Gasoline Price Effects on Traffic Safety in Urban and Rural Areas: Evidence from Minnesota, 1998–2007

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Abstract

A large literature base has found that economic factors have important effects on traffic crashes. A small but growing branch of literature also examines the role that gasoline prices play in the occurrence of traffic crashes. However, no studies have investigated the possible difference of these effects between urban and rural areas. In this study, we used the monthly traffic crash data from 1998–2007 at the county level in Minnesota to investigate the possibly different effects gasoline prices may have on traffic crashes in urban versus rural areas. The results indicate significant difference of gasoline price effects on total crashes in urban versus rural areas. Gasoline prices also significantly affect the frequency of injury crashes in both urban and rural areas; however, the difference is not significant. Gasoline prices have no significant effects on the frequency of fatal crashes in urban and rural areas. As expected, vehicle miles traveled play a bigger role on the incidence of injury and fatal crashes. The results concerning the differences between urban and rural areas have important policy implications for traffic safety planners and decision makers.

1. Introduction

A large body of literature has found that economic factors have important effects on traffic safety (see Traynor, 2008, for a review of the literature). These studies generally found that, in a stable or prosperous economy, people drive more and drive more aggressively, leading to a decreased level of traffic safety; in contrast, in economic downturn, people drive less and drive more carefully, leading to improved traffic safety. Income and unemployment are the two most thoroughly studied economic factors linked to traffic safety in existing studies.

An increasing, but still limited, number of studies has also examined the possible role that gasoline prices play in affecting traffic safety (e.g., Chi, Cosby, Quddus, Gilbert, & Levinson, 2010). These studies have found that rising gasoline prices lead to fewer people on the road, which in turn reduces occurrence of traffic crashes. These studies analyzed the association of gasoline prices to total traffic crashes (Chi et al., 2010, 2011; Huang & Levinson, 2010), fatal crashes (Grabowski & Morrisey, 2004, 2006; Leigh & Geraghty, 2008; Leigh & Wilkinson, 1991), drunk-driving crashes (Chi et al., 2011), and motorcycle crashes (Hyatt, Griffin, Rue, & McGwin, 2009; Wilson, Stimpson, & Hilsenrath, 2009), as well as the demographic variations of the association (Chi et al., 2010, 2011; Grabowski & Morrisey, 2004; Hyatt et al., 2009).

However, no studies have examined the possible variation of the association of gasoline prices to traffic crashes in urban versus rural areas. The response to rising gasoline prices may differ between urban and rural areas because of their different commuting behavior characteristics, transportation infrastructure, and socioeconomic contexts (Levinson & Wu, 2005). In this study, we use monthly traffic crash data from 1998–2007 at the county level in Minnesota to investigate the possibly different effects of gasoline prices on total crashes, injury crashes, and fatal crashes in urban versus rural areas.

This manuscript is organized into five additional sections. The next section provides an extensive summary of existing studies on the relationship between gasoline prices and traffic safety. The two following sections introduce the data related to monthly traffic crashes in Minnesota from 1998–2007 and address the methods that directed our analyses. The results section reports our findings. Finally, the present study concludes with a summary and discussion of our results.

2. Prior research

A large body of literature has found an association between economic factors and traffic safety (e.g., Kopits & Cropper, 2005; Scuffham, 2003; Sivak & Schoettle, 2010; Traynor, 2008, 2009). The literature suggests that, in developed countries, economic downturn generally leads to improved traffic safety. Income and employment have been studied the most among economic factors linked to traffic safety. Lower income forces people to drive less by reducing trip frequency and distance, switching from personal vehicles to public transportation, converting single-purpose trips to multi-purpose trips, and reducing vacation trips in order to save on gasoline expenditures. Higher unemployment rates reduce work-related trips. However, the possible linkage of gasoline prices to traffic safety is largely neglected in existing literature.

The relationship between gasoline price changes and traffic safety has been studied in a limited body of literature. Our literature search resulted in nine journal articles that are specifically focused on gasoline prices (or taxes) and traffic crashes. These studies produced understanding on the relationship between gasoline prices and traffic crashes from six perspectives: gasoline price effects on total traffic crashes, gasoline price effects on fatal crashes, gasoline price effects on drunk-driving crashes, gasoline price effects on motorcycle crashes, the effects by demographic characteristics, and the short-term or long-term effects (Table 1).

[Table 1 about here]

First, the three most recent studies examined gasoline price effects on total traffic crashes. Using Mississippi monthly traffic crash data from April 2004–December 2008, Chi et al. (2010, 2011) examined the relationship of gasoline prices with traffic crashes. Their findings indicate that rising gasoline prices lead to reduction in both the frequency and rate of traffic crashes. They argued that traffic crash frequency is reduced because drivers may reduce travel frequency and distance for non-work trips as well as switch from personal vehicles to carpool or public transportation in response to gasoline price increases. They also argued that the rate of traffic crashes was reduced because drivers may improve their driving behaviors by reducing immediate braking or speeding in response to gasoline price increases. Similarly, Huang and Levinson (2010) found that higher gasoline prices reduced traffic levels and reduced traffic reduced total crashes from 2001–2007 in Minnesota.

Second, the majority of the literature (five out of eight articles) is focused on fatal crashes. All these studies used the Fatality Analysis Reporting System (FARS) data (with one exception, which used data from the Centers for Disease Control and Prevention) to study gasoline price effects on incidence of fatal crashes in the United States over a relatively long time period. For example, the study by Wilson et al. (2009) was conducted over an eighteen-year period. Grabowski and Morrisey (2004, 2006) conducted their studies over an eight-year period. The respective studies of Leigh and Wilkinson (1991) and Leigh and Geraghty (2008) were each conducted over a four-year period. These studies found that gasoline price increases lead to reduction in automobile traffic fatalities, but increase in motorcycle traffic fatalities.

Third, only one study has examined gasoline price effects on occurrence of drunk-driving crashes. Still using Mississippi monthly traffic crash data from April 2004–December 2008, Chi et al. (2011) found that increasing gasoline prices do lead to reduction in drunk-driving crashes. Gasoline prices have greater effects on less severe crashes (e.g., property damage only crashes), whereas alcohol consumption has greater effects on more severe crashes. Overall, gasoline prices and alcohol consumption have greater effects on drunk-driving crashes than on total crashes.

Fourth, two studies (Hyatt et al., 2009; Wilson et al., 2009) have examined the association between gasoline price increases and motorcycle crashes. They found that as gasoline prices rise, more people switch to motorcycles as the main mode of transportation. That, in turn, leads to more motorcycle injury and fatal crashes. Controlling for the number of registered motorcycles, however, motorcycle crash rates remain relatively constant (Hyatt et al., 2009). This suggests that the association between gasoline prices and motorcycle crashes are a result of the increasing number of motorcycles on the road rather than a function of driving behaviors.

Fifth, some of the studies mentioned above have also addressed the demographic variation of the effects. In general, gasoline price increases have a higher impact on younger drivers than on older drivers (Chi et al., 2010; Grabowski & Morrisey, 2004), a higher impact on female drivers than on male drivers (Chi et al., 2010; Chi et al., 2011), and a similar impact on white drivers and black drivers (Chi et al., 2010; Chi et al., 2011). While Hyatt et al. (2009) also found that the association between gasoline prices and traffic crashes differed statistically significantly by age and gender, the actual differences were found to be negligible.

Sixth, gasoline prices were also found to have both short-term (immediate) and long-term (delayed) effects. While most of the studies only examined the short-term effects of gasoline price changes on traffic crashes, two studies (Chi et al., 2010; Grabowski & Morrisey, 2004) investigated both the immediate and delayed effects. They found that the immediate effects are generally stronger than the delayed effects.

In summary, existing studies have examined gasoline price effects on traffic crashes by crash types, demographic characteristics, and the endurance of effects. Nevertheless, the possible difference of the effects between urban and rural areas has not been investigated. Urban and rural areas have different commuting behavior characteristics and transportation infrastructure levels (Levinson & Wu, 2005), which may alter gasoline price effects on traffic crashes.

3. Data

In this study, we examine the possibly different effects of gasoline prices on the incidence of traffic crashes in urban versus rural areas on the basis of county-level data from 1998–2007 in Minnesota. The data include monthly total crashes, fatal crashes, and injury crashes, monthly retail gasoline prices, and urban status. We also obtained data on variables that are potentially related to traffic crashes; these included vehicle miles traveled (VMT), percentages of young population, unemployment rate, road types, percentages of employees by industry, and drunkenness. The descriptive statistics of the variables are shown in Table 2.

[Table 2 about here]

3.1. Total crashes, fatal crashes, and injury crashes

The crash data used in this study are vehicle-related crashes from 1998–2007 at the county level in Minnesota. The dataset, collected and compiled by the Minnesota Office of Traffic Safety, catalogues each crash's time, date, location, and level of severity. From this dataset, we generated the number of total crashes, fatal crashes, and injury crashes for each county for every month from 1998–2007.

3.2. Gasoline prices

Gasoline prices were obtained from the U.S. Department of Energy's Energy Information Administration (2010). The per-gallon prices are the average retail prices from all gasoline outlets in Minnesota. The data were collected for every month from 1998–2007. Gasoline prices are adjusted for inflation in January 2008 dollars.

3.3. Urban/rural status

There are many urban and rural classifications, but a standard does not exist (Balk, 2009). In this study, we classify our urban and rural counties by using a combination of the 1990 Census Urbanized Areas as delineated by the U.S. Census Bureau and the 2003 Metropolitan and Micropolitan Statistical Areas (MMSAs) as defined by the U.S. Office of Management and Budget. The 1990 Census Urbanized Areas are mostly principal cities, which consist of densely settled territory that contains at least 50,000 people. The counties that fall into the metropolitan statistical areas and contain urbanized areas are classified as urban counties, which include Anoka, Carver, Dakota, Hennepin, Ramsey, Scott, Washington (the seven major Twin Cities counties), Olmsted (Rochester), St. Louis (Duluth), and Stearns (St. Cloud). The other 77 counties are classified as rural counties. The urban and rural status is illustrated in Figure 1.

[Figure 1 about here]

3.4. Control variables

Traffic crashes in general are affected by four categories of variables: traffic characteristics, road characteristics, socioeconomic factors, and drunk driving (Quddus, 2008). In this study, we control for the four categories of variables.

First, VMT is an important variable to explain the variation of crashes on road (Huang & Levinson, 2010). We use VMT estimates by county and month in this study. The Minnesota Department of Transportation compiled and reported the annual VMT by county from 1998–2007. We estimate monthly VMT at the county level on the basis of the hourly traffic volume data from 1998–2007 collected by Automatic Traffic Recorder Stations (ATR) set up on the state's interstates, trunk highways, county state aid highways, and municipal state aid streets.[1]

Second, road characteristics are found to be associated with crash occurrences (Quddus, 2008). Road types are used in this study to represent road characteristics. Minnesota has three types of roads: freeways, arterial roads, and local roads. Road type data are obtained from the Minnesota Department of Transportation (2010). The percentages of arterial roads and locals roads in each county are calculated and used in the analysis.

Third, four socioeconomic variables measuring young population and employment are controlled for in the analysis. The percentage of the young population (ages 16–25) is used as a control variable. Young drivers are more likely to get involved in crashes than older drivers. The cohort with the highest crash rate consists of younger drivers under the age of 24. Their high crash rates have been attributed to immaturity and driving inexperience, poor risk perception, excessive risk-taking, poor vehicle handling skills, and comparatively high incidences of nighttime driving (e.g., Arnett, 2002; Williams, 2003; Williams, Preusser, & Ferguson, 1998).

Unemployment rates are used as a control variable because economic conditions affect consumers' ability to afford gasoline, which, in turn, affects the occurrence of traffic crashes (Graham & Glaister, 2003; Leigh & Wilkinson, 1991; Quddus, 2008). The unemployment rates for each county for each month from 1998–2007 are obtained from the Minnesota Department of Employment and Economic Development (2011). The percentages of employees working in the service industries and the agricultural industry, the two main industries in Minnesota, are also used to represent employment. The data are derived from the 2000 U.S. Census Bureau and are available at the county level.

Fourth, drunkenness in each county is used as a control variable. Alcohol intoxication impairs a driver's risk assessment and safe driving skills (Leigh & Wilkinson, 1991). The drunkenness measure is obtained from the County Health Rankings, a collaborative project conducted by the University of Wisconsin-Madison Population Health Institute (2011) and the Robert Wood Johnson Foundation. Their data measure excessive drinking in each county on the basis of the 2003–2009 Behavioral Risk Factor Surveillance System (BRFSS) by the Centers for Disease Control and Prevention (2011).

These variables, however, do not all vary by month and county (Table 2). Only crashes, unemployment, and VMT are both time-variant and space-variant. Gasoline prices are time-variant but space-invariant. Other variables (percentage of young population, road types,

[1] Some counties have ATR stations, but others do not. The procedures for estimating their VMTs are different. For a county that has at least one ATR station, the monthly traffic counts from the ATR stations in the county are calculated, based on which the ratio of traffic counts in each month to annual traffic counts is further computed. One important assumption to estimate monthly VMT is that the distribution of VMT by month in a county is the same as the distribution of the traffic counts by month in the county. Thus the ratio of traffic counts in each month to annual traffic counts is used as the ratio of VMT by month. Based on the annual VMT and the ratio of VMT by month, we can estimate the monthly VMT for the county with at least one ATR. For a county without ATR stations, we calculate the state-wide monthly traffic count ratio based on the traffic counts from all stations and use the monthly traffic ratio as the monthly VMT ratio.

percentage of employees by industry, and drunkenness) are space-variant but time-invariant. The invariance by time or by space limits the robustness of the results.

4. Methods

The objective of this study is to develop a relationship between incidence of traffic crashes and gasoline prices while controlling for other factors using the data related to traffic crashes in Minnesota as discussed above. Two issues need to be considered when selecting a suitable statistical model:

1. traffic crashes are random and non-negative count events
2. the data are panel or longitudinal (i.e., cross-sectional and time-series)

According to the crash modeling literature (e.g., Shankar, Albin, Milton, & Mannering, 1998; Chin & Quddus, 2003), appropriate models for panel count data are random- or fixed-effects Poisson models and random- or fixed-effects negative binomial models. These models are adequate tools on the condition that panel data should preserve stationarity (i.e., the monthly crash data are not serially correlated). Since crash data normally exhibit overdispersion (i.e., mean is higher than variance), the application of Poisson models may be inappropriate (c.f., Lord & Mannering, 2010). A random- or fixed-effects negative binomial model should be employed. This is expressed as follows:

$$\left.\begin{aligned} Y_{it} &\sim Poisson(\alpha_i \lambda_{it}, k_i) \\ \log(\lambda_{it}) &= \beta_0 + X_{it}\beta + u_i \end{aligned}\right\} \qquad (1)$$

in which $\alpha_i = \exp(u_i)$.

Y_{it} represents the annual number of observed traffic crashes recorded in a county i at month t . This is assumed to be a Negative Binomial (NB) distributed with parameters $\alpha_i \lambda_{it,}$ and k_i, where α refers to the individual effect (county-specific); k_i is the NB overdispersion parameter; β_0 is the intercept term. In the fixed-effects model, α_i is assumed to be a fixed and unknown parameter. $\boldsymbol{X_{it}}$ stands for the vector of explanatory variables, and $\boldsymbol{\beta}$ is the vector of parameters to be estimated. In the random-effects model, α_i is assumed to be an independently and identically distributed (iid) random variable. Y_{it} has mean $\alpha_i\lambda_{it}/k_i$ and variance $(\alpha_i\lambda_{it}/k_i)\times(1+\alpha_i/k_i)$, in which $(1+\alpha_i/k_i)^{-1}$ is assumed to be beta distributed with Beta (r, s).

On the one hand, a fixed-effects model cannot handle time-invariant variables but county-specific unobserved variables are allowed to be correlated with the regressors. On the other hand, a random-effects model can handle time-invariant variables, but there is a strong assumption that country-specific unobserved factors are uncorrelated with the regressors. Since the dataset contains some time-invariant variables, a random-effects NB model is preferred. However, one can employ a Hausman (1978) test to identify the suitable model.

Since the panel data used in this study have a large number of temporal units (i.e., T=120) for each of the counties (N=87), the Levin-Lin-Chu (LLC) unit-root test (Levin, Lin, & Chu, 2002) suitable for panel data was performed to see whether the monthly crashes exhibit stationarity.

The null hypothesis for the test states that all the panels contain a unit root. Different specifications of the LLC test (i.e., cross-sectional correlation) were examined, and the results suggest that the monthly traffic crashes by county in Minnesota are not serially correlated. This implies that a random-effects NB model can be applied to the data.

It may be argued that gasoline price may be correlated with VMT. The data, however, show a correlation coefficient of only 0.02 between gasoline prices and VMT. Some of the other independent variables were found to be highly correlated with each other (e.g., population and monthly VMT; the percentage of non-Hispanic blacks and road density); therefore, less interesting variables were excluded from the analysis.

Based on the stated hypotheses, two models were estimated. In the first model, crash counts are a function of gasoline prices and control variables. In the second model, crash counts are a function of gasoline prices, urban status, the interaction term of gasoline prices and urban status, and control variables. Since the effect of gasoline prices on traffic crashes may vary by crash types, each of the two models were estimated for three crash categories: total crashes, injury crashes and fatal crashes. The results are discussed in the next section.

5. Results

5.1. Gasoline prices and crashes

The first step is to illustrate the relationship between gasoline prices and traffic crashes. For that purpose, Figure 2 shows gasoline prices (adjusted for inflation in January 2008 dollars), total traffic crashes, fatal crashes, and injury crashes from 1998–2007 in Minnesota. The data were aggregated to the quarterly level in order to eliminate monthly fluctuations. Gasoline prices and crashes are further standardized by indices (the first quarter of 1998 = 100) to better illustrate the relationship between their corresponding lines. Figure 2 approximately demonstrates a negative association between gasoline prices and traffic crashes: as gasoline prices rise, incidence of the three types of crashes is reduced; as gasoline prices fall, incidence of the three types of crashes increases. A strong negative association marks the relationship between gasoline prices and total crashes, whereas the negative association between gasoline prices and fatal crashes is weak.

[Figure 2 about here]

The results from the random-effects negative binomial regression models support the above observation (Appendix A). To facilitate the interpretation, we calculate the coefficients (in terms of both factor change and percentage change) of explanatory and control variables, when they are statistically significant at the level of $p \leq 0.1$ for a two-tail test (Table 3). Formulas (2) and (3) are employed to calculate the effect of a specific explanatory variable (e.g., gasoline prices) on a dependent variable (e.g. total traffic crashes) in terms of factor change and percentage change by using the estimated coefficient for that explanatory variable.

$$\text{Factor change} = \exp(\beta) \qquad (2)$$

$$\text{Percentage change} = 100 \times \{\exp(\beta) - 1\} \qquad (3)$$

For a one-unit increase in gasoline prices (i.e., $1), the expected total traffic crashes decrease by a factor of 0.741, or by 25.9%, holding all other variables constant (Table 3). Total crash counts are also affected by other variables. Total crash counts seem to be affected by VMT statistically significantly—for every one-million increase in monthly VMT, total crash counts increase by 0.03%. The drunkenness score and the percentage of service employees are positively associated with total crash counts. The percentage of the young population, unemployment rate, and the percentage of agricultural employees are associated negatively with total crash counts.

[Table 3 about here]

According to our results, gasoline prices, however, do not have statistically significant effects on injury and fatal crashes. One reason for this outcome may be that VMT is the major causal factor for injury and fatal crashes—VMT is the most statistically significant variable in the models examining injury and fatal crashes (Appendix A). For a one-million increase in monthly VMT, the frequency of injury crashes increases by 0.12%, and the frequency of fatal crashes increases by 0.3% (Table 3). The unemployment rate also has statistically significant effects on reducing injury and fatal crashes (Appendix A). For a one-percent increase in the unemployment rate, injury crashes decrease by 4.83% and fatal crashes decrease by 6.68%. The drunkenness score affects fatal crashes: a one-unit increase in the drunkenness score is associated with a 14% increase in the number of fatal crashes.

5.2. Difference of the effects between urban and rural counties

We further examine the possible variations of gasoline price effects on crashes between urban and rural counties. For each one of Models 1, 2, and 3, we added a dummy variable indicating urban status (1=urban; 0=rural) and an interaction variable between gasoline prices and urban status (Appendix B). The coefficients (in terms of both factor change and percentage change) of explanatory and control variables (when statistically significant at the level of $p \leq 0.1$ for a two-tail test) are shown in Table 4. Formulas (4–7) are employed to calculate the effect of gasoline prices on a dependent variable (e.g., total traffic crashes) in rural and urban areas in terms of factor change and percentage change by using the estimated coefficients from Appendix B.

$$\text{Factor change in rural counties} = \exp(\beta_{gasoline}) \tag{4}$$

$$\text{Factor change in urban counties} = \exp(\beta_{gasoline} + \beta_{interaction}) \tag{5}$$

$$\text{Percentage change in rural counties} = 100 \times \left\{ \exp(\beta_{gasoline}) - 1 \right\} \tag{6}$$

$$\text{Percentage change in urban counties} = 100 \times \left\{ \exp(\beta_{gasoline} + \beta_{interaction}) - 1 \right\} \tag{7}$$

Higher gasoline prices reduce the total traffic crashes in both rural and urban areas (Table 4). For a $1 increase in gasoline prices, the expected total crashes in rural areas decrease by a factor of 0.718, or 28.15%, holding all other variables constant; the expected total crashes in urban areas decrease by a factor of 0.816, or 18.40%, holding all other variables constant. Being an urban county increases the expected number of traffic crashes by 14%, holding all other variables constant.

[Table 4 about here]

Higher gasoline prices also reduce injury crashes in both rural and urban areas. For a $1 increase in gasoline prices, the number of injury crashes in rural areas decreases by 3.9%, and the number of fatal crashes in urban areas decreases by 18.4%, holding all other variables constant. However, urban status is not associated significantly with injury crashes. Similar to the results from Model 2, in which the interaction term between gasoline prices and urban status is not considered, VMT shows a statistically significant association with injury crashes—for every one-million increase in the monthly VMT, the incidence of injury crashes increases by 0.11%.

Gasoline prices do not have significant effects on fatal crashes, even when considering rural and urban areas. Urban status, nevertheless, is associated significantly with incidence of fatal crashes. Being an urban county increases the expected number of fatal crashes by 40%, holding all other variables constant. Similar to the results from Model 3, in which the interaction term between gasoline prices and urban status is not considered, VMT is statistically significant associated with fatal crashes—for every one-million increase in the monthly VMT, fatal crashes increase by 0.27%.

6. Summary and discussion

An increasing body of literature examines the role of gasoline prices in the occurrence of traffic crashes. Nevertheless, no studies have investigated the possibly different effects in urban versus rural areas. In this study, we use traffic crash data from 1998–2007 in Minnesota to investigate the possible difference of gasoline price effects on traffic crashes in urban versus rural areas. The results indicate a significant difference of gasoline price effects on total crashes in urban versus rural areas. The effects of gasoline prices are stronger in rural than in urban areas. Gasoline prices also have significant effects in reducing injury crashes in both urban and rural areas; however, the effect difference between urban and rural areas is not significant. Gasoline prices have no significant effects in reducing fatal crashes in urban and rural areas. Vehicle miles traveled play a bigger role in reducing incidence of injury and fatal crashes.

Nevertheless, this study did not examine what factors cause the difference in gasoline price effects on traffic crashes between urban and rural areas. The potential causal factors could include modes of transportation, income, and others. First, the modes of transportation could cause the difference of gasoline price effects in urban versus rural areas. In urban areas, people can switch from personal vehicles to public transportation for work-related trips, or even non-work related trips, in response to higher gasoline prices. In most rural areas, however, public transportation does not exist. People will still have to drive their own cars. The variable mode of transportation could be represented by the percentage of workers using non-auto transportation to travel to work, or by dummy variables indicating whether subway or bus services are available. Second, the income level could also cause the difference of gasoline price effects in urban versus rural areas. Urban residents tend to have higher income levels than rural residents, and thus the same or similar amount of gasoline price increases would matter less to urban residents than to rural residents. That could in turn cause the difference in traffic crash levels.

In future research, we would like to test if the spatial variation of gasoline price effects is due to the modes of transportation and income levels. In addition, 2-stage least squares (2SLS) models might improve model estimates as injury and fatal crash counts are likely endogenous with VMT but are not associated with gasoline prices. The 2SLS models could include two parts—the reduced function to predict VMT and the structural function to predict crash counts (Huang & Levinson, 2010). Furthermore, future research could benefit from Bayesian spatial analysis. Our data cover the 87 counties of Minnesota; crashes might show spatial correlation, and gasoline price effects might show spatial variations. Models incorporating spatial dependence and/or heterogeneity might provide further insights into the spatial variation of gasoline price effects on crashes.

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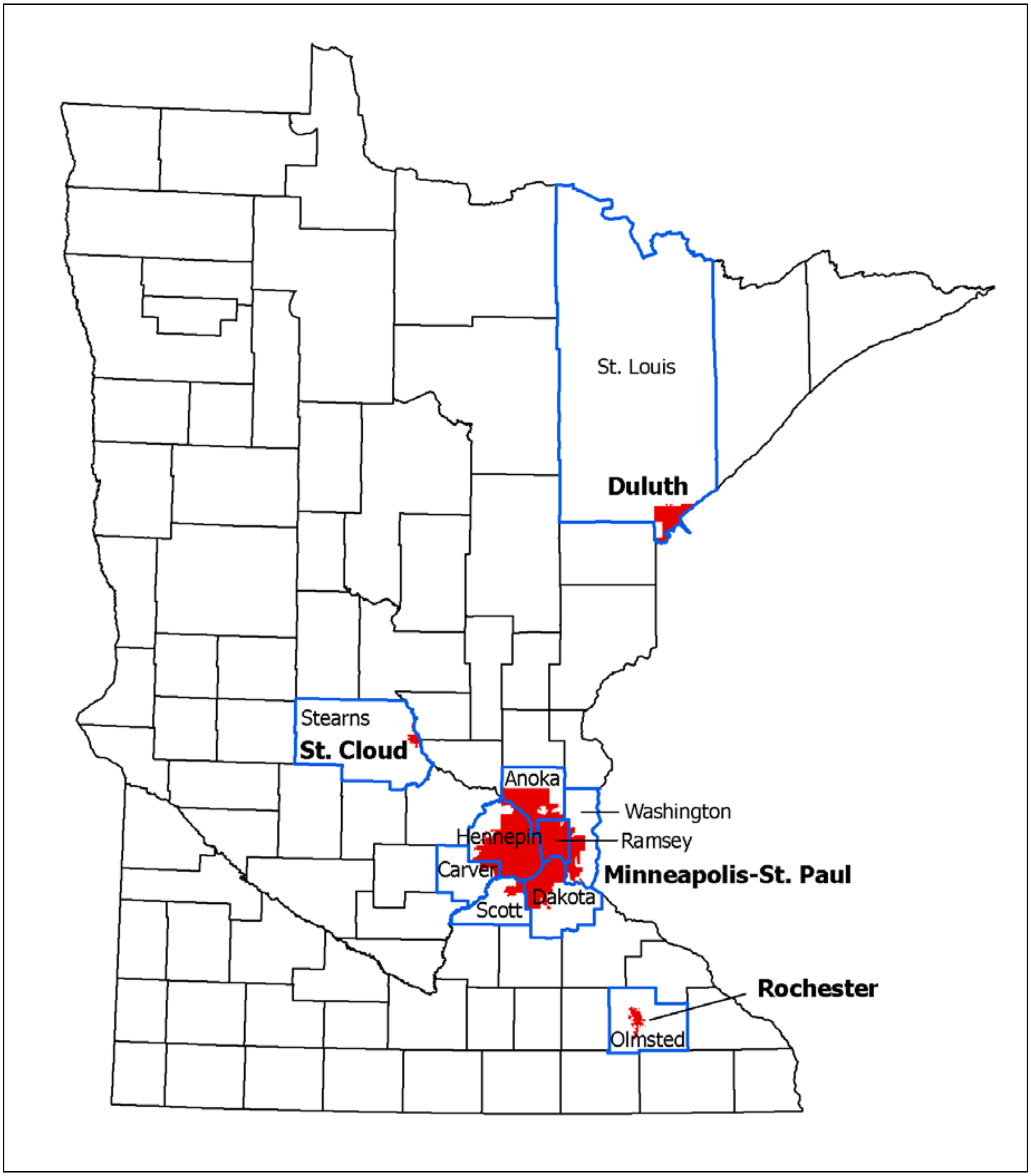

Figure 1. Urban counties and major cities in Minnesota

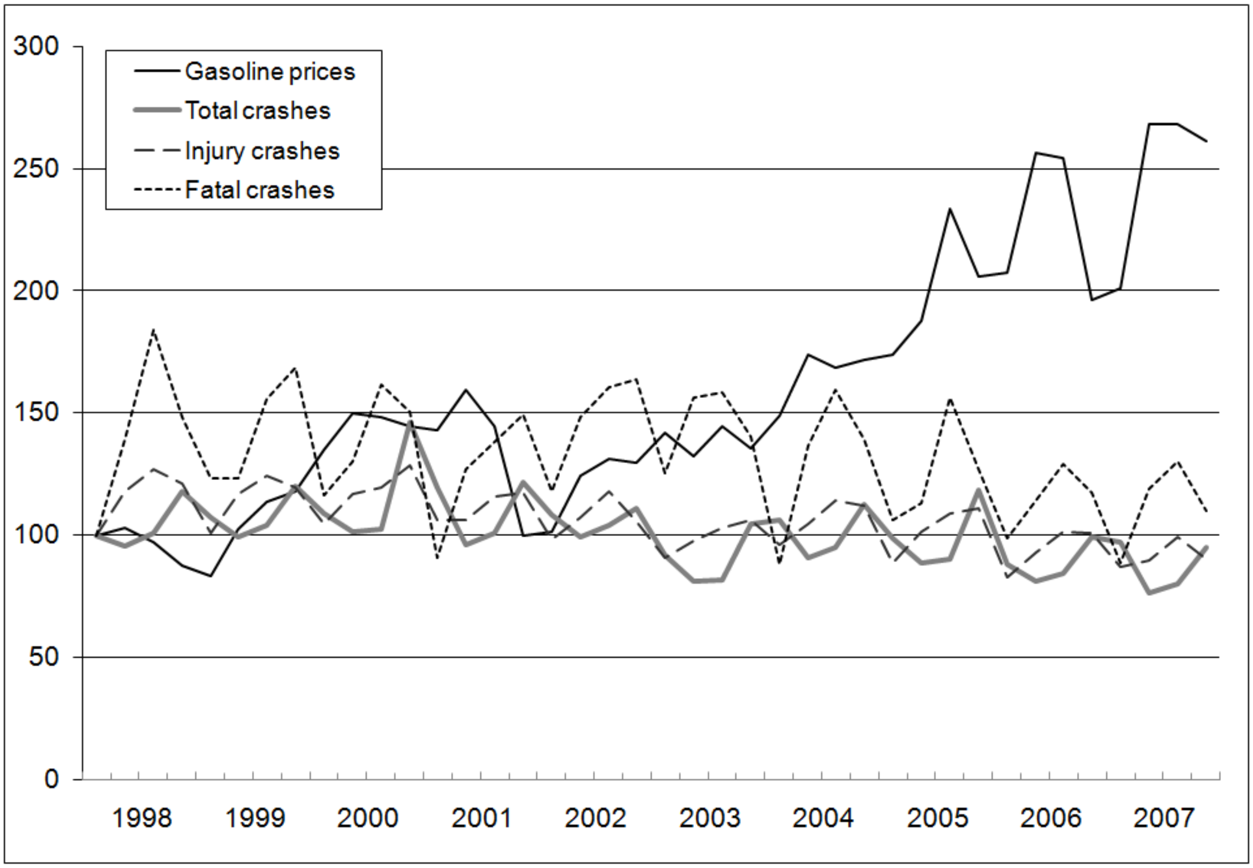

Figure 2. Gasoline prices and traffic crashes, 1998–2007, Minnesota. Gasoline prices and crashes are standardized by indices (the first quarter of 1998 = 100).

Table 1

Prior studies on gasoline prices and traffic safety

Study	Study area	Data set/source	Time period	Crash types	Demographic groups	Short- or long-term effects
Leigh & Wilkinson (1991)	US	FARS	1976–1980	Fatal crashes	None	Short-term
Grabowski & Morrisey (2004)	US	FARS	1983–2000	Fatal crashes	Variation by age	Both
Grabowski & Morrisey (2006)	US	FARS	1982–2000	Fatal crashes	None	Short-term
Leigh & Geraghty (2008)	US	CDC	1999–2003	Fatal crashes	None	Short-term
Wilson et al. (2009)	US	FARS	1990–2007	Motorcycle fatal crashes and vehicle fatal crashes	None	Short-term
Hyatt et al. (2009)	US	NASS GES and FARS	1992–2007	Motorcycle fatal crashes, motorcycle injury crashes, vehicle fatal crashes, and vehicle injury crashes	Variation by age and gender	Short-term
Huang & Levinson (2010)	Minnesota	MnOTS	2001–2007	Total traffic crashes, and fatal crashes	None	Short-term
Chi et al. (2010)	Mississippi	MHP	04/2004–12/2008	Total traffic crashes	Variation by age, gender, and race	Both
Chi et al. (2011)	Mississippi	MHP	04/2004–12/2008	Total traffic crashes, drunk-driving crashes, fatal crashes, injury crashes, and property-damage-only crashes	Variation by age, gender, and race	Short-term

Note. FARS = Fatality Analysis Reporting System; CDC = the Centers for Disease Control and Prevention; NASS GES = the National Automotive Sampling System General Estimates System; MnOTS = Minnesota Office of Traffic Safety; MHP = Mississippi Highway Patrol
The last column “Short- or long-term effects” refers to whether a study considered and found both short- and long-term effects.

Table 2

Descriptive statistics of the variables

	N	Mean	Standard deviation	Minimum	Maximum	Time-variant	Space-variant
Total crashes	10,440	85.600	256.402	0	4,003	Yes	Yes
Injury crashes	10,440	26.549	75.527	0	887	Yes	Yes
Fatal crashes	10,440	0.503	0.924	0	10	Yes	Yes
Gasoline prices	120	1.318	44.337	66.280	239.950	Yes	No
Monthly VMT (million)	10,440	52.210	110.454	3.095	997.331	Yes	Yes
Arterial roads (%)	87	0.040	0.023	0	0.121	No	Yes
Local roads (%)	87	0.927	0.027	0.799	0.965	No	Yes
Young population 16–25 (%)	87	12.840	3.368	0.088	0.265	No	Yes
Unemployment rate (%)	10,440	4.641	1.906	1.200	18.500	Yes	Yes
Service employees (%)	87	63.520	6.278	44.300	77.500	No	Yes
Agriculture employees (%)	87	7.229	4.489	0.200	20.100	No	Yes
Drunkenness score	87	0	0.778	–2.145	2.007	No	Yes
Urban status (urban=1; rural=0)	87	0.115	0.321	0	1	No	Yes

Table 3

Coefficients (in both factor change and percentage change) from random-effects negative binomial regression models without the interaction term between gasoline prices and urban status, 1998–2007, Minnesota

	Model 1 (Total crashes)		Model 2 (Injury crashes)		Model 3 (Fatal crashes)	
	Factor change	Percentage change	Factor change	Percentage change	Factor change	Percentage change
Gasoline prices	0.741	–25.91%				
Monthly VMT (million)	1.000	0.03%	1.001	0.12%	1.003	0.30%
Arterial roads (%)					0.944	–5.64%
Local roads (%)						
Young population 16–25 (%)	0.986	–1.37%	1.044	4.39%		
Unemployment rate (%)	0.982	–1.79%	0.952	–4.83%	0.933	–6.68%
Service employees (%)	1.010	1.03%			1.017	1.69%
Agriculture employees (%)	0.965	–3.49%	0.936	–6.43%	0.912	–8.84%
Drunkenness score	1.073	7.32%			1.141	14.07%

Note. Only the statistically significant ($p \leq 0.10$ for a two-tail test) coefficients are shown in the table.

Table 4

Coefficients (in both factor change and percentage change) from random-effects negative binomial regression models with the interaction term between gasoline prices and urban status, 1998–2007, Minnesota

	Model 4 (Total crashes)		Model 5 (Injury crashes)		Model 6 (Fatal crashes)	
	Factor change	Percentage change	Factor change	Percentage change	Factor change	Percentage change
Gasoline prices in rural areas	0.718	–28.15%	0.961	–3.90%		
Gasoline prices in urban areas	0.816	–18.40%	0.996	–0.40%		
Urban status	1.141	14.10%			1.405	40.48%
Monthly VMT (million)			1.001	0.11%	1.003	0.27%
Arterial roads (%)						
Local roads (%)						
Young population 16–25 (%)			1.042	4.20%		
Unemployment rate (%)	0.979	–2.07%	0.950	–4.95%	0.936	–6.38%
Service employees (%)						
Agriculture employees (%)	0.970	–3.03%	0.939	–6.14%	0.915	–8.46%
Drunkenness score	1.072	7.23%			1.138	13.76%

Note. Only the statistically significant ($p \leq 0.10$ for a two-tail test) coefficients are shown in the table.

Appendix A

Table A.1.

Results of random-effects negative binomial regression models without the interaction term between gasoline prices and urban status, 1998–2007, Minnesota

	Model 1 (Total crashes)		Model 2 (Injury crashes)		Model 3 (Fatal crashes)	
Variables	Coef.	t-score	Coef.	t-score	Coef.	t-score
Gasoline prices	–0.2999	–18.87	–0.0250	–1.47	0.0860	1.06
Monthly VMT (million)	0.0003	2.36	0.0012	9.68	0.0030	5.74
Arterial roads (%)	0.0118	0.79	0.0271	0.96	–0.0580	–1.76
Local roads (%)	0.0097	0.61	0.0292	1.03	–0.0228	–0.84
Young population 16-25 (%)	–0.0138	–2.02	0.0430	3.07	–0.0080	–0.49
Unemployment rate (%)	–0.0181	–7.11	–0.0495	–15.47	–0.0691	–5.07
Service employees (%)	0.0102	2.40	–0.0025	–0.31	0.0168	1.87
Agriculture employees (%)	–0.0355	–4.87	–0.0665	–5.08	–0.0926	–6.90
Drunkenness score	0.0706	2.32	0.0200	0.35	0.1316	2.08
Year 1998 (Reference)	–	–	–	–	–	–
Year 1999	0.0357	2.95	–0.0204	–1.60	–0.0187	–0.31
Year 2000	0.1945	13.95	0.0142	0.96	–0.0777	–1.10
Year 2001	0.1696	12.36	0.0048	0.32	–0.1337	–1.87
Year 2002	0.1086	8.14	0.0064	0.43	0.0702	1.05
Year 2003	0.0654	4.33	–0.0255	–1.53	0.0596	0.79
Year 2004	0.1780	10.29	0.0004	0.02	–0.0891	–1.02
Year 2005	0.2348	11.38	–0.0608	–2.70	–0.1865	–1.76
Year 2006	0.2397	9.96	–0.1157	–4.41	–0.3089	–2.48
Year 2007	0.2237	8.10	–0.1490	–4.95	–0.3231	–2.27
Intercept	2.1895	1.41	0.8942	0.32	6.0025	1.86
Parameter: r	1.9737	6.85	5.1240	6.11	751.6784	0.63
Parameter: s	2.7424	6.48	2.0463	6.20	6.0381	5.70
Log-likelihood at convergence	–37,928.70		–28,590.91		–8,366.85	
Number of observations	N=87, T=120		N=87, T=120		N=87, T=120	

Appendix B

Table B.1.

Results of random-effects negative binomial regression models with the interaction term between gasoline prices and urban status, 1998–2007, Minnesota

	Model 4 (Total crashes)		Model 5 (Injury crashes)		Model 6 (Fatal crashes)	
Variables	Coef.	t-score	Coef.	t-	Coef.	t-score
Gasoline prices	–0.3306	–20.41	–0.0398	–2.23	0.1153	1.36
Urban status (urban=1; rural=0)	0.1319	1.79	0.0653	0.54	0.3399	1.73
Gasoline prices X Urban status	0.1273	9.42	0.0358	2.85	–0.0347	–0.59
Monthly VMT (million)	–0.0002	–1.36	0.0011	8.43	0.0027	4.58
Arterial roads (%)	0.0158	1.06	0.0333	1.17	–0.0520	–1.61
Local roads (%)	0.0137	0.86	0.0322	1.13	–0.0180	–0.67
Young population 16-25 (%)	–0.0110	–1.57	0.0411	2.94	–0.0059	–0.37
Unemployment rate (%)	–0.0209	–8.11	–0.0508	–15.67	–0.0659	–4.76
Service employees (%)	0.0072	1.58	–0.0047	–0.54	0.0127	1.40
Agriculture employees (%)	–0.0308	–4.08	–0.0634	–4.59	–0.0884	–6.62
Drunkenness score	0.0698	2.29	0.0236	0.42	0.1289	2.10
Year 1998 (Reference)	–	–	–	–	–	–
Year 1999	0.0378	3.14	–0.0196	–1.53	–0.0188	–0.31
Year 2000	0.1972	14.25	0.0153	1.03	–0.0828	–1.17
Year 2001	0.1757	12.88	0.0073	0.49	–0.1381	–1.93
Year 2002	0.1169	8.79	0.0099	0.67	0.0662	0.99
Year 2003	0.0760	5.05	–0.0212	–1.26	0.0527	0.70
Year 2004	0.1884	10.95	0.0044	0.23	–0.0988	–1.12
Year 2005	0.2438	11.91	–0.0576	–2.56	–0.1999	–1.88
Year 2006	0.2484	10.41	–0.1125	–4.28	–0.3257	–2.60
Year 2007	0.2405	8.78	–0.1440	–4.78	–0.3436	–2.41
Intercept	1.9775	1.27	0.7473	0.27	5.4320	1.80
Parameter: r	2.0013	6.84	5.1213	6.09	634.6290	0.78
Parameter: s	2.7583	6.47	2.0485	6.17	6.4103	5.50
Log-likelihood at convergence	–37,882.20		–28,586.52		–8,365.37	
Number of observations	N=87, T=120		N=87, T=120		N=87, T=120	