,667	6,870,480	5,248,544	14,147,851
1972	105,894,765	8,194,403	7,304,336	23,263,599
1977	129,678,583	9,748,840	10,410,602	32,277,732
1982	145,539,545	11,675,467	12,924,908	56,675,977
1987	152,311,890	11,125,679	15,265,094	87,623,777
1992	164,501,469	11,250,884	16,847,207	115,559,885

[1] 1000s of Dollars

3.4 COMPARISON WITH OTHER STUDIES

Several prior studies have examined the impacts of relief routes. These studies have considered different indicators of impact, used data at different levels of aggregation, considered cities where relief routes were opened to traffic at different points in time, and used a wide array of methodologies. This section briefly examines how the current approach compares with some of the major relief route studies.

A study in Kansas (Burress 1996) examined the impact of the relief route on the local economy in terms of a broader range of indicators (sales, employment, payroll, startups, and closures) than the current study. The research also studied the impacts at the town and the county levels, both in the short and long term. The effort included calibration of a gravity model to obtain estimates of through and local traffic; the current study lacks this distinction of through and local traffic. However, most of the models developed in the Kansas study have few explanatory variables. The impacts of the relief route were predominantly captured in terms of indicator variables, and several variables not related to relief routes were not controlled for. The current effort strives to do better in this direction by capturing the marginal influence of the relief route after controlling for several other factors that can impact the local economy.

Work done by Buffington and Burke (1991) examined the impacts of highway improvements on employment levels and wages. This study also used a panel data set but used four points in time, as opposed to nine in the current study. Also, all the cities included in the Buffington study had some form of highway improvement (relief route, radial, or loop). There were no control cites in the data set. This could lead to biased results as all cities that receive a highway improvement could have certain characteristics that are different from those cities that did not receive any such improvements. Recognizing this limitation, nineteen control cities have been included in this research effort. Additionally, the Buffington et al. models did not control for demographic and regional variables.

The models developed in the current study have several similarities and differences when compared to an earlier effort undertaken at The University of Texas at Austin (Anderson et al. 1992). Both focused on cities in Texas that have a single relief route and considered sales in four industrial sectors as indicators of impact. However, the current work employed a different empirical specification and modeling methodology. The sales dollars were normalized by the population of the city and per capita sales were used as dependent variables, as opposed to the total sales dollars used in the previous work. There were more variables and better characterizing city demographics included. The panel was longer (nine years, as opposed to six), so there are more observations in the data set. As will be described in Chapter 4, the random-effects modeling approach was adopted recognizing the panel nature of the data. The current results, therefore, can be expected to be more robust than those obtained in the previous study.

3.5 LIMITATIONS

The methodology used in the current study also has limitations. The sales data used for modeling are reported at the aggregate, city level. The models capture only city-level changes and do not capture any relocation of businesses within the city that may occur. No information is available on the nature of the traffic that is rerouted. Rerouting truck traffic may have a totally different effect than rerouting motorists who are more likely to stop and shop in the city. There is also no distinction between through traffic and traffic headed to the city. It is not possible to distinguish sales to local residents from sales to through traffic using available data.

It is assumed in the model that the influence of the relief route is the same regardless of when the relief route opened. However, opening a relief route during a period of recession can be expected to hurt a city more than a relief route opened during a period of sound economic health. Changes are taking place in each industrial sector over the years that are independent of the presence of a relief route. When national chains replace local businesses, the revenue generated by these stores may be lost to the city. Such effects have not been controlled for effectively in the model.

In addition, the long- and short-term effects of a relief route may be quite different. Activity during the construction of the relief route may cause increased sales. The sudden drop in through traffic volumes with the opening of the relief route may have a short-term impact on the sales levels. However, the city can adjust in the long run. Because the time points in the data set are approximately five years apart, any immediate effects could not be efficiently captured.

The approach relies on sales levels in four different industries as primary indicators of impact. These industries are the ones that can be expected to have the most significant negative impacts. It is to be noted that the drop in sales in certain industrial sectors can be offset by gains in other sectors. Hence, a drop in sales in these sectors does not necessarily mean an overall negative impact on the community's economy.

Finally, any steps taken by the city to plan for the relief route could influence the impact of the relief route. The effects of local policies are not directly captured in the models.

CHAPTER 4. ECONOMETRIC MODELING

This chapter describes the econometric modeling process adopted to model the impact of a relief route on the local economy. The variable specification is described first, and then the modeling methodology is elaborated. The model results are then presented and discussed.

4.1 VARIABLE SPECIFICATION

Several variables were identified to explain the four types of industrial sectors investigated. The impact of city demographics on the local economy is captured by introducing the fraction of the population that is elderly, the fraction of the labor force that is unemployed, and the per capita income as explanatory variables. Population is expected to have a positive impact on the local economy. Per capita income is expected to have a positive impact on the local economy, while the unemployment rate is expected to have a negative impact. Elderly people may be more likely to shop locally, as opposed to driving out in search of more variety. Hence, an a priori expectation for this explanatory variable may be for a positive effect.

It also is hypothesized that the economies of small and medium cities are significantly influenced by the proximity of a large city. The closer and more populated the large city, the greater its influence tends to be. Thus, the ratio of the population of the nearest large city to its distance from the community under study is introduced as an explanatory variable (LARGECITY POP/DIST). The presence of a large city nearby could mean a greater market for the businesses in the cities studied; therefore, a positive impact of this variable could be expected. Conversely, this could also mean the presence of better markets in the large city, which could draw business away from the smaller cities under study. This would translate into a negative coefficient on the variable. More traffic moving through the city indicates a larger market for local goods and services; thus, a positive effect is expected for the variable TOT TRAFFIC (and TOT TRAFFIC PERCAP).

Cities with relief routes are identified through a set of variables that describe the characteristics of the relief route. First, the indicator variable RELIEF ROUTE takes a value of one once the relief route has opened in the city. There is no a priori expectation on the sign of this coefficient as it picks up the influence of the relief route after controlling for several characteristics of the relief route. Second, the variable NUM YEARS is introduced to capture changes in the impacts of a relief route with time. The impacts may lag several years behind the opening of the relief route or decline over time, for example. The sign on this variable can again be either positive or negative. Third, the impact of a relief route likely depends on how much traffic and how far away traffic is diverted from a city's downtown. An estimate of the magnitude of the traffic diverted from the old route to the relief route is obtained as the ratio of traffic volume on the relief route to the total traffic volume approaching the city (TRAFFIC SPLIT). The greater the diversion, the greater the expected adverse impact on the local economy. The ratio of distance along the relief route to the distance along the old route (DIST RATIO) suggests how relatively far the traffic is diverted from the downtown. The greater the DIST RATIO, the greater the expected adverse impact. It should be noted that the data used is at the aggregate, city level. If the relief route is predominantly within city limits, the traffic diverted is not lost to the city though it is lost to the old route. In such a case, the magnitude of diversion and how far from the downtown the traffic is moved may not have a significant negative impact on total sales. Finally, whether a facility is built with controlled access (with frontage roads, in all cases in this dataset) or uncontrolled access might influence the amount and type of new development along the relief route. There is no a priori expectation on the sign for the ACCESS CONTROL variable.

Population of the city and the total traffic volumes approaching the city are interacted with the RELIEF ROUTE indicator variable. This is used to capture any differences on the impact of population and traffic on the economy between cites with relief routes and control cities. There is no a priori expectation on the sign of these interaction variables.

State level sales and number of establishments are introduced to capture and control for more global trends over time. The 1982 economic census provided sales data only for those establishments with payrolls. Data for all other economic-census years were available for all establishments. To characterize this data issue, an indicator variable

(YEAR 1982) was introduced for observations in 1982 in all but the total-retail-sales model (this data problem was not observed for data for the retail industry).

4.2 MODEL SPECIFICATION

The model developed is of the following structure:

$$Y_{it} = \alpha + X_{1,it}\,\beta_1 + X_{2,t}\,\beta_2 + u_{it}$$
$$i = 1 \text{ to } N$$
$$t = 1 \text{ to } T$$

Where:

Y_{it}	is the dependent variable (Per Capita Sales, Number of Establishments, and Total Sales),
$X_{1,it}$	are independent variables that vary over both city and time (for example POPLTN, UNEMP RATE, etc.),
X_{2t}	are independent variables that are time specific (STATE SALES, STATE NUM EST, STATE SALES PERCAP YEAR and YEAR 1982) but do not vary by city,
N	is the number of cross-sectional units in the sample (= 42),
T	is the length of time-series data for each cross section (=9),
α, β_1 and β_2	are the coefficients to be determined by the model, and
u_{it}	is the error term.

The data set used for modeling consists of observations drawn from several cities. Each city also has several observations over time. This kind of a data set, in which observations are pooled across several cases and several points in time, is called a panel data set. Such a data set has more data points than cross-sectional data sets (where observations come from several cities, but at the same point in time) or time-series data sets (where observations fall over time, but for the same city). This setup can identify both trends over time and variability across cities (Greene 2000).

With a panel data set, the error term can be broken down into unobservable cross-section-specific (i.e., city specific) effects (μ_i) and a remaining term (ν_{it}). This is the conventional "one-way error components model" (see Baltagi 1995). Alternate model formulations arise depending on the assumptions made regarding the cross-sectional error term. One such formulation is called the fixed-effect model (where the cross-sectional error term is estimated as a single constant for each city); another is the random-effects model (where the cross-sectional error term is assumed to be randomly distributed with a variance of σ^2_μ). The random-effects formulation has several statistical and practical advantages over the fixed-effects formulation (Maddala 1987), and hence is more suitable for the current work. This is the adopted methodology. The mathematical model formulation and the statistical tests used are presented in Appendix 1.

Models are developed separately for the four different industrial sectors. As population itself is a significant determinant of the sales levels in a city, sales normalized by population and corrected for inflation are expected to be a good indicator to study the impact of the opening of a relief route. Total sales and number of establishments in each industrial sector are also modeled to provide a sense of the magnitude of the changes in sales and also possible changes in the size and number of establishments.

4.3 RESULTS

The estimation method for the random-effects model was coded in the matrix programming language GAUSS (Aptech 1995); the code used in this analysis is presented in Appendix 2. In each case, the initial specification uses all the explanatory variables; statistically insignificant variables were removed in a stepwise manner to arrive at the final specification. Appropriate statistical tests were used to ensure that the empirical specification is statistically correct.

The initial and final specifications of the random-effects models developed for the four industrial sector cases are presented (Tables 4.1 to 4.12). The marginal influence of the different variables of interest on the dependent variables is discussed in detail. *Note that the net impact of the relief route can be determined only by looking at the influence of all of the variables related to the relief route*. The magnitude of the net impact depends on values of the explanatory variables in addition to the coefficients estimated. The interpretation of the models as to the net impact of the relief route is discussed in greater detail in the subsequent Section 4.4.

4.3.1 Models for Retail Industry

Table 4.1 Model for Per Capita Total Retail Sales

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	5.497E+05	8.49	5.314E+05	8.40
STATE SALES PERCAP	1.355E+00	4.67	1.268E+00	4.50
YEAR	-2.858E+02	-8.37	-2.760E+02	-8.28
ELDERLY	2.053E+02	3.63	1.904E+02	3.44
UNEMP RATE	1.872E+02	2.45	1.657E+02	2.23
INCOME PERCAP	6.849E-01	5.22	6.922E-01	5.30
LARGECITY POP/DIST	1.111E-01	2.84	1.051E-01	2.77
TOT TRAFFIC PERCAP	2.778E+03	10.31	2.892E+03	12.76
RELIEF ROUTE	4.515E+03	1.66	2.771E+03	1.87
NUM YEARS	-9.097E+01	-2.22	-9.068E+01	-2.26
TRAFFIC SPLIT	-1.250E+04	-4.07	-1.329E+04	-5.37
DIST OLD	2.936E+01	0.13		
DIST RATIO	-2.989E+03	-1.19		
ACCESS CONTROL	-3.188E+02	-0.40		
RR*POPLTN	2.531E-01	2.28	1.998E-01	2.18
RR*TOT TRAFFIC PERCAP	1.873E+02	0.64		
R^2	0.489		0.486	
$R^2_{adj.}$	0.467		0.471	
σ^2_ν	4.508E+06		4.510E+06	
σ^2_μ	4.608E+06		4.542E+06	

In the model for per capita retail sales, the coefficient on the variable TRAFFIC SPLIT is negative. This suggests that the higher the magnitude of traffic drawn away to the relief route, the more adverse the impact. Other characteristics of the relief routes, such as the access provided and the ratio of distance between the new route and the old route, do not seem to have a statistically significant impact. The indicator variable for the relief routes has a positive and statistically significant coefficient, due to effects not picked up by the other relief-route-related variables. Cities that have had relief routes for a long time seem to have lower per capita sales when compared to cities where relief routes have recently opened. Cities with larger populations fare better with the relief route, in terms or retail sales per capita. The net impact of the relief route could therefore be positive or negative, depending on the characteristics of the relief route. In addition, several variables that describe the city characteristics are also statistically significant and positively related to per capita sales.

Table 4.2 Model for Number of Retail Establishments

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	5.388E+03	8.61	5.330E+03	8.56
STATE NUM EST	5.852E-04	5.60	5.396E-04	5.72
YEAR	-2.781E+00	-8.51	-2.752E+00	-8.45
POPLTN	1.144E-02	18.09	1.141E-02	17.94
ELDERLY	1.916E+00	4.43	2.013E+00	4.72
UNEMP RATE	-5.947E-01	-1.05		
INCOME PERCAP	2.634E-03	2.68	2.872E-03	3.05
LARGECITY POP/DIST	4.063E-04	1.48	3.873E-04	1.42
TOT TRAFFIC	2.179E-03	5.93	2.164E-03	5.91
RELIEF ROUTE	8.159E+00	0.44	5.427E+00	0.45
NUM YEARS	-1.173E+00	-3.87	-1.173E+00	-3.89
TRAFFIC SPLIT	-4.239E+01	-1.89	-4.357E+01	-2.09
DIST OLD	-1.242E+00	-0.75		
DIST RATIO	1.574E+00	0.09		
ACCESS CONTROL	14.480834	2.46	1.378E+01	2.63
RR*POPLTN	-8.570E-04	-1.09	-1.044E-03	-1.50
RR*TOT TRAFFIC	8.884E-04	2.27	8.896E-04	2.28
R^2	0.686		0.676	
$R^2_{adj.}$	0.672		0.666	
σ^2_{ν}	2.478E+02		2.475E+02	
σ^2_{μ}	1.753E+02		1.848E+02	

The model for number of retail establishments suggests that the magnitude of traffic drawn away from the old routes adversely impacts the number of establishments in the city. However, the ratio of the distance of the new route to the distance of the old route does not have a statistically significant impact. A controlled-access relief route with frontage roads seems to have a positive influence on the number of establishments relative to an uncontrolled-access facility. The model also suggests that cities that have had relief routes longer have fewer retail establishments than cities that have had relief routes constructed recently. Again, several variables that capture the influence of the city are found to be statistically significant and their signs make intuitive sense.

Table 4.3 Model for Total Retail Sales

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	4.756E+06	5.30	4.939E+06	5.99
STATE SALES	3.679E-04	2.59	4.026E-04	2.97
YEAR	-2.474E+03	-5.33	-2.570E+03	-6.03
POPLTN	9.604E+00	15.59	9.699E+00	16.05
ELDERLY	1.884E+03	4.69	1.906E+03	5.16
UNEMP RATE	-2.292E+02	-0.47		
INCOME PERCAP	3.941E+00	4.38	4.374E+00	5.50
LARGECITY POP/DIST	1.415E-01	0.53		
TOT TRAFFIC	4.535E+00	12.93	4.335E+00	15.75
RELIEF ROUTE	2.514E+04	1.45	1.396E+04	1.40
NUM YEARS	-1.225E+03	-4.45	-1.350E+03	-5.18
TRAFFIC SPLIT	-3.375E+04	-1.62	-2.816E+04	-1.71
DIST OLD	9.528E+02	0.62		
DIST RATIO	-8.918E+03	-0.53		
ACCESS CONTROL	3.584E+02	0.07		
RR*POPLTN	-1.357E+00	-1.86	-1.353E+00	-2.20
RR*TOT TRAFFIC	-4.133E-01	-1.13		
R^2	0.771		0.768	
$R^2_{adj.}$	0.761		0.762	
σ^2_ν	2.065E+08		2.080E+08	
σ^2_μ	1.841E+08		1.892E+08	

The model developed for total retail sales indicates an adverse impact as a result of an increase in the ratio of traffic on the relief route to total traffic entering the city. The number of years since the relief route was opened has a negative influence on total retail sales as indicated by the negative coefficient on the NUM YEARS variable. Population and the total traffic approaching the city are found to be important predictors of total retail sales, as expected. Several variables that characterize the city were also found to significantly influence retail sales.

4.3.2 Models for Gasoline Service Stations

Table 4.4 Model for Per Capita Gasoline Service Station Sales

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	3.954E+04	4.25	3.690E+04	6.17
STATE SALES PERCAP	2.153E+00	3.67	2.254E+00	5.58
YEAR	-2.058E+01	-4.20	-1.916E+01	-6.13
YEAR 1982	-3.447E+02	-4.20	-3.463E+02	-4.40
ELDERLY	3.458E+00	0.38		
UNEMP RATE	7.072E+00	0.51		
INCOME PERCAP	1.919E-02	0.88		
LARGECITY POP/DIST	-4.664E-03	-0.79		
TOT TRAFFIC PERCAP	4.150E+02	9.31	4.148E+02	9.73
RELIEF ROUTE	9.111E+02	1.94	2.076E+02	1.71
NUM YEARS	-3.269E+00	-0.45		
TRAFFIC SPLIT	1.976E+02	0.37		
DIST OLD	5.661E-01	0.01		
DIST RATIO	-5.555E+02	-1.28		
ACCESS CONTROL	-1.616E+02	-1.15		
RR*POPLTN	-1.085E-02	-0.57		
RR*TOT TRAFFIC PERCAP	-3.063E+02	-6.05	-2.814E+02	-6.32
R^2	0.299		0.289	
$R^2_{adj.}$	0.268		0.278	
σ^2_{ν}	1.432E+05		1.427E+05	
σ^2_{μ}	7.663E+04		7.771E+04	

In the model for per capita sales by gasoline service stations, the coefficient estimated on the relief route indicator is positive and statistically significant. Other characteristics of the relief route, including the ratio of traffic on the relief route to total traffic entering the city and the ratio of the distance on the relief route to the distance on the old route, do not have a statistically significant influence on per capita sales. Also, demographic variables such as unemployment and the fraction of elderly population do not seem to have a significant influence on per capita gas station sales. The model suggests that sales are significantly impacted by per capita traffic volumes. The R^2 value of this model is the lowest among all estimated models, however, indicating that the variables included in the model explain only a small amount of the variation in the per capita sales.

Table 4.5 Model for Number of Gasoline Service Stations

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	4.178E+02	4.79	3.676E+02	6.64
STATE NUM EST	9.621E-04	8.40	9.765E-04	10.05
YEAR	-2.162E-01	-4.79	-1.905E-01	-6.75
YEAR 1982	-2.484E+00	-2.86	-2.367E+00	-3.10
POPLTN	9.200E-04	6.61	9.716E-04	8.34
ELDERLY	2.538E-02	0.26		
UNEMP RATE	3.525E-03	0.03		
INCOME PERCAP	5.734E-04	2.59	5.887E-04	2.95
LARGECITY POP/DIST	-3.441E-05	-0.56		
TOT TRAFFIC	1.116E-04	1.30		
RELIEF ROUTE	-5.253E-01	-0.12	1.166E+00	0.96
NUM YEARS	-4.792E-02	-0.68		
TRAFFIC SPLIT	-2.385E+00	-0.46		
DIST OLD	-4.317E-01	-1.12		
DIST RATIO	4.687E+00	1.12		
ACCESS CONTROL	2.384E+00	1.73		
RR*POPLTN	-2.781E-04	-1.53	-3.077E-04	-2.21
RR*TOT TRAFFIC	-5.557E-05	-0.61		
R^2	0.624		0.617	
$R^2_{adj.}$	0.606		0.610	
σ^2_ν	1.359E+01		1.379E+01	
σ^2_μ	7.747E+00		8.159E+00	

In the model for number of gasoline service stations, none of the relief route-related variables is statistically significant. This suggests that no characteristic of the relief route has any marginal impact on the number of gasoline stations in the city. Population and per capita income are the only demographic characteristics included here that appear to have an effect. Surprisingly, traffic volumes were not significant predictors of the number of service stations.

Table 4.6 Model for Gasoline Service Station Sales

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	1.763E+05	1.05	5.452E+02	0.51
STATE SALES	3.657E-04	0.89		
YEAR	-9.081E+01	-1.05		
YEAR 1982	-1.830E+03	-2.43	-1.314E+03	-3.03
POPLTN	4.621E-01	4.98	4.789E-01	5.75
ELDERLY	-6.330E+00	-0.10		
UNEMP RATE	-1.498E+02	-1.71	-1.956E+02	-2.81
INCOME PERCAP	3.617E-01	2.45	3.250E-01	2.51
LARGECITY POP/DIST	-2.745E-02	-0.68		
TOT TRAFFIC	2.573E-01	4.55	2.296E-01	4.78
RELIEF ROUTE	2.478E+03	0.85	2.075E+03	2.01
NUM YEARS	-8.238E+01	-1.73	-9.704E+01	-2.35
TRAFFIC SPLIT	1.111E+01	0.00		
DIST OLD	-1.088E+02	-0.42		
DIST RATIO	3.457E+02	0.12		
ACCESS CONTROL	-4.925E+02	-0.53		
RR*POPLTN	-1.604E-01	-1.31	-1.655E-01	-1.74
RR*TOT TRAFFIC	-1.689E-01	-2.69	-1.658E-01	-2.84
R^2	0.329		0.322	
$R^2_{adj.}$	0.297		0.305	
σ^2_ν	6.128E+06		6.074E+06	
σ^2_μ	3.493E+06		3.619E+06	

The positive coefficient on the relief route indicator implies that cities with relief routes have higher total gasoline service station sales when compared to control cities after controlling for several relief-route-related variables. However, the coefficient on the variable NUM YEARS is negative. Hence, over time, the positive effect of the relief route is likely to decline. Demographic variables like unemployment levels and per capita income are found to have a statistically significant influence on total sales, as expected. Also, the impact of population and traffic volumes on sales is found to be greater for control cities than for cities with relief routes. Again, the R^2 value for this model is smaller than that for the per capita model for sales at gasoline service stations, indicating that most of the variation in total sales for gasoline service stations is unexplained by the model.

4.3.3 Models for Eating and Drinking Places

Table 4.7 Model for Per Capita Sales at Eating and Drinking Places

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	2.340E+04	2.80	2.363E+04	2.86
STATE SALES PERCAP	7.854E-01	3.73	7.860E-01	3.77
YEAR	-1.220E+01	-2.82	-1.232E+01	-2.88
YEAR 1982	-1.184E+02	-3.41	-1.183E+02	-3.42
ELDERLY	1.043E+01	2.22	1.070E+01	2.32
UNEMP RATE	9.908E+00	1.65	1.016E+01	1.73
INCOME PERCAP	3.173E-02	2.93	3.173E-02	2.94
LARGECITY POP/DIST	1.342E-02	4.12	1.354E-02	4.26
TOT TRAFFIC PERCAP	1.583E+02	6.86	1.584E+02	6.88
RELIEF ROUTE	-5.843E+02	-2.53	-5.545E+02	-5.29
NUM YEARS	-1.283E+01	-3.76	-1.281E+01	-4.08
TRAFFIC SPLIT	-1.283E+01	-0.05		
DIST OLD	-4.146E-01	-0.02		
DIST RATIO	3.788E+01	0.18		
ACCESS CONTROL	-1.019E+02	-1.49	-1.062E+02	-1.99
RR*POPLTN	4.943E-02	5.23	4.974E-02	6.16
RR*TOT TRAFFIC PERCAP	8.741E+01	3.51	8.700E+01	3.54
R^2	0.568		0.568	
$R^2_{adj.}$	0.549		0.552	
σ^2_{ν}	3.319E+04		3.295E+04	
σ^2_{μ}	2.993E+04		3.034E+04	

The model for per capita sales in eating and drinking places suggests that cities with relief routes have lower per capita sales when compared to control cities. Also, cities that have had relief routes for a long time have lower per capita sales when compared to cities where relief routes have recently opened. The ratio of the traffic on the relief route to the traffic entering the city and the ratio of the distance on the relief route to the distance on the old route do not seem to significantly influence the per capita sales. Controlled-access facilities with frontage roads seems to adversely impact the sales per capita relative to uncontrolled-access facilities. The influence of population and per capita traffic volumes on per capita sales is greater for cities with relief routes than it is for control cities, as indicated by positive coefficients on the interaction terms. All city demographic variables included in the model are found to have a statistically significant influence on the sales levels.

Table 4.8 Model for Number of Eating and Drinking Places

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	-1.381E+02	-0.66	3.390E+00	2.84
STATE NUM EST	-7.834E-05	-0.49		
YEAR	7.291E-02	0.67		
YEAR 1982	-9.379E+00	-6.37	-8.876E+00	-11.81
POPLTN	1.762E-03	9.27	1.742E-03	11.05
ELDERLY	-5.049E-02	-0.39		
UNEMP RATE	1.121E-01	0.68		
INCOME PERCAP	8.209E-05	0.28		
LARGECITY POP/DIST	1.939E-04	2.37	2.069E-04	2.67
TOT TRAFFIC	2.943E-04	2.77	3.968E-04	5.84
RELIEF ROUTE	4.172E+00	0.78	1.008E+00	0.45
NUM YEARS	-3.921E-02	-0.45		
TRAFFIC SPLIT	-1.210E+01	-1.89	-1.322E+01	-2.64
DIST OLD	5.345E-01	1.12		
DIST RATIO	-7.245E+00	-1.38		
ACCESS CONTROL	4.179E+00	2.48	5.293E+00	3.66
RR*POPLTN	-1.161E-04	-0.52		
RR*TOT TRAFFIC	1.600E-04	1.43		
R^2	0.544		0.532	
$R^2_{adj.}$	0.523		0.523	
σ^2_ν	1.996E+01		1.977E+01	
σ^2_μ	1.698E+01		1.845E+01	

The model developed for number of eating and drinking places indicates that the greater the ratio of traffic on the relief route to total traffic entering the city, the more adverse the impact. Population, traffic volumes, and the presence of a large city nearby have a positive influence on the number of eating and drinking places in the city. Controlled-access facilities with frontage roads have a positive influence on the number of establishments. This positive influence on number of establishments coupled with the estimated negative influence on total sales may be due to the nature of the establishments. For example, the presence of a frontage road may stimulate more and smaller stores, each with lower average sales; however, any reasoning for such a relationship is not obvious. It also may be that frontage roads are provided where many small stores already exist, in order to avoid issues of too-frequent driveways along a highway. In such a case, the frontage-road-provision variable becomes endogenous (i.e., dependent and determined by the nature of sales, rather than independent).

Table 4.9 Model for Sales in Eating and Drinking Places

	Initial Model		Final Model	
Variable	Coefficient	t statistic	Coefficient	t statistic
CONSTANT	2.212E+05	3.06	1.864E+05	2.83
STATE SALES	2.248E-04	2.59	1.926E-04	2.44
YEAR	-1.160E+02	-3.11	-9.793E+01	-2.89
YEAR 1982	-6.927E+02	-2.74	-5.953E+02	-2.50
POPLTN	5.549E-01	10.59	5.792E-01	11.28
ELDERLY	1.131E+02	3.13	1.139E+02	3.34
UNEMP RATE	-6.085E+00	-0.13		
INCOME PERCAP	7.221E-02	0.88		
LARGECITY POP/DIST	1.317E-02	0.58		
TOT TRAFFIC	4.218E-01	13.20	4.182E-01	16.99
RELIEF ROUTE	-4.743E+03	-2.98	-5.822E+03	-6.34
NUM YEARS	-5.668E+01	-2.21	-6.674E+01	-2.75
TRAFFIC SPLIT	5.232E+03	2.72	4.706E+03	3.13
DIST OLD	3.840E+00	0.03		
DIST RATIO	-8.284E+02	-0.54		
ACCESS CONTROL	-3.812E+02	-0.75		
RR*POPLTN	3.854E-01	5.78	3.567E-01	6.32
RR*TOT TRAFFIC	-4.040E-02	-1.21		
R^2	0.774		0.771	
$R^2_{adj.}$	0.764		0.764	
σ^2_ν	1.819E+06		1.802E+06	
σ^2_μ	1.143E+06		1.240E+06	

The model developed for total sales in eating and drinking places indicates that cities with relief routes have lower sales than the control cities, after controlling for several other variables. Also, cities that have long had relief routes have lower sales than those cities where relief routes have recently opened. It is interesting to note, however, that the ratio of traffic on the new route to total traffic entering the city has a positive impact on total sales in this sector. It is not possible to determine from the available data whether this increase in sales occurs in existing businesses or in new businesses or both. The influence of population on sales levels is also greater for a city with a relief route when compared to a city without a relief route.

4.3.4 Models for Service Industries

Table 4.10 Model for Per Capita Service Receipts

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	1.580E+05	5.19	1.559E+05	5.15
STATE SALES PERCAP	8.261E-01	9.69	8.226E-01	9.70
YEAR	-8.185E+01	-5.21	-8.072E+01	-5.17
YEAR 1982	9.369E+00	0.08	5.051E+00	0.04
ELDERLY	5.756E+01	3.15	5.588E+01	3.08
UNEMP RATE	-4.522E+01	-1.78	-4.635E+01	-1.83
INCOME PERCAP	1.918E-01	4.53	1.912E-01	4.54
LARGECITY POP/DIST	4.306E-02	3.62	4.142E-02	3.54
TOT TRAFFIC PERCAP	2.307E+02	2.70	2.334E+02	2.74
RELIEF ROUTE	-2.973E+03	-3.41	-2.752E+03	-3.25
NUM YEARS	-6.376E+01	-4.78	-6.533E+01	-4.95
TRAFFIC SPLIT	-2.076E+03	-2.10	-1.592E+03	-1.98
DIST OLD	6.503E+01	0.89		
DIST RATIO	1.946E+03	2.41	1.791E+03	2.41
ACCESS CONTROL	9.661E+01	0.37		
RR*POPLTN	1.134E-01	3.21	1.293E-01	4.04
RR*TOT TRAFFIC PERCAP	4.822E+02	5.21	4.795E+02	5.19
R^2	0.703		0.702	
R^2_{adj}.	0.690		0.691	
σ^2_{ν}	4.743E+05		4.735E+05	
σ^2_{μ}	3.630E+05		3.628E+05	

The model developed for per capita service receipts suggests that the ratio of traffic on the relief route to total traffic entering the city has an adverse impact on per capita sales. Also, the cities that have had relief routes the longest have lower per capita sales levels than those with more recent relief routes. The relief route indicator variable also has a negative coefficient, suggesting that there are other effects not captured by the relief-route-related variables that cause the per capita sales in these cities to be lower than the sales in control cities. All city demographic variables that were included in the study were found to exert a statistically significant influence on the per capita sales levels. In addition, the influence of population on the per capita sales is greater for cities with relief routes than it is for control cities.

Table 4.11 Model for Number of Service Industries

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	7.478E+03	5.35	7.372E+03	5.39
STATE NUM EST	5.113E-04	12.46	4.994E-04	14.14
YEAR	-3.907E+00	-5.42	-3.855E+00	-5.46
YEAR 1982	-1.808E+01	-1.56	-2.053E+01	-1.83
POPLTN	1.195E-02	8.62	1.196E-02	8.88
ELDERLY	4.148E+00	4.13	4.308E+00	4.60
UNEMP RATE	-7.430E-01	-0.44		
INCOME PERCAP	7.366E-03	3.02	7.148E-03	3.09
LARGECITY POP/DIST	-3.522E-05	-0.06		
TOT TRAFFIC	5.369E-03	5.49	5.395E-03	5.98
RELIEF ROUTE	-9.905E+01	-1.90	-8.155E+01	-4.20
NUM YEARS	-2.385E+00	-2.67	-2.433E+00	-2.96
TRAFFIC SPLIT	-5.728E+01	-0.90		
DIST OLD	-5.460E+00	-1.20		
DIST RATIO	5.850E+01	1.16		
ACCESS CONTROL	3.391E+01	2.01		
RR*POPLTN	4.354E-03	1.99	4.947E-03	2.88
RR*TOT TRAFFIC	3.365E-03	2.96	3.255E-03	2.88
R^2	0.807		0.805	
$R^2_{adj.}$	0.798		0.799	
σ^2_ν	2.205E+03		2.204E+03	
σ^2_μ	5.136E+02		5.121E+02	

The model developed for the number of service industries suggests that cities with relief routes have fewer industries than other cities after controlling for several other variables. The magnitude of the traffic diverted does not seem to have a significant influence on the number of establishments. Also, cities that have had relief routes for longer have fewer establishments than those that have recently received relief routes. Population, fraction of elderly people, and income per capita are city demographics that are found to significantly influence the number of establishments. The influence of population and traffic volumes on the number of establishments is found to be greater for cities with relief routes than it is for control cities.

Table 4.12 Model for Service Receipts

	Initial Model		Final Model	
Variable	**Coefficient**	**t statistic**	**Coefficient**	**t statistic**
CONSTANT	1.308E+06	3.97	1.157E+06	4.28
STATE SALES	2.743E-04	5.50	2.286E-04	6.03
YEAR	-6.809E+02	-4.00	-6.055E+02	-4.35
YEAR 1982	8.342E+02	0.55	1.335E+03	0.89
POPLTN	2.159E+00	7.08	2.231E+00	7.69
ELDERLY	6.507E+02	2.98	7.117E+02	3.49
UNEMP RATE	-4.649E+02	-1.48		
INCOME PERCAP	-1.376E-01	-0.27		
LARGECITY POP/DIST	-1.110E-01	-0.83		
TOT TRAFFIC	1.769E+00	9.19	1.606E+00	10.79
RELIEF ROUTE	-2.089E+04	-2.11	-8.215E+03	-2.83
NUM YEARS	-3.970E+02	-2.41	-2.912E+02	-1.94
TRAFFIC SPLIT	1.699E+04	1.42		
DIST OLD	5.800E+02	0.66		
DIST RATIO	5.389E+03	0.56		
ACCESS CONTROL	-3.085E+03	-0.98		
RR*POPLTN	7.693E-01	1.85	5.203E-01	1.63
RR*TOT TRAFFIC	-2.130E-01	-1.01		
R^2	0.644		0.638	
$R^2_{adj.}$	0.627		0.629	
σ^2_ν	7.225E+07		7.318E+07	
σ^2_μ	3.436E+07		3.350E+07	

In the model for total service receipts, the coefficients on the variables RELIEF ROUTE and NUM YEARS are both negative. This suggests that cities with relief routes have lower service receipts than other cities after controlling for other variables. Also, cities that have had the relief route longer have lower sales than cities that have had the relief route for only a few years. None of the other relief-route characteristics considered in this study is found to exert any statistically significant marginal impact on total service receipts. The fraction of elderly people, along with population and traffic levels, is found to exert an influence on the total sales. The effect of population on the sales is found to be more for cities with relief routes than it is for control cities.

4.4 MAGNITUDE OF IMPACT

The estimated models indicate the influence of several variables on the local economy as represented by sales and number of establishments in four different industrial sectors. It was also possible to obtain the marginal impact of several relief route characteristics, such as the ratio of traffic on the relief route to total traffic entering the city, the ratio of the distance on the relief route to the distance on the old route, and the nature of access provided on the relief route. The direction of the marginal impact can be understood from the sign on the coefficients, as summarized in Table 4.13. However, the net impact of the relief route depends on the impact of all the relief route variables in the model: the positive impact of one variable may be offset by the negative impact of another, and vice versa. To estimate the net impact of the relief route, the estimated percentage difference in the economic indicator (per capita sales, total sales, and number of establishments) of a city before and two years after the opening of the relief route is calculated.

Table 4.13 Summary of Marginal Effects of Relief Route Characteristics*

Indicator	NUM YEARS	TRAFFIC SPLIT	DIST RATIO	ACCESS CONTROL	RELIEF ROUTE	RR* POPLTN	RR*TOT TRAFFIC
Total Retail							
Per Capita Sales	-	-			+	+	
Establishments	-	-		+	+	-	+
Total Sales	-	-			+	-	
Service Stations							
Per Capita Sales					+		-
Establishments					+	-	
Total Sales	-				+	-	-
Eating &Drinking							
Per Capita Sales	-			-	-	+	+
Establishments		-		+	+		
Total Sales	-	+			-	+	
Services							
Per Capita Sales	-	-	+		-	+	+
Establishments	-				-	+	+
Total Sales	-				-	+	

* Variables reflecting relief route characteristics are defined in Section 3.3.

Because there is much variability in the values of the variables, two hypothetical cases are considered — a small city and a medium city. All cities were classified into two groups: cities that have a population less than the mean population (averaged over all the forty-two cities in the year 1992) and those that have a population greater than the mean. The characteristics of the cities falling in the first group were averaged. These average values define the hypothetical "small city." Similarly the "medium city" was defined as the average of all cities that have a population greater than the mean population. The characteristics of the relief route were assumed to be the same in each case and equal to the average characteristics of all relief routes in 1992. The characteristics of the small and medium cities are presented in Table 4.14.

Table 4.14 Characteristics of Hypothetical Cities

Variable	Small City	Medium City
POPLTN	4,864	12,773
ELDERLY (%)	20.37	14.44
UNEMP RATE (%)	9.07	10.57
INCOME PERCAP	8,302	9,674
LARGECITY POP/DIST	6,879	12,065
TOT TRAFFIC	16,163	21,239
TOT TRAFFIC PERCAP	3.43	1.78
NUM YEARS	2	2
TRAFFIC SPLIT	0.47	0.47
DIST OLD	5.11	5.11
DIST RATIO	0.973	0.973

It is interesting to note that the small city has a significantly higher fraction of elderly population. Also, the magnitude of the variable LARGECITY POP/DIST for the medium city is almost twice that of the small city. This suggests that the medium city is closer to a more populous large city than the small city. The estimated impact measure is presented below (Table 4.15). The impact measure is the percentage difference in the economic indicator (per capita sales, total sales, and number of establishments) before and two years after the relief route is opened.

Table 4.15 Estimates of the Impact Measure

	Retail	Gasoline	Eat/Drink	Service
"Small" City (4,864 population)				
Per Capita Sales	-17.6%	-47.6%	-3.7%	9.9%
Number of Establishments	-7.4%	-5.2%	-26.4%	-3.4%
Total Sales	-11.1%	-21.4%	-31.0%	-22.1%
"Medium" City (12,773 population)				
Per Capita Sales	-10.0%	-32.3%	24.3%	17.3%
Number of Establishments	25.6%	-18.6%	-4.6%	47.0%
Total Sales	-1.9%	-62.7%	0.9%	-0.6%

For the hypothetical small city, the estimated impacts of the relief route are negative for all but one measure, per capita sales in the service sector. For the hypothetical medium city, the estimated impacts of the relief route are mixed — positive for some measures and negative for others — suggesting that medium-size cities are in a better position to weather potential negative effects and to capitalize on potential positive effects of the relief route. Per capita sales increase for eating and drinking places and for the service sector but decline for retail as a whole and for gasoline service stations. The number of establishments increases for retail as a whole and for the service sector but declines for gasoline service stations and eating and drinking places. The finding that the number of retail establishments increases but the retail sales per capita decreases after the construction of the relief route seems contradictory but may reflect differential lag times in the effect of the relief route on these measures. The finding that the number of eating and drinking places declines while sales per capita increases suggests a consolidation in this sector. For both the small and medium city, the gasoline service industry experiences the greatest declines. However, it should be noted that models for this sector had the poorest fit among all models estimated, suggesting that factors other than those captured in the demographic variables and relief route characteristics explain the changes in this industry.

It is important to note that this analysis provides an estimation of the impact of the relief route for an average small or medium city. Obviously, the actual impacts in any particular city depend on the specific values of the model variables for that city as well as factors not accounted for in the models. Nevertheless, the model results provide important insights into the effects of relief routes on local economies and thus provide guidance on how negative effects can be minimized and positive effects maximized.

CHAPTER 5. STUDY FINDINGS

This report described models developed to study the influence of a relief route on selected sectors of the local economy of the city. As indicators of impact, the models use per capita sales, total sales, and the number of establishments in four industrial sectors most likely to be impacted by changes in traffic levels: retail trade, gasoline service stations, eating and drinking places, and service industries. Separate models were developed for each indicator as a function of various explanatory variables for a sample of Texas cities with and without relief routes over nine points in time. Given the panel data set, a random-effects modeling approach was adopted.

The models show that relief routes have both positive and negative impacts on these sectors of the economy. For small cities, the impacts are mostly negative, but for medium cities, the results are more mixed. The models also show the marginal impact of different characteristics of the relief route. Most notably, a shift in traffic to the relief route (measured as the ratio of the traffic on the relief route to the total traffic entering the city) leads to a decline in several indicators, particularly those for total retail. In other words, the better the relief route works from a traffic standpoint, the greater the adverse impact on the economy of the community. Total sales for eating and drinking places increases, however, as the traffic split increases. Other characteristics of the relief route are less often significant. Relative to uncontrolled-access facilities, controlled-access facilities (with frontage roads) have a positive impact on the number of retail and eating /drinking establishments and a negative impact on per capita sales in eating and drinking places. The ratio of the distance on the relief route to the distance on the old route has a positive impact on per capita sales for the service sector but does not significantly impact other indicators. Most indicators decline with time after the opening of the relief route, suggesting that initial positive impacts may eventually disappear.

The models also captured the marginal effects of factors other than the relief routes that impact the economic indicators. Demographics of the local population, including income per capita, the fraction of elderly persons, and unemployment rates, proved significant in many of the models. Several of the models suggest a positive impact from the nearby presence of a large city. The bigger this "large city," the greater its positive impact; the closer this large city, the greater its positive impact. In some situations, the impacts of these factors can outweigh the impacts of the relief route.

The models provide important insights that may help to guide the planning and design of relief routes in small- and medium-size communities, but they do not tell the entire story. The models presented here focus on those sectors of the local economy most dependent on traffic levels and thus potentially most impacted by the shift in traffic that results from the opening of a relief route. They evaluate net changes in these sectors but do not assess underlying changes, such as geographic shifts, changes in ownership, or openings and closings in the local business community. They do not assess the net impact of relief routes on the total economies of these communities. In addition, the models do not capture all of the factors that influence the economies of these communities and thus do not fully explain the variations in the data set. To address these limitations, the case studies, summarized in Report 1843-3, qualitatively explore the nature of the impacts of relief routes on a sample of these communities and the range of factors that determine those impacts. These two complementary approaches—econometric modeling and case studies—together provide a more comprehensive understanding of the impacts of relief routes on small- and medium-size communities.

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APPENDIX 1

RANDOM-EFFECTS MODEL FORMULATION AND STATISTICAL TESTS

This section briefly describes the random-effects model formulation and statistical tests employed to test the empirical specification.

The model developed is of the following form:

$$
\begin{aligned}
&Y_{it} = \alpha + X_{1,it}\,\beta_1 + X_{2,t}\,\beta_2 + u_{it} \\
&i = 1 \ to\ N \\
&t = 1 \ to\ T
\end{aligned}
$$

Because the data are a panel, the error term can be broken down into unobservable cross-section-specific effects (μ_i) and a remaining term (ν_{it}). In a random-effects specification, the cross-sectional disturbance term is assumed to be randomly distributed over all the cross sections with zero mean and variance σ^2_{μ}. The remaining terms, $\nu_{it,}$ are assumed to be independently and identically distributed with a zero mean and variance σ^2_{ν} .

The covariance matrix is of the following form:

$$
\begin{aligned}
&\Omega = \sigma^2_\mu(I_N \otimes J_T) + \sigma^2_\nu(I_N \otimes I_T), \\
&\text{where } I_N \text{ is an identity matrix of size } N, \\
&I_T \text{ is an identity matrix of size } T, \\
&\text{and } J_T \text{ is a } T \times T \text{ square matrix of ones.}
\end{aligned}
$$

This model permits Feasible Generalized Least Squares (FGLS) estimation. Following Fuller and Battese (see pp. 14–15, Baltagi 1995), the same can be accomplished by performing OLS on a set of transformed variables. The transformation matrix, *TM*, is of the following form:

$$
\begin{aligned}
&TM = I_N \otimes \sigma^2 \Sigma^{-1/2} \\
&where\ \Sigma^{-1/2} = \left(I_T - \theta\left(\frac{J_T}{T}\right)\right) \\
&and\ \theta = 1 - \frac{\sigma^2_\nu}{\sqrt{(T\sigma^2_\mu + \sigma^2_\nu)}}
\end{aligned}
$$

Computation of the transformation matrix requires an initial estimation of the variance components. These can be obtained from a method-of-moments approach (see pp. 570–572, Greene 2000). In the original, pooled model, the error term u_{it} has variance $\sigma^2_{\mu}+\sigma^2_{\nu}$ Hence, OLS residuals from the pooled model can be used to obtain a consistent estimate of $\sigma^2_{\mu}+\sigma^2_{\nu}$.

Averaging all the variables over time yields,

$$\overline{Y}_{i.} = \alpha + \overline{X}_{1,i.}\beta_1 + \overline{X}_{2,t}\beta_2 + \overline{u}_{i.}$$

Deviations from the group means can therefore be obtained as:

$$(Y_{it}-\overline{Y}_{i.}) = (X_{1,it} - \overline{X}_{1,i.})\beta_1 + (X_{2,t}-\overline{X}_{2,t})\beta_2 + (u_{it} - \overline{u}_{i.})$$
$$\text{and } Y^*_{it} = X^*_{1,it}\beta_1 + X^*_{2,t}\beta_2 + \varepsilon_{it}$$

The error term ε_{it} has a variance σ^2_{ν}. Therefore, OLS residuals from the above model can be used to obtain a consistent estimate of σ^2_{ν}

Testing for the presence of random effects involves testing the null hypothesis that $\sigma^2_{\mu} = 0$. This is done using the Lagrange multiplier test devised by Breusch and Pagan (see pp. 572–573, Greene 2000). The test statistic is based on OLS residuals and is the following:

$$LM = \frac{NT}{2(T-1)}\left[\frac{\sum_{i=1}^{N}\left[\sum_{t=1}^{T} e^2_{it}\right]^2}{\sum_{i=1}^{N}\sum_{t=1}^{T} e^2_{it}} - 1\right]^2$$

This test statistic is chi-squared distributed with one degree of freedom.

One of the critical assumptions of the random-effects model is that the error term is uncorrelated with any of the explanatory variables. If this is violated, a fixed-effects model is a better specification. The specification test devised by Hausman and Taylor (1981) shown below can be used to test if the error is indeed correlated to the explanatory variables. This is essentially used to choose between the fixed- and random-effects models.

$$H_o\text{:}E[\mu_i|X_{1,it},X_{2,t}]=0$$
$$H_1\text{:}E[\mu_i|X_{1,it},X_{2,t}]\neq 0$$
$$\rightarrow \textit{Test statistic:}\,m=(\hat{\beta}_{Within}\text{-}\hat{\beta}_{GLS})'\hat{\Sigma}^{-1}(\hat{\beta}_{Within}\text{-}\hat{\beta}_{GLS}),$$
$$\textit{where }\hat{\Sigma}=Var[\hat{\beta}_{Within}]-Var[\hat{\beta}_{GLS}],$$
$$\hat{\beta}_{Within}=\textit{ Fixed-effects slope coefficients,}$$
$$\&\ \hat{\beta}_{GLS}=\textit{Random-effects slope coefficients.}$$

The above test statistic, *m*, is chi-squared distributed with degrees of freedom equal to the number of slope coefficients estimated.

APPENDIX 2

GUASS CODE FOR ESTIMATION OF RANDOM-EFFECTS MODELS

```
/* estimation of random effects models */
new;
cls;
print " enter the file name ";;
filename = cons;
n=42;
t=9;
obs= n*t;

print " enter the number of independent variables ";;
invar = con(1,1);
c=invar+1;
print " Output file name with complete path ";;
outfile = cons;
load data[obs,c] = ^filename;

x=data[.,2:c];
y=data[.,1];
const=ones(obs,1);
z=const~x;


/* estimation of the variance components */

/* ols on nt observations */
/* we get an estimate of sigmasqu + sigmasqv */

betaols=(z'y)/(z'z);
yhatols=z*betaols;
eols=y-yhatols;
sigmasq=(eols'eols)/(obs-c);


/* estimation of sigmasqv from the within (Q) transformed equation */

In=eye(n);
Iobs=eye(obs);
Jt=ones(t,t);
Jtbar=Jt./t;


P=In.*.Jtbar;  /* between transformation -- gives the means over time  */
Q=Iobs-P;   /* within transformation -- gives difference from the means over time */
```

```
Qy=Q*y;
Qx=Q*x;
betaQ=(Qx'Qy)/(Qx'Qx);
sigmasqv= ((y'*Q*y)-( (y'*Q*x)*inv(x'*Q*x)*(x'*Q*y) ) )/( obs-n-c+1);
covbQ=sigmasqv*inv(Qx'*Qx);



/* c-1 parameters are estimated as a constant if not estimated */
/* n means have to be estimated */

sigmasqv=sigmasqv*(t-1)/t;

sigmasqu=sigmasq-sigmasqv;

if sigmasqu < 0;
sigmasqu=0;
endif;

sigmasq1=(sigmasqu*t)+sigmasqv;
theta=1-sqrt(sigmasqv/sigmasq1);


/* OLS on the transformed equation */

It=eye(t);
iota=ones(t,1);
iit=iota*iota';
T1=It-(theta*iit/t);
Tr=In.*.T1;   /* transformation matrix */

Tz=Tr*z;
Ty=Tr*y;

betagls=(Tz'*Ty)/(Tz'*Tz);

/* computation of GLS r squared */

Tyhat=Tz*betagls;
egls=Ty-Tyhat;
RSS=(egls'egls);
a=eye(obs);
b=ones(obs,1);
bbt=b*(b');
A=a-(bbt/obs);
```

```
TSS = Ty'*A*Ty;
ESS=TSS-RSS;
rsq=1-(RSS/TSS);
factor=(obs-1)/(obs-c);
rsqadj=1-((1-rsq)*factor);

/* ols r squared, just to compare */

/* Oyhat=z*betagls;
e=y-Oyhat;
ESS1=Oyhat'*A*oyhat;
TSS1=y'*A*y;    */


covbgls=sigmasqv*inv(Tz'*Tz);
varbgls=diag(covbgls);
SEbetag=sqrt(varbgls);
tbetag=betagls./ SEbetag;

/* testing for the presence of random effects */
/* essentially uses OLS residuals */

/* ols on nt data points */

betaols=(z'y)/(z'z);
yhatols=z*betaols;
eols=y-yhatols;
sumsq=eols'eols;
Peolstmp=P*eols;

Peols=Peolstmp[1];
count =1;
do while count < n;
        pos=(count*t)+1;
        etemp=Peolstmp[pos];
        Peols=Peols|etemp;
        count=count+1;
endo;
sumtot = (t*t)*(Peols'Peols);
LMstat = ((sumtot/sumsq)-1)*((sumtot/sumsq)-1)*n*t/(2*(t-1));

/* this test statistic is distributed chi squared with 1 df */

/* regression of eols on x variables */
esq=eols.*eols;
ebeta=(z'*esq)/(z'z);
```

```
esqhat=z*ebeta;
eresid=esq-esqhat;
eRSS=eresid'eresid;
eTSS=esq'*A*esq;

ersq=1-(eRSS/eTSS);

/* Hausman specification test */
betagls1=betagls[2:c];
q1=betaQ-betagls1;
covbgls1=covbgls[2:c,2:c];
covq1=covbQ-covbgls1;
m=q1'*inv(covq1)*q1;


/* to save the results onto an ASCII file */
output file = ^outfile reset;
screen off;
outwidth  132;
print " Random effects model regression results";
print " Data set = ";;
print filename;
print "# observations";;
print obs;
print "ANOVA results ";
print " ESS RSS TSS  ";
print ESS;
print RSS;
print TSS;
print " R squared  and R squared adjusted" ;
print rsq ;
print rsqadj;
print " sigmasqv sigmasqu and sigmasq1 " ;
print sigmasqv;
print sigmasqu;
print sigmasq1;
print " theta " theta;
print " beta coefficients ";
print betagls;
print " standard errors of beta parameters";
print SEbetag;
print " t stats";
print tbetag;
print " betas from within regression ";
print betaQ;
```

```
print " LM statistic for testing for random effects " LMstat;
print " this is chi squared distributed with 1 df ";
print " m statistic for Hausman specification test ";
print m;
print " r squared of the regression of ols residuals on the x variables " ersq;

output off;
screen on;
print " ";
print " Analysis done! ";
print " Saved results to file " outfile;
end;
```