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Mind the Weather: A Panel Data Analysis of Time-Invariant Factors and Traffic Fatalities

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Abstract

Many important determinants of traffic fatalities have been identified using the widely popular fixed-effects (FE) estimator for panel data. However, the FE estimator precludes an analysis of time-invariant or rarely changing variables, thereby obscuring their relative impact on traffic fatalities. This study estimates the effect of time-invariant and rarely changing variables (climate, geography, laws, etc.) on the U.S. state traffic fatality rate using alternative econometric methods in addition to the FE estimator. We find that alcohol consumption, air temperature, and precipitation have the largest effect on traffic fatalities. Our findings suggest that policy makers and the insurance industry practitioners may want to re-evaluate the role of climate in road safety.

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1. Introduction

According to the Center for Disease Control and Prevention (2007), traffic fatalities are the leading cause of death in the United States among people between the ages of 1 and 34 years old. In the United States, traffic fatalities have increased on average by 4.7% from 1994 to 2006. During this period, states like North Dakota and Wyoming have experienced double digit increases in their traffic fatality rates, while states like Utah and Minnesota have seen a decrease in their traffic fatality rate by over 30%.

Numerous policies have been adopted with the specific intention of reducing the traffic fatality rate. These policies include drinking and driving regulations, seat belt laws, and speed limits, among others. The increased availability of longitudinal panel data for the U.S. states together with the fixed-effects (FE) estimator have improved the analysis of the effectiveness of these policies in reducing traffic fatalities. However, the FE estimator absorbs the time-invariant or rarely changing variables, preventing us from estimating the relative contribution of these factors to traffic fatalities. In the context of road safety, the relevant time-invariant or rarely changing variables may include geography, climate, traffic laws and regulations, alcohol policies, culture, and habits. The effect of these factors on traffic fatalities may not be trivial, but they are often excluded from the FE estimator. This obscurity warrants an analysis of these factors.

This study estimates the impact of several time-invariant and rarely changing variables on the traffic fatality rate using a balanced longitudinal panel of 48 contiguous U.S. states from 1982 to 2006. We discern the impact of several rarely changing variables on traffic fatalities from state fixed effects using random effects (RE) and fixed-effects vector decomposition (FEVD) econometric techniques. The strongest determinants of traffic fatalities in our model, as measured by estimated elasticity coefficients, are alcohol consumption, air temperature, and precipitation. Population density and crime rate also have a rather strong effect on the traffic fatality rate. Overall, our estimates suggest that climate is one of the strongest determinants of traffic fatalities in the United States. Even though climate is outside of policy makers' control, our estimates suggest that climate considerations may need to play a more important role in the design of transportation infrastructure and auto insurance policies.

2. The Empirical Model and Data

According to the model specification search by Park et al. (2008), the log-linear model of traffic fatalities is statistically reliable. Furthermore, the log-linear model used in this study passes the Ramsey (1969) model specification test, indicating that the model does not suffer from significant omitted variable bias. The log-linear model specification also allows for nonlinear relationships to be estimated via OLS. Moreover, the regression coefficients in the log-linear model can be interpreted as constant elasticity estimates, simplifying the comparison of coefficients. For these reasons, we propose estimating the following log-linear model of the traffic fatality rate, where all strictly positive (non-zero) variables are transformed via natural logarithms:

$$y_{it} = \alpha + X_{it}\beta + Z_i\gamma + u_i + \varepsilon_{it} . \qquad (1)$$

Where y_{it} is the traffic fatality rate, X_{it} is a vector of time-variant regressors, Z_i is a vector of time-invariant or rarely changing regressors, u_i is the unobserved time-invariant (i.e. fixed) state effect, ε_{it} is the disturbance, and the subscripts i=1,…,48 and t = 1982,…, 2006 represent states and years, respectively. The parameters β, γ, u_i , and ε_{it} are unobserved (i.e. to be estimated). The chosen regressors in our model are dictated by previous studies and economic intuition.[1] The choice of the time span and 48 contiguous states is dictated by data availability. Variable definitions, sources, and summary statistics are available in Table 1. The variance inflation analysis of the model in equation 1 and the pair-wise correlations in Table 2 reveal that the chosen regressors are not multicollinear (results available upon request).

The time-variant regressors are alcohol consumption, per capita income, gasoline price, population density, percentage of young and old population, and the crime rate. The time-invariant and rarely changing regressors are mountainous and coastal state dummies, speed limits, precipitation, air temperature, primary seatbelt law dummy, compulsory insurance law dummy, and no-fault liability law dummy. Some of these variables are completely time-invariant (coastal and mountainous terrain), while others exhibit questionable degree of variation over time. For example, few states revised their speed limit levels more than once between 1982 and 2006. States that adopted primary seat belt, compulsory insurance and no-fault liability laws had not changed them, while states that did not adopt these laws retained zero for the entire time span of the dataset, making these variables rarely changing. Although temperature and precipitation do vary from year to year, these variations are rather small, compared to cross-sectional variations, and are highly collinear with the state fixed effects. Because some ambiguity exists as to the degree of time-invariance and, therefore, multicollinearity of these variables with the state fixed effects, it is prudent to examine the effect of these variables on traffic fatalities using different estimators.

The unit or within FE estimator is a popular panel data regression technique because it is designed to control for unobserved heterogeneity (i.e. the correlation of regressors with relevant omitted variables). According to the Hausman test (results available upon request), the FE estimator is more consistent than the RE estimator for our dataset. However, the FE estimator absorbs the time-invariant variables, precluding us from learning about their effects on traffic fatalities. Even rarely-changing variables in the FE estimator may have imprecise coefficient estimates with large standard errors because of high correlation with the unit fixed effects (Breusch et al., 2010). Previous attempts to analyze the time-invariant variables in longitudinal panel data have relied on the RE, pooled OLS, and Hausman-Taylor estimators, which have their own disadvantages compared to the ubiquitous FE estimator. Recently, Plümper and Troger (2007) developed the fixed-effects vector decomposition (FEVD) estimator, which they claim is more efficient and reliable than the pooled OLS, RE, and Hausman-Taylor estimators when both time-invariant and time-varying variables are correlated with the fixed effects. Nevertheless, Plümper and Troger (2007) acknowledge that the inclusion of time-invariant variables in the RE estimator may serve as the second best alternative to the FEVD procedure. For the aforementioned reasons, we estimate the effect of time-invariant and rarely changing variables using three different regressions techniques: FE, RE, and FEVD.

[1] The following studies, among other, were reviewed: Beck et al. (2007), Nelson et al. (1998), Peltzman (1975), Glassbrenner (2005), Garbacz (1990a, 1990b, 1991, 1992), Risa (1994), Calkins and Zlatoper (2001), Sen (2001), Cummins et al. (2001), Cohen and Dehejia (2004).

A brief description of the newly developed FEVD estimator is warranted here. In essence, FEVD is a three stage procedure. The first stage implements the conventional fixed-effects model to obtain an estimate of the unit fixed effects. The second stage decomposes the fixed-effects vector into a part explained by the time-invariant variables and an unexplainable part (the residual). The third stage re-estimates the original model by pooled OLS, including the time-invariant variables and the residual from the second stage.

In this paper, however, we utilize only the second stage of the FEVD estimator given the criticisms made by Greene (2010) and Breusch et al. (2010) regarding the variance-covariance matrix implemented in the third-stage by Plümper and Troger (2007). The second stage of the FEVD estimator is sufficient to analyze the effects of time-invariant and rarely changing variables on traffic fatalities since the coefficients for time-invariant variables are identical in the second and third stages, making the third stage of FEVD redundant. The first stage of the FEVD procedure estimates the standard within fixed effects model including only the time-variant, right-hand-side variables:

$$y_{it} = \alpha + X_{it}\beta + u_i + e_{it} . \qquad (2)$$

Where y_{it} is the time-variant dependent variable, X_{it} is a vector of time-variant variables, u_i is the unit (state) fixed effect, and e_{it} is the normally distributed error component. This unit (within) fixed-effects estimator effectively de-means the data, removing the unit effects u_i and giving us the group-average of the unexplained component in the dependent variable $\hat{u}_i = \bar{y}_i - \bar{X}_i\hat{\beta}_{FE}$, which is also the fixed-effects vector. Now, we can analyze the effects of time-invariant and rarely changing variables in Z_i on the unexplained portion of traffic fatalities $\hat{u}_i$ by estimating equation (3) via pooled OLS:

$$\hat{u}_i = \omega + Z_i\gamma + \eta_i . \qquad (3)$$

Where ω is the intercept and η_i is the error term. The OLS estimates of γ from equation (3) are included in the third column in Table 3, allowing us to infer about the impact of time-invariant and rarely changing variables on the portion of the traffic fatality rate that is not explained by the time-variant variables.

3. The Estimates

The results from three different estimators are shown in Table 3. The first (FE) regression shows the impact of time-variant variables on the traffic fatality rate, excluding completely time-invariant variables such as mountainous and coastal state dummies because of their perfect multicollinearity with the state fixed effects. Most of the variables in the FE regression are statistically significant (at the 5% level) with the exception of young and old population shares, air temperature, compulsory insurance and no-fault liability laws. However, the FE estimates for the rarely-changing variables such as precipitation, compulsory insurance and no-fault liability laws have counterintuitive negative signs. Cummins et al. (2001) and Cohen and Dehejia (2004) find compulsory insurance and no-fault liability laws to be associated with moral hazard and higher traffic fatalities. Perhaps, the insignificant and negative coefficients for the two insurance variables reflect their low time-variance and possible endogeneity bias.

The second (RE) regression estimates in Table 3 should be less consistent than the FE estimates as suggested by our Hausman test. Nevertheless, the RE regression allows for the inclusion of completely time-invariant variables such as mountainous and coastal state dummies, and is therefore useful. In contrast to the FE estimates, the RE regression indicates that the share of old in state populations, temperature, coastal and mountainous state dummies, as well as compulsory insurance and no-fault liability laws have significant effects on traffic fatalities. Also, precipitation switches from having a negative and significant coefficient in the FE regression to having a positive and significant coefficient in the RE regression, which is more logical.

The third regression in Table 3 that is based on the second stage of the FEVD procedure yields very qualitatively different estimates for many time-invariant and rarely changing variables compared to the FE and RE regressions. For instance, the third regression yields much larger, positive, and statistically significant coefficients for temperature and precipitation, while producing a stronger negative coefficient for the coastal state dummy. Moreover, the third regression shows that speed limits, mountainous state dummy, primary seat belt, compulsory insurance and no fault liability laws are not statistically significant.

Can anything be learned from the three regressions in Table 3? The short answer is yes. We recommend using the FE estimates for inference about the impact of the following time-variant variables on traffic fatalities: young and old population shares, population density, crime rate, income, alcohol consumption, and gasoline price. These variables have the expected effects on the traffic fatality rate and most of them are statistically significant. The top three strongest time-variant determinants of traffic fatalities in the FE regression are alcohol consumption, population density, and crime rate with corresponding elasticity coefficients of 0.9, -0.41, and 0.25, respectively.

As for the time-invariant and rarely changing variables, it is difficult to make unequivocal inference recommendations given the ambiguous degree of time-invariance for some of these variables and drastically different estimates across the three regressions. However, armed with the knowledge of previous research, economic intuition, and RE as the benchmark estimator, we can make the following cautious inference suggestions.

The statistically significant, positive, and rather large coefficient estimate of 0.55 for the natural log of precipitation in the third (FEVD) regression makes sense. One would expect higher precipitation (rain, snow, sleet, etc.) to increase traffic fatalities, but the FE and RE regressions tell us the opposite story. Similarly, the third regression's estimate for air temperature is positive, statistically significant, and has the highest elasticity coefficient (1.35) of all other variables. This positive relationship between traffic fatalities and temperature also makes sense given that higher temperature may increase fatigue and sleepiness in drivers, thereby leading to more accidents and traffic fatalities. Furthermore, higher air temperature may proxy for better roads and higher traffic speeds, which would increase traffic fatalities according to the Peltzman (1975) risk compensation theory. The risk compensation theory postulates that people have an optimal level of risk they are willing to tolerate and will counteract the gains in safety by driving more aggressively. For example, an increase in seat belt usage may lead to more careless driving, which may increase traffic accidents and fatalities. Several studies corroborate this argument (Garbacz, 1990a, 1990b, 1991, 1992; Risa, 1994; Calkins and Zlatoper, 2001; and Sen, 2001).

Unlike the mountainous state dummy, the coastal state dummy has a consistently negative and significant coefficient across the second and third regressions. Geographic factors, like coastal state dummy, may proxy for cultural habits that pertain to seat belt usage, risk preference, and other driving habits. Several studies find that younger, less educated, and poorer males are less likely to wear a seat belt (Beck et al., 2007; Nelson et al., 1998; Glassbrenner, 2005). If coastal states tend to have better educated and older populations, then the negative association between traffic fatalities and coastal state dummy makes sense.

The decreasing magnitude and significance of the positive coefficient for speed limits from the first to the third regression is somewhat puzzling. Both FE and RE regressions suggest that lower speed limits reduce traffic fatalities. This relationship has been supported by Friedman et al. (2009) and challenged by Lave (1985) and Graves et al. (1993), for example. Estimation of the relationship between traffic fatalities and speed limits is complicated by the fact that enforcement of speed limits may vary substantially across states and the potential for speed limit levels to be endogenous (i.e. depend on the de-facto traveling speeds and enforcement). Furthermore, the FE estimate for speed limits may not be accurate given that this is a rarely changing variable. The third regression also yields positive coefficients for compulsory insurance and no-fault liability laws, similar to Cummins et al. (2001) and Cohen and Dehejia (2004). However, these coefficient estimates are not statistically significant.

Due to the potentially endogenous and rarely changing nature of speed limits, seat belt usage, compulsory and no-fault liability laws, we cannot make unequivocal recommendations as to which of our three estimators are better suited for statistical inference about these variables. However, the remaining time-variant and not so time-variant variables seem to have plausible estimates.

4. Conclusion

Using three different estimators (FE, RE, and FEVD), this study performs a comparative analysis of how time-invariant and rarely changing variables may affect the U.S. state traffic fatality rate. The commonly utilized unit or within fixed-effects estimator (FE) is not compatible with time-invariant or rarely changing variables due to multicollinearity between the rarely changing variables and the unit fixed effects. Thus, the FE estimator precludes us from estimating the relative impact of the time-invariant and, perhaps even, rarely changing variables on the traffic fatality rate. Using the random effects (RE) and fixed-effects vector decomposition (FEVD) estimators, this paper examines the effect of several time-invariant and rarely changing variables on the traffic fatality rate. These variables are precipitation, air temperature, mountainous and coastal terrain, seat belt laws, speed limits, compulsory insurance and no-fault liability laws. Using a longitudinal panel of 48 contiguous U.S. states from 1982 to 2006, we find that alcohol consumption, air temperature, and precipitation have the strongest effects on traffic fatalities. Our findings suggest that the policy makers and insurance industry practitioners may want to re-evaluate the contribution of geography and climate to traffic fatalities.

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Appendix

Table 1: Variables and Sources

Variable Name	Variable Description	Mean (Std. Dev.)
Traffic fatality rate	Traffic fatalities divided by state population (population/1000),	0.18 (0.06)
Young population	The percentage of people 18-24 years of age in state population.	0.08 (0.07)
Old population	The percentage of 65 and older people in a state population.	0.12 (0.02)
Real gas price	Per gallon gasoline price in constant dollars.	1.90 (0.41)
Real per capita income	Real GDP/total population (in thousands).	39.74 (10.38)
Population density	Total population/square miles of land.	0.17 (0.24)
Primary seat belt law	Dummy variable: 1 if state has a primary seatbelt law, 0 if otherwise	0.22 (0.42)
No-fault liability law	Dummy variable: 1 if state has a no-fault liability law, 0 if otherwise.	0.28 (0.45)
Compulsory insurance law	Dummy variable: 1 if state has a compulsory liability law, 0 if otherwise.	0.79 (0.41)
Alcohol consumption	Alcohol consumption in gallons per capita of total population over the age of 17.	2.39 (0.56)
Precipitation	Average weighted annual precipitation (rain, snow, sleet, or hail).	3.09 (1.26)
Temperature	Average weighted annual temperature (adjusted for time of observation bias).	52.50 (7.61)
Speed limit	Average (rural and urban) speed limit in miles per hour.	60.03 (6.15)
Crime rate	Combined violent and property crime rate.	0.05 (0.01)
Coastal state	Dummy variable: 1 if state with a sea coast, 0 if otherwise.	0.46 (0.50)
Mountainous state	Dummy variable: 1 if state is a member of the Rocky mountain Census region, 0 if otherwise.	0.16 (0.37)

Data sources for the above variables in descending order:

1. The Fatal Accident Reporting System (FARS), www.fars.nhtsa.dot.gov/States/StatesCrashesAndAllVictims.aspx, and US Census Bureau Statistical Abstract, http://www.census.gov/compendia/statab/past_years.html
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4. Energy Information Association, www.tonto.eia.doe.gov/dnav/pet/pet_pri_gnd_a_epmr_pte_cpgal_w.htm
5. Bureau of Economic Analysis, http://www.bea.gov/
6. US Census Bureau Statistical Abstract, http://www.census.gov/compendia/statab/past_years.html
7. National Highway Traffic and Safety Administration, http://www.nhtsa.gov/people/outreach/state_laws-belts04/safeylaws-states.htm and the Fatal Accident Reporting System (FARS), http://www-fars.nhtsa.dot.gov/States/StatesLaws.aspx
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12. National Climatic Data Center, "Average Annual Temperature", http://www1.ncdc.noaa.gov/pub/data/cirs/drd964x.tmpst.txt
13. Insurance Institute for Highway Safety, "Maximum Posted Speed Limits", http://www.iihs.org/laws/SpeedLimits.aspx
14. Bureau of Justice Statistics, http://bjs.ojp.usdoj.gov/
15. U.S. Census Bureau.

Table 2: Pair-wise Correlations

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Young	1												
2	Old	0.0463	1											
3	Pop density	0.0035	0.1960*	1										
4	Crime	-0.2362*	-0.2368*	-0.0528	1									
5	Income	0.2207*	-0.1124*	0.3220*	-0.0175	1								
6	Gas price	0.4450*	-0.1026*	-0.047	-0.0735*	-0.0058	1							
7	Alcohol	-0.0531	-0.1320*	0.0473	0.1836*	0.2024*	0.1586*	1						
8	Precipitation	0.0130	0.2619*	0.3832*	-0.0616*	-0.0443	0.0535	-0.1898*	1					
9	Speed limit	0.4544*	-0.0229	-0.1396*	-0.1684*	0.1254*	-0.0594*	-0.1112*	-0.1284*	1				
10	Coastal	-0.0162	-0.0675*	0.4708*	0.2416*	0.2060*	-0.0223	0.1562*	0.5003*	-0.0458	1			
11	Mountainous	0.0285	-0.3666*	-0.2911*	0.2021*	-0.0545	-0.0292	0.2085*	-0.6782*	0.1699*	-0.3944*	1		
12	Seat belt	0.2385*	-0.0685*	0.1191*	0.1026*	0.2204*	-0.0267	-0.1686*	0.0661*	0.2101*	0.2788*	-0.1183*	1	
13	Compulsory	0.0934*	-0.1650*	0.0824*	-0.0503	0.2393*	-0.1369*	-0.1545*	-0.2480*	0.1197*	-0.0943*	0.1565*	0.1371*	1
14	No-fault	-0.0077	0.0972*	0.2997*	0.0127	0.1396*	-0.0157	-0.1206*	-0.015	-0.0476	-0.0337	-0.0242	-0.0465	0.1833*
15	Temperature	0.0416	-0.0115	0.0254	0.4191*	-0.0535	0.0275	-0.2093*	0.4430*	0.0648*	0.3782*	-0.2166*	0.1938*	-0.1435*

* Indicates statistical significance at the 5% level.

Table 3: Determinants of the U.S. State Traffic Fatality Rate

Dependent variable:	Traffic Fatality Rate	Traffic Fatality Rate	Fixed effects vector ($\hat{u}_i = \bar{y}_i - \bar{X}_i \hat{\beta}_{FE}$)
Estimator:	FE via OLS	RE via GLS	Pooled OLS
Young population	0.01 (0.01)	-0.01 (0.01)	-
Old population	-0.11 (0.08)	-0.17*** (0.05)	-
Population density	-0.41*** (0.13)	-0.22*** (0.02)	-
Crime rate	0.25*** (0.05)	0.23*** (0.02)	-
Real per capita income	0.07*** (0.02)	0.06*** (0.02)	-
Real gasoline price	-0.09** (0.04)	-0.04* (0.02)	-
Alcohol consumption	0.90*** (0.11)	0.80*** (0.05)	-
Temperature†	-0.02 (0.11)	0.60*** (0.10)	1.34*** (0.22)
Precipitation†	-0.09*** (0.02)	0.04** (0.02)	0.55*** (0.09)
Speed limit†	0.23*** (0.08)	0.08* (0.04)	0.17 (0.13)
Primary seat belt law (dummy) †	-0.05*** (0.02)	-0.06*** (0.01)	0.02 (0.04)
No-fault liability law (dummy) †	-0.05 (0.05)	-0.06** (0.03)	-0.002 (0.07)
Compulsory insurance (dummy) †	-0.02 (0.02)	-0.03** (0.01)	0.07 (0.07)
Mountainous state (dummy) †	-	-0.36*** (0.07)	0.10 (0.10)
Coastal state (dummy) †	-	-0.14*** (0.05)	-0.31*** (0.08)
R-squared	0.64	0.62	0.63

All variables are in natural logarithms except for the dummy variables. †Time-invariant or rarely changing variables. Robust clustered standard errors are reported in parentheses. Significance levels: *** at 1%, ** at 5%, and * at 10%. Observations: 1200 (48 contiguous U.S. states, 1982-2006). The constant and state fixed effects are not reported to conserve space.