Safer Roads Owing to Higher Gasoline Prices: How Long It Takes

Guangqing Chi, PhD, Willie Brown, MS, Xiang Zhang, PhD, and Yanbing Zheng, PhD

Objectives. We investigated how much time passes before gasoline price changes affect traffic crashes.

Methods. We systematically examined 2004 to 2012 Mississippi traffic crash data by age, gender, and race. Control variables were unemployment rate, seat belt use, alcohol consumption, climate, and temporal and seasonal variations.

Results. We found a positive association between higher gasoline prices and safer roads. Overall, gasoline prices affected crashes 9 to 10 months after a price change. This finding was generally consistent across age, gender, and race, with some exceptions. For those aged 16 to 19 years, gasoline price increases had an immediate (although statistically weak) effect and a lagged effect, but crashes involving those aged 25 to 34 years was seemingly unaffected by price changes. For older individuals (≥75 years), the lagged effect was stronger and lasted longer than did that of other age groups.

Conclusions. The results have important health policy implications for using gasoline prices and taxes to improve traffic safety. (*Am J Public Health.* 2015;105: e119–e125. doi:10.2105/AJPH.2015.302579)

More than 40 000 traffic fatalities have occurred in the United States every year from 1963 to 2007 (except in 1992; data available as a supplement to the online version of this article at http://www.ajph.org). In 2008, US roadway deaths fell to 37 313, which is the lowest point since 1963 and is 9.1% lower than the 2007 rates. The recent decline in traffic fatalities started in 2005 and continued steadily through 2011, with a slight increase in 2012. This trend is similar in many other developed countries.

Despite the steady decline in traffic fatalities, road crashes remain a major public health and economic concern worldwide. Road deaths are a calamity for all affected, and injuries can cause distress and have life-changing effects. In the United States, crashes resulted in an economic loss of $277 billion in 2010 and an additional $594 billion in social and health impacts related to loss of life and decreased quality of life owing to injuries.[1] Drunk driving resulted in a $49 billion economic loss and a $199 billion societal and health impact, and failing to use seat belts cost $14 billion and $58 billion, respectively. To help address these problems, the Moving Ahead for Progress in the 21st Century Law (Pub L. No. 112–141, 126 Stat. 405, HR 4348), enacted in 2012, requires states to increase their focus on transportation safety performance targets and implement programs that best use limited resources for reaching their goals.

A large body of literature links traffic crashes to their contributing factors. Among those factors are road infrastructure[2,3]; systems operations and management[4]; road user behaviors such as seat belt use, drunk driving, and texting while driving[2]; demographic and cultural changes, such as an aging population and the iPhone culture of the younger population[5]; vehicle safety advancements[6,7]; emergency response and trauma care advancements[8]; and training and education campaigns and law enforcement interventions.[9,10]

The literature also suggests that economic conditions are a contributing factor in traffic crashes; that is, when the economy grows, people drive more often and with less reserve, which results in more traffic crashes.[11] States with higher per capita income have higher traffic-related fatality and injury rates.[2,8] However, when the economy declines, people drive less frequently and more conservatively, resulting in safer traffic conditions. Three tangible links between the economy and traffic safety are income, unemployment rates, and gasoline prices. Lower-income drivers are limited in their ability to buy gasoline, which reduces the frequency and distance of their trips. They might also reduce frequent single-purpose trips in favor of multipurpose trips taken less often. Some may even forego automobile ownership. Likewise, the higher unemployment rates that occur in a weak economy mean fewer work-related trips and could have many of the effects that lower income has.

A limited but increasing body of literature associates fewer traffic crashes with higher gasoline prices or taxes.[12–24] Overall, studies found a positive association between gasoline prices and traffic safety. Increased gasoline prices improve traffic safety by discouraging the amount of driving and by encouraging safer driving behavior.[12] Specifically, when gasoline prices are high, drivers might reduce non–work-related trips and switch to carpooling or public transportation.[17] Drivers also might drive in a more fuel-efficient manner by accelerating and braking more conservatively, thus reducing the rate of traffic crashes.[12]

The finding of the positive association between gasoline prices and traffic safety applies to total crashes, fatal crashes, and drunk-driving crashes; however, as gasoline prices increase, people retreat to less expensive modes of transportation, such as motorcycles, which in turn leads to more motorcycle crashes.[23] In addition, the association between gasoline prices and traffic safety varies by age, gender, and race. Gasoline prices have a greater impact on younger drivers than on older drivers, a slightly greater impact on female drivers than on male drivers, and a similar impact on White drivers and Black drivers.

What remains an open question, though, is how long it takes before gasoline price increases affect traffic safety. Although some studies found both short-term (immediate) effects and long-term (lagged) effects,[12,13,15,16,18] the lag, which is the difference in time between gasoline price at a point and crashes at a later point, was measured in yearly intervals and did not provide the necessarily fine calibration: the effects could change from month to month. Further, those studies were not designed to specifically and comprehensively explore the possible lagged effects that gasoline prices have on crashes.

We systematically investigated how long it takes gasoline price changes to affect traffic crashes. We hypothesized that the effects take some time to occur because many commuting activities such as driving to work cannot be reduced immediately; it takes time for drivers to find alternatives. We further hypothesized that the effects vary across the stages of life because reducing travel costs in response to higher gasoline prices is prioritized at different levels in relation to income, responsibilities, life goals, and others factors.

METHODS

We linked gasoline prices to all crashes rather than to fatal crashes only. Although fatal crashes are the most serious, they represent a small portion of all crashes and do not represent overall traffic safety.[25] Ideally, we would have examined data on all crashes in the entire or the continental United States; however, such a data set was not available. In this study, therefore, we used Mississippi crash data from April 2004 through December 2012, to which we had full access. The data included all crashes except property damage–only crashes with property loss less than $500, but we included all fatal and injury crashes. Approximately 2% of law enforcement agencies in Mississippi did not report crashes electronically in the study period; thus, we did not include their records in the analysis.[14]

Variables

The Mississippi crash data included the demographic information of drivers involved in the crashes, which allowed us to enumerate all crashes by demographic characteristics. We aggregated the data to the monthly level for the entire state of Mississippi (data available as a supplement to the online version of this article at http://www.ajph.org). We partitioned crashes by age, gender, and race. We categorized the age groups into 16 to 19 years (adolescents, risk taking), 20 to 24 years (young adults, social drinkers), 25 to 34 years (adults), 35 to 64 years (middle age), 65 to 74 years (young old), and 75 years or older (old old). Demographers typically use this age classification.[25] More important, this classification represents different stages of driving behavior over the lifecycle.[26] We categorized crashes by race only for non-Hispanic Whites and Blacks because Hispanics make up a very small portion (2.9% as of 2012)[27] of the Mississippi population.

We obtained 2004 to 2012 monthly price data for regular unleaded gasoline from the US Department of Energy's Energy Information Administration.[28] The per-gallon prices were the average retail prices from all gasoline outlets in Mississippi. We adjusted these data for inflation in January 2013 dollars and used them as the primary explanatory variable.

Traffic crashes are also affected by other factors. We controlled 4 factors. First, we used unemployment rate as a control variable because economic conditions affect drivers' ability to purchase gasoline. People who are unemployed will likely use less gasoline and have less exposure to traffic crashes than will people who are employed.[20,29–31] We obtained monthly employment data from the US Bureau of Labor Statistics.[32]

Second, seat belt use was employed as a measure of driving behaviors because our study encompassed 9 years of data—and overall driving behaviors and attitudes may shift over 9 years. Previous studies[18] measured seat belt use as a dummy variable for representing whether seat belt laws were in effect for the particular time and place. This may not be the most precise measure because the presence of a seat belt law does not guarantee that all drivers wear seat belts. We measured seat belt use as the percentage of drivers wearing a seat belt. The Mississippi Department of Public Safety collected the data annually in 409 observation stations from 2004 to 2007 and in 168 observation stations from 2008 to 2012.[33]

Third, we used alcohol consumption as a control variable because driving behaviors are affected by alcohol consumption. We used annual alcohol consumption data in gallons per capita, which we obtained from the Beer Institute.[34]

Fourth, climate has been shown to affect traffic crashes,[30] so we used it as a control variable. We obtained mean precipitation and temperature data from the Southeast Regional Climate Center.[35]

Statistical Analysis

Both traffic crashes and gasoline prices could have trend and seasonal variations. The first step of the analysis was to detect the possible patterns (Figure 1a and 1b). The monthly crash data showed a general uptrend for 2004 to 2006 and a general downtrend for 2006 to 2012. In addition, the data exhibited multiple seasonal variations: traffic accidents went down for the first few months of a year and then up for the rest of the year; the variation was complicated by holiday travel. Similarly, gasoline prices displayed trend patterns: a general uptrend 2004 to 2008, a sharp decline 2008 to 2009, and then a general uptrend 2009 to 2012; prices had seasonal variations as well.

To estimate the association between traffic accidents and gasoline prices, we adjusted for trend and seasonal patterns (Figure 1c and 1d). Although single seasonal smoothing methods are widely used forecasting procedures, little research has been conducted on smoothing complicated seasonal patterns. We adopted and modified a multiple seasonal smoothing method called the BATS model.[36] BATS is an acronym for key features of the model: Box–Cox transformations, ARMA errors, Trend, and Seasonal components.

We made the modification to avoid potential problems associated with nonlinear models (e.g., the association between accidents and gasoline prices may not be linear). We restricted our model specifications to linear homoscedastic models but allowed some types of nonlinearity using Box–Cox transformations.[37] Our modified model is as follows:

$$y_t^{(\omega)} = \begin{cases} \frac{y_t^{\omega}-1}{\omega}, & \omega \neq 0 \\ \log(y_t), & \omega = 0 \end{cases}$$

$$\begin{aligned} y_t^{(\omega)} &= l_{t-1} + \phi b_{t-1} + \textstyle\sum_{i=1}^{T} S_{t-m_i}^{(i)} + d_t \\ l_t &= l_{t-1} + \phi b_{t-1} + \alpha d_t \\ b_t &= (1-\phi)b + \phi b_{t-1} + \beta d_t \\ S_t^{(i)} &= S_{t-m_i}^{(i)} + \gamma_i d_t \\ d_t &= \textstyle\sum_{i=1}^{p} \varphi_i d_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t \end{aligned} \tag{1}$$

where $y_t^{(\omega)}$ represents the Box–Cox transformed observations (we added a tiny number,

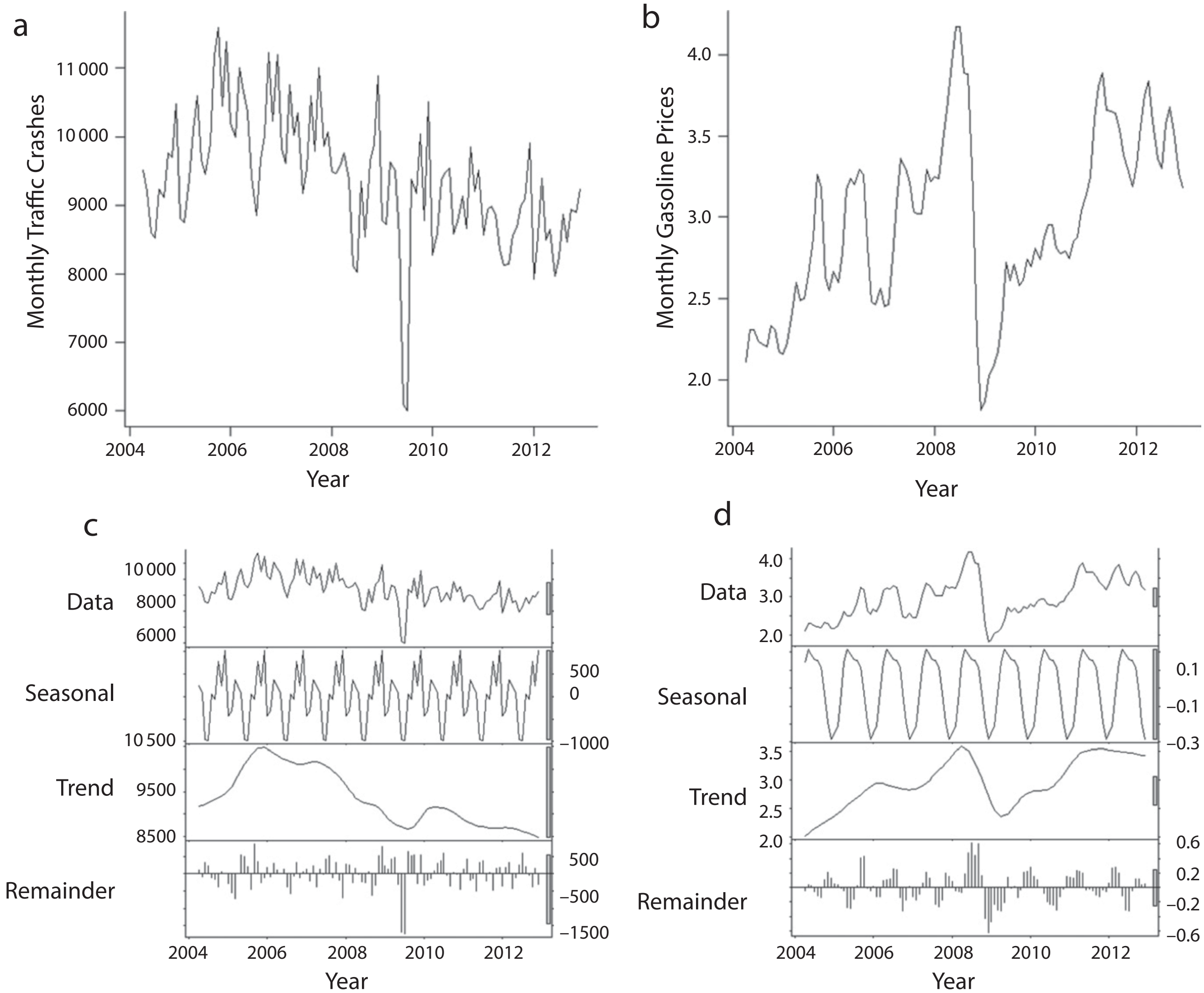


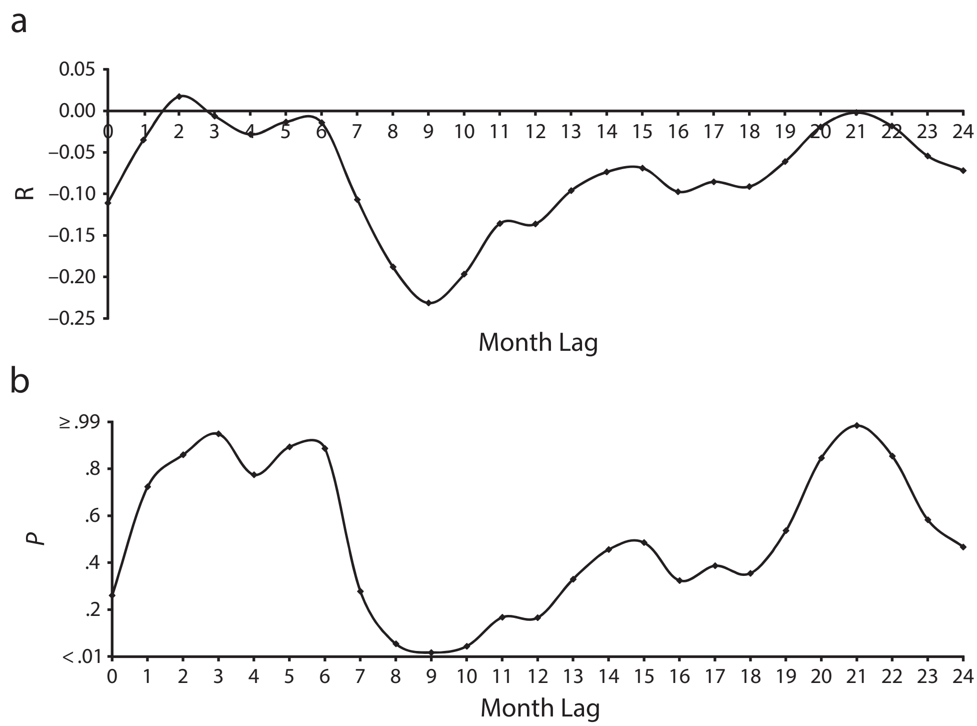
FIGURE 1—Association between traffic accidents and gasoline prices by (a) monthly traffic crashes, (b) monthly gasoline prices, (c) decomposition of monthly traffic crashes, and (d) decomposition of monthly gasoline prices: Mississippi, April 2004–December 2012.

0.0000001, to the 0 counts) with the parameter ω; y_t is the observation at time t; $m_1 \ldots, m_T$ denote the seasonal periods; l_t is the local level in period t; b is the long-run trend; b_t is the short-run trend in period t; $S_t^{(i)}$ represents the ith seasonal component at time t; d_t denotes an ARMA(p,q) process; and ε_t is a Gaussian white noise process with zero mean and constant variance σ^2. $\alpha, \beta, \gamma_i, i1, \ldots, T$ are smoothing parameters, and ϕ is a damping parameter.

We calculated the Pearson correlation between the number of crashes and gasoline price lags (up to 24 months) after removing the trend and seasonal variations from the original time series. We measured gasoline price lags up to 24 months because previous research did not find any significant association beyond 2 years.[12] We also calculated the P value to identify the month lags at which gasoline prices were significantly correlated with traffic crashes. We calculated the Pearson correlation and P value for each demographic group. We performed this step using the package "forecast" in R.[38]

Negative Binomial Regression

For the month lags in which gasoline prices had correlation with crashes at $P < .1$, we further examined the relationships with appropriate statistical models by controlling for other factors. The Poisson regression model is often employed because data relating to traffic crashes are random, discrete, and nonnegative events.[39,40] One of the model's assumptions is that the mean of crashes equals the variance of crashes. If this assumption is violated, which was the case for our data, Poisson-γ (or negative binomial) regression models (Equation 2) are used.[41,42] To facilitate



Note. For traffic crashes that occurred in December 2012, 0-month lagged gasoline prices were measured in December 2012, 1-month lagged prices in November 2012, 2-month lagged prices in October 2012, and so on, up through 24-month lagged prices in January 2011.

FIGURE 2—Association between monthly total crashes and monthly lagged gasoline prices by (a) Pearson correlation and (b) corresponding *P* values: Mississippi, April 2004–December 2012.

the interpretation, we calculated the elasticities of crashes with respect to gasoline prices:

$$(2)\quad \begin{aligned} &Y_t \sim Poisson(\mu_t) \\ &\log(\mu_t) = \log(E_t) + \beta_0 + \sum_{j=1}^{k} \beta_j X_{jt} + \gamma_t \end{aligned}$$

where Y_t refers to the observed monthly crash count; μ_t refers to the expected monthly crash count; X_t refers to the explanatory variables, and k is the number of explanatory variables; E_t refers to the crash exposure variable, such as vehicle miles traveled; γ_t is a random term that captures an unobserved effect over time and $\exp(\gamma_t) \sim Gamma(1/\alpha, \alpha)$, in which α is the overdispersion parameter; and β_0 and β_j are parameters to be estimated.

RESULTS

Our overarching finding was that gasoline prices and traffic crashes had a negative relationship and that gasoline prices did not significantly affect traffic crashes until months later. Figure 2 depicts the Pearson correlations between gasoline prices and traffic crashes. The negative correlation was strongest and statistically significant 8 to 10 months after a change in gasoline price; there was no statistically significant effect before that period or after it. In other words, if gasoline prices increased in a particular month, there was a consequent decrease in traffic crashes 8 to 10 months later.

The finding that the effect of gasoline price did not occur until months later was further supported by the results from negative binomial regression models. Table 1 outlines the month lags for which the negative binomial regressions produced parameter estimates measuring gasoline price effects on crashes with $P < .1$. It took 9 to 10 months for gasoline price effects to be observed in the total number of crashes.

To interpret the findings, elasticities of crashes per capita with respect to gasoline prices are presented in Table 2 for gasoline price variables for which $P < .1$ in negative binominal regression models. We calculated the elasticities at the mean price of the studied period, $2.96. We have presented the elasticities for both the immediate and lagged effects. When the lagged effects lasted more than 1 month, we measured them as the mean of the corresponding elasticities. We found that for total crashes in Mississippi, a 10.0% increase in gasoline prices corresponded with a 1.5% decrease in traffic crashes per capita; this is a lagged effect. There was no immediate effect of gasoline price on reducing traffic crashes for total crashes.

Variations of the effects by race and gender were minimal. A 10.0% increase in gasoline price corresponded with a lagged effect of 1.2% and 1.7% decreases in traffic crashes for male and female drivers, respectively. The effects on White and Black drivers were similar: gasoline prices had statistically significant effects in months 9 and 10 on Black drivers, whereas for White drivers, a significant effect was observed in month 9. A 10.0% increase in

TABLE 1—Month Lags for Which $P \leq .1$ in Negative Binomial Regression Models and Their *P* Values: Mississippi, April 2004–December 2012

Variable	0	9	10	11	12	13
All		.018	.003			
Age, y						
16–19	.105	.024	.015			
20–24		.093				
25–34						
35–64		.011	.001			
65–74		.024	.003			
≥ 75		.001	.005	.001	.005	.04
Gender						
Male		.086	.021			
Female		.008	.001			
Race						
White		.006				
Black		.024	.004			

Note. Models were run for 24 lag months; only lag months for which $P \leq .1$ are displayed.

gasoline price corresponded with a lagged effect of a 1.6% decrease in traffic crashes for both Black and White drivers.

However, the effects varied greatly across age groups. The lagged effects for drivers aged 35 to 64 and 65 to 74 years were similar to those for total crashes, but this observation did not apply to other age groups: (1) the immediate (although statistically weak) effect for drivers aged 16 to 19 years, (2) the complete lack of effect for drivers aged 25 to 34 years, and (3) the longer (months 9–13) lagged effect for drivers aged 75 years and older.

Immediate Effects on Adolescent Drivers

Gasoline price changes had immediate effects on reducing crashes involving drivers aged 16 to 19 years (Table 1; other data available as a supplement to the online version of this article at http://www.ajph.org); the effect was statistically weak in the negative binomial regression model but statistically significant in the correlation analysis. Drivers aged 16 to 19 years were the only demographic group for which immediate effects occurred. There are 2 possible reasons. One, adolescents have relatively lower incomes and less discretionary money than do other age groups[44]; thus, they are more vulnerable to gasoline price increases and would be more immediately affected by changes in prices. Two, adolescents often participate in optional activities such as team sports or gym workouts, which could be the first to be reduced when adolescents or their parents face financial pressure.[43] A 10.0% gasoline price increase immediately corresponded with a 1.2% decrease in traffic crashes involving drivers aged 16 to 19 years.

No Effects on Adult Drivers

Another exception was adult drivers (aged 25–34 years), who were the only group for which gasoline prices had no significant effect on traffic crashes at any lag time when other pertinent factors were taken into account (Table 1). This finding was further confirmed by comparing the statistical significances of negative binomial parameter estimates for the 6 age groups: 16 to 19, 20 to 24, 25 to 34, 35 to 64, 65 to 74, and 75 years or older (data available as a supplement to the online version of this article at http://www.ajph.org). Each age group except the 25 to 34 years group showed effects 9 to 11 months after a change in gasoline prices. The *P* values of the estimates for those drivers (all $P > .211$) were far from the level of statistical significance. That age group generally is just entering the job market and creating families. Those responsibilities often preclude a reduction in the amount of driving.

Longer-Lasting Effects on Old-Old Drivers

Although most age groups (except adult drivers) experienced a lagged effect of gasoline price on traffic safety for 9 to 10 months after the price change, drivers aged 75 years and older experienced a longer-lasting effect, from months 9 to 13 (Table 1). The effect was also more significant than for any other age group. A 10.0% increase in gasoline price corresponded to a 2.3% decrease in traffic crashes for the most elderly drivers. People in that age group are more conservative about spending. Therefore, gasoline price increases had stronger and longer effects on their driving behaviors and the consequent change in traffic safety.

DISCUSSION

We had 3 aims: (1) to demonstrate a positive association between higher gasoline prices and safer roads; (2) to test whether the positive association applies to accidents by age, gender, and race; and (3) to identify the number of months it takes for gasoline price changes to affect crashes. Overall, gasoline price changes affected traffic crashes 9 to 10 months after the price change. This finding was generally consistent for both male and female drivers, across age groups, and for both White and Black drivers. However, there were 3 exceptions. For drivers aged 16 to 19 years, gasoline price increases had an immediate (although statistically weak) effect in reducing crashes. Crashes involving drivers aged 25 to 34 years, by contrast, were seemingly unaffected by changes in gasoline prices. For drivers aged 75 years and older, the lagged effects were stronger and lasted longer than those for other age groups.

Our findings suggest that higher gasoline prices lead to fewer traffic crashes. However, how many traffic crashes would or would not have occurred if gasoline prices remained at very low or very high rates, respectively? The lowest gasoline price during the studied period was $1.81. Using the elasticity of −0.154

TABLE 2—Elasticities for Immediate and Lagged Effects: Mississippi, April 2004–December 2012

Variable	Immediate Effect	Lagged Effect
All		−0.154
Age, y		
16–19	−0.124	−0.174
20–24		−0.167
25–34		
35–64		−0.160
65–74		−0.166
≥ 75		−0.225
Gender		
Male		−0.119
Female		−0.172
Race		
White		−0.161
Black		−0.155

Note. We determined the elasticities by the midpoint method,[43] and we calculated them at the mean gasoline price of $2.96 for the studied period. We adjusted gasoline prices to January 2013 dollars. The immediate effects occurred concurrently with gasoline price changes, and lagged effects occurred months later.

obtained from the results, had the gasoline price remained that low throughout the entire study period, 57 461 (5.7%) more traffic crashes would have occurred (data available as a supplement to the online version of this article at http://www.ajph.org). Had the gasoline price remained at its highest point of $4.17 for the entire period, 70 655 (7.0%) fewer traffic crashes would have occurred.

These findings suggest that decision-makers could improve traffic safety by increasing gasoline taxes. This increased revenue could contribute to improved mass transit systems, which could further decrease traffic crashes. Drivers who are more vulnerable to these tax increases might switch to the improved mass transit system. Higher gasoline prices (or taxes) could also lead to lower gasoline demand and consumption,[45] which could reduce carbon emissions and slow global warming. In addition, higher gasoline prices may lead to more research and investment in renewable energy production and low-emission or zero-emission vehicles.[46] However, raising gasoline taxes is not favorable to consumers and could increase transportation inequality because low-income groups would suffer more from higher gasoline prices. The complexity of the social implications of gasoline price increases should be well studied before making any major policy changes.

This research is not without limitations. First, the findings drawn from this study may not be generalizable to other regions of the United States or other countries. Second, we measured seat belt use, one of the control variables, by the overall rate of seat belt use. Whether individuals who were involved in a crash use seat belts would provide a more sensitive measure. Similarly, we measured alcohol use at the state level. The status of alcohol use recorded with crash data would be a more accurate measure.

Future research could explore the time lag of gasoline price effects on fatal, injury, and drunk-driving crashes separately. Gasoline price increases have been found to have less of an effect on more serious crashes and on discouraging heavy drinkers from drunk driving.[13–16] More knowledge about the specific effects by crash type and demographic variation could provide insight into the relevance of gasoline prices (and taxes) as a means to improving public health.

Furthermore, future research could compare the effects of gasoline price increases and other possible factors in affecting traffic crashes. The United States and other developed countries have experienced dramatic declines in traffic fatalities and crashes in the past 10 years. However, no comprehensive understanding exists about the factors that contribute to that decline and to what extent. Although research has examined some possible factors, no studies have employed comprehensive crash data to systematically identify the contributing factors and determine their relative impacts. It is essential, therefore, to identify the contributing factors systematically and estimate their effects robustly because transportation decision makers and planners need such information for designing and implementing the most efficient programs to reduce traffic crashes. ■

About the Authors

Guangqing Chi is with the Department of Agricultural Economics, Sociology, and Education, the Population Research Institute, and the Social Science Research Institute, Pennsylvania State University, University Park. Willie Brown is with the Information Technology Laboratory, United States Army Engineer Research and Development Center, Vicksburg, MS. Xiang Zhang and Yanbing Zheng are with the Department of Statistics, University of Kentucky, Lexington.

Correspondence should be sent to Guangqing Chi, Department of Agricultural Economics, Sociology, and Education, Pennsylvania State University, 103 Armsby Building, University Park, PA 16802-5600 (e-mail: gchi@psu.edu). Reprints can be ordered at http://www.ajph.org by clicking the "Reprints" link.

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Contributors

G. Chi designed the study, conducted the literature review, and wrote the article. W. Brown conducted negative binomial regression analysis and generated tables and figures. X. Zhang provided the analysis of trend and seasonal variations and calculated the Pearson correlations. Y. Zheng designed the method for removing trend and seasonal variations.

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Human Participant Protection

No institutional review board approval was required because this study involved analyses of aggregated data for which the authors did not have access to individual records.

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