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Driving through the Great Recession: Why does motor vehicle fatality decrease when the economy slows down?

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Abstract

The relationship between short-term macroeconomic growth and temporary mortality increases remains strongest for motor vehicle (MV) crashes. In this paper, I investigate the mechanisms that explain falling MV fatality rates during the recent Great Recession. Using U.S. state-level panel data from 2003–2013, I first estimate the relationship between unemployment and MV fatality rate and then decompose it into risk and exposure factors for different types of MV crashes. Results reveal a significant 2.9 percent decrease in MV fatality rate for each percentage point increase in unemployment rate. This relationship is almost entirely explained by changes in the risk of driving rather than exposure to the amount of driving and is particularly robust for crashes involving large commercial trucks, multiple vehicles, and speeding cars. These findings provide evidence suggesting traffic patterns directly related to economic activity lead to higher risk of MV fatality rates when the economy improves.

Keywords

motor vehicle deaths; the Great Recession; unemployment; pro-cyclical mortality; large trucks

Introduction

The relationship between short-term macroeconomic fluctuation and mortality is rather counterintuitive. During economic recessions, when economic activities experience significant declines, job losses are linked to worse individual health outcomes through pathways such as losing health insurance coverage and experiencing greater financial and material hardships (Burgard, Ailshire, & Kalousova, 2013). Instead, temporary economic downturns are often associated with *lower* than expected mortality at the population level. Previous literature suggests that these observed short-term benefits may occur because individuals on the aggregate have more time to engage in healthy behaviors and less money to spend on alcohol and cigarettes (Burgard, Ailshire, & Kalousova, 2013; Ruhm, 2000). Consistently, a strong relationship between macroeconomic fluctuation due to motor vehicle deaths has remained persistent through at least the past three decades (Ruhm, 2000,2015).

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Motor vehicle crashes represent a major public health hazard and are the leading cause of death for those aged 5 to 25 in the United States (Centers for Disease Control and Prevention 2014). An average of 37,850 people have died from motor vehicle crash each year from 2004 to 2012, amounting to one death almost every 14 minutes (author's calculation based on FARS). Despite their significance, motor vehicle death rates in the United States actually fell every year since 2006 until its recent uptick in 2012 (NHTSA, 2013). Most dramatically, the number of motor vehicle deaths plummeted 18 percent in just two years from 41,259 deaths in 2007 to 33,808 deaths in 2009 (NHTSA, 2009, 2010). These temporary declines in motor vehicle fatalities coincide with the Great Recession of 2007–2009, the longest economic recession since the Great Depression.

In this paper, I examine the relationship between macroeconomic fluctuations and motor vehicle fatality through exposure and risk factors. I augment previous literature by exploring fatal risk factors relating to large trucks, speeding, and other types of collisions. The findings uncover substantial mechanisms that have not been taken into account in previous studies. More broadly, this study provides more insight into the pro-cyclical relationship for motor vehicle deaths and carries important policy implications to combat rising traffic fatalities during economic expansions.

Background

In an influential paper using panel data models, Ruhm (2000) establishes that all-cause mortality varies pro-cyclically with state unemployment rate in the United States over a 20-year period. To be precise, pro-cyclical mortality means that mortality moves in the same direction as macroeconomic conditions deviate above or below the long-term linear trend. This relationship suggests that mortality temporarily rises during economic expansions (i.e. when unemployment decreases) and falls during economic contractions (i.e. when unemployment increases). Thus, falling and rising mortality in this paper refers to *temporary* higher and lower than expected mortality given that the expectation is a linear trend. As unemployment climbs by one percentage point, Ruhm (2000) predicts a 0.5 percent decrease in total mortality rate. While the magnitude of the effect appears to be small, unemployment often rises by more than one percentage point annually during recessionary periods, thus leading to significant declines in mortality (Bureau of Labor Statistics 2015). Other papers using data from Germany (Neumayer, 2004), Japan (Tapia Granados, 2008), and OECD countries (Gerdtham and Ruhm, 2006) also produce results that mirror Ruhm's (2000) findings.

When researchers decompose this relationship by cause-specific deaths, they find that the pro-cyclicality is largely driven by acute causes of death especially those due to motor vehicle crashes, cardiovascular diseases, and pneumonia (Ruhm, 2000; Tapia Granados, 2008; Gerdtham and Ruhm, 2006). Mortality patterns for acute causes of death respond strongly to short-term macroeconomic change unlike those for causes of death with slower disease progression, such as cancer (Ruhm 2000, 2003). In particular, motor vehicle fatalities in the United States have consistently shown a strong, pro-cyclical relationship. Ruhm (2000) suggests that a one-percentage point increase in unemployment lowers the motor vehicle fatality rate by 3 percent, compared to a 0.5 percent reduction for all-cause

mortality. In more recent estimates, Ruhm (2015) finds that the association of a one-percentage point increase in unemployment rate for motor vehicle fatality rate has attenuated to 0.9 percent in 2010, but remains significant. Two recent studies that specifically examine the impact of macroeconomic indicators on motor vehicle fatality also arrive at similar conclusions. Cotti and Tefft (2011) use state-quarter-year panel data models and estimate that motor vehicle fatality rate decreases by 1.63 percent for each percentage point increase in state unemployment rate between 2003 and 2009. In a study of motorcycle fatalities, which account for 14 percent of all traffic deaths, French and Gumus (2014) also find the effect of unemployment rate to be 1.8 for motorcycle mortality over several decades in the United States.

Previous studies examine the association between macroeconomic indicators on motor vehicle fatality by evaluating various exposure and risk factors. Exposure relates to changes in the amount of driving at the population level. During economic downturns, overall traffic volume has been hypothesized to shrink because fewer individuals are commuting to work and less commercial activity is occurring on the road (Burgard, Ailshire, & Kalousova, 2013; Ruhm, 2000). At the same time, individual consumption patterns might also change as people tend to make fewer leisure trips such as going to restaurants and shopping (Cotti and Tefft, 2011; Burgard, Ailshire, & Kalousova, 2013). Using vehicle miles travelled (VMT), a widely accepted measure of driving exposure, existing papers provide conflicting evidence on the importance of driving exposure in explaining pro-cyclical trends for motor vehicle deaths. In an earlier study, Wagenaar's (1984) time series analysis did not find VMT to explain the link between macroeconomic fluctuations and motor vehicle mortality rates in Michigan. More recently, Cotti and Tefft (2011) find state personal income per capita, but not state unemployment rate, to be positively associated with VMT per capita between 2003 and 2009 in the United States.

In this literature, studies also direct their attention to the risk of certain types of fatal crashes given a fixed exposure of driving. Most studies focus on drunk driving as a risky behavior that might explain increases in motor vehicle fatalities when the economy improves (Wagenaar and Streff, 1989; Ruhm, 1995, Cotti and Tefft, 2011). During economic downturns, individuals are hypothesized to have less disposable income to spend on detrimental normal goods such as alcohol and cigarettes (Ruhm, 2000). Although others contend that higher unemployment has no effect (Xu 2013) or might even increase alcohol consumption (Frijters, Johnston, Lordan, & Shields, 2013), Cotti and Tefft (2011) recently find unemployment rates to be negatively associated with drunk-driving fatalities at the state level. In the context of the Great Recession, they suggest that alcohol-related driving fatalities account for a significant amount of the decline in motor vehicle fatalities between 2007 and 2009.

The existing literature does not adequately address the link between macroeconomic indicators and motor vehicle fatality. Most importantly, previous literature has insufficiently explored the scope of mechanisms that could help explain cyclical variations in fatal motor vehicle crashes. Alcohol-impaired driving fatalities should be examined in conjunction with other types of potentially risky driving behaviors or crash types. Several other plausible factors have been hypothesized to explain the pro-cyclical nature of motor vehicle fatality

but have not yet been empirically tested. First, there may be changes in the composition of vehicles during economic downturns, namely in a decrease in the proportion of commercial trucks. French and Gumus (2014) suggest that fewer commercial vehicles during economic downturns can help improve overall road safety because commercial trucks may pose greater danger than passenger cars. Recent statistics show only four percent of all registered vehicles are large trucks (henceforth defined as having a gross weight over 10,000 lbs), but they are involved in crashes accounting for 12 percent of all fatalities each year (Lyman and Braver, 2003). In another study, Wagenaar (1984) only includes fatalities including passenger cars noting that the economy might have a direct effect on truck traffic. However, the ability to differentiate among these various crash types is essential for policy interventions when the economy improves. Because large trucks are generally tied to commercial and economic activity, they could play an important role in the relationship between macroeconomic fluctuations and motor vehicle fatality rate. Another important risk factor that is missing in this empirical literature is speeding, which is a factor in up to one-third of all fatal motor vehicle crashes (Liu, Chen, Subramanian, & Utter, 2005). Cotti and Tefft (2011) suggest that the risk behavior of speeding might increase when the economy improves because of the rising opportunity cost of time. Further, speeding-related fatalities may be tied to drunk driving. A government report find speeding involved in over 40 percent of drunk driving crashes compared to just 14 percent of sober crashes (Liu, Chen, Subramanian, & Utter, 2005).

Additionally, no study has examined this specific relationship past the recent U.S. Great Recession, officially dated December 2007 to June 2009 (National Bureau of Economic Research). The large macroeconomic fluctuations over the Great Recession presents an ideal setting for understanding the relationship between macroeconomic change on motor vehicle fatality. Although Cotti and Tefft's (2011) study period stretches through the year 2009, which marks the end of the Recession, macroeconomic conditions had not yet subsided to pre- Recession levels. In fact, unemployment rate remained at 10 percent in late-2009, doubled what it was in late-2007 (Bureau of Labor Statistics, 2015). By 2013, unemployment rate had already reached its peak and fallen for three consecutive years (Bureau of Labor Statistics, 2015).

Objective

Despite compelling evidence supporting the strong empirical relationship between motor vehicle fatality rates and macroeconomic conditions, few papers have attempted to understand the link between the two. Using panel data methods, I will analyze the rise and fall of motor vehicle fatality in the recent recessionary period in order to answer the following research questions: 1) Has the pro-cyclical relationship between motor vehicle fatality and unemployment persisted through the recent Great Recession? 2) How do exposure and risk factors explain the associations between unemployment and motor vehicle fatality rate?

This paper will first analyze new data after the Great Recession through 2013 to capture recent improvements in macroeconomic conditions. More importantly, I will expand the current understanding of pro-cyclical motor vehicle fatalities by providing a deeper analysis

into the specific exposure and risk factors that drive pro-cyclical motor vehicle fatality rates. By disaggregating types of motor vehicle crashes, I provide alternative explanations to better understand the mechanisms linking macroeconomic conditions and motor vehicle fatality. My results will show that the story of pro-cyclical motor vehicle fatality aligns more with an explanation of direct changes in commercial activities on the road and cannot simply be explained by changes in drunk driving fatalities.

Methods

Data and Measures

Combining several government data sources, I produce a panel dataset in order to model the relationship between unemployment and motor vehicle fatality rate. Consistent with past research, the level of analysis in this paper is at the state-level. My sample includes 550 (50×11) state-year observations with 50 U.S. states excluding the District of Columbia from 2003 to 2013.

The main dependent variable is motor vehicle fatality rate per 100,000 people. Motor vehicle death counts come from the Fatal Analysis and Reporting System (FARS) database. Under the umbrella of the National Highway Traffic Safety Administration (NHTSA), FARS is a national census that details every motor vehicle crash which occurs on a public road and results in at least one death within 30 days. The NHTSA compiles state-level documents such as police reports, hospital reports, and registration records for the FARS database and coding of crash type. The American Community Survey and the Decennial Census from the U.S. Census Bureau provide mid-year population estimates used in the denominator to calculate fatality rates.

I also use FARS to identify five different types of motor vehicle crashes and calculate fatality rates for each type. Specifically, I examine crashes involving large trucks, crashes involving a speeding vehicle, crashes involving a drunk driver, crashes involving a single vehicle or multiple vehicles, and crashes in urban areas or rural areas. A few terms need additional clarification. As previously stated, large trucks are defined by the NHTSA as over 10,000 lbs. Figure 1 shows examples of trucks that meet the specifications of that definition. Drunk driving is best determined through direct police reports of driver's blood alcohol content. Because a large percentage of driver's BAC is missing in FARS, NHTSA also releases a multiple imputation dataset for imputed BAC values based on other characteristics of the crash (Subramanian, 2002). Consistent with French and Gumus' (2014) definition, I define crashes involving a drunk driver when a driver's blood alcohol content (BAC) is at or above 0.08 g/dL. This group is compared with crashes involving no drunk drivers. In supplementary analysis, I present results for noalcohol involved crashes where all drivers have a BAC of 0.

I further decompose the dependent variable, motor vehicle fatality rates, into the product of two terms: risk and exposure of motor vehicle crashes. Following Cotti and Tefft's (2011) decomposition, risk is operationalized as motor vehicle deaths divided by million vehicle-miles travelled (VMT) while exposure is defined as million VMT divided by the population. VMT estimates for each state are from the Federal Highway Administration (FHWA). The

motivation for the decomposition is to understand whether fluctuations in motor vehicle fatality rates are mainly due to changes in the amount of driving (i.e. exposure) or in the number of deaths given a fixed amount of driving (i.e. risk). An increase in the exposure term can occur if there are more drivers on the road or if the same number of drivers are travelling greater distances. On the other hand, an increase in the risk term suggests higher likelihood of experiencing motor vehicle fatalities given a fixed amount of VMT. These terms are also important for interventions that might target how much versus how dangerously people are driving.

Unemployment rate is the main explanatory variable and serves as a proxy for macroeconomic conditions in previous studies (Ruhm, 2000; French and Gumus, 2014; Cotti and Tefft, 2011). Data on unemployment rates are obtained from the United States Bureau of Labor Statistics.

Moreover, I account for a host of state- and year-specific policy controls that have been shown to affect motor vehicle fatalities (Dee, Grabowski, & Morrissey, 2005; Ferdinand et al., 2015). In line with previous research, I include beer tax and gasoline prices in 2013 dollars (Cotti and Tefft, 2011; French and Gumus, 2014; Grabowski and Morrissey, 2004; Morrissey and Grabowski, 2011). On the policy side, I include the following driving-related laws: bans on handheld devices, bans on texting and driving, primary enforcement of seatbelt laws, 0.08 legal BAC limit, and presence of graduated driver licensing (GDL) program for teenage drivers. The policy controls are coded as dummy variables for the years with the laws enacted. If a law becomes effective in the during the calendar year, I use a fractional value for the year as others have done in similar analysis. (Dee, Grabowski, & Morrissey, 2005). Table A1 summarizes the definitions and sources for each of the control variables.

Analytical Strategy

In the results, I will first show descriptive trends of the main independent and dependent variables. I will then illustrate detrended, bivariate relationships for unemployment and the five types of motor vehicle crashes.

Following the descriptive analysis, I will estimate regression models using Ruhm's (2000) baseline model in Equation 1:

$$H_{jt} = \gamma E_{jt} + \beta X_{jt} + S_j + \alpha_t + \varepsilon_{jt} \quad (\text{Eq.1})$$

The outcome, H , is the natural logged motor vehicle fatality rate for state j at year t . E is unemployment rate, the macroeconomic indicator. X is a set of tax and policy controls at the state-year level. The equation also includes national year effects with year dummy variables and state fixed effects. Time effects capture national level time trends, such as improvements in car safety, which might also influence the outcome variable (Muazzam and Nasrullah, 2011). State fixed effects eliminate possible endogeneity from time invariant state characteristics. Finally, the equation includes an error term and robust standard errors.

First, I run the regression with the outcome, H , as total motor vehicle fatality rate to determine the magnitude of the pro-cyclical relationship during the study period. I also test whether using age-standardized fatality rates as the outcome would change the magnitude of the relationship since motor vehicle fatality rates are not constant across ages and the population composition changes over time. After standardizing fatality rates to the 2010 U.S. age distribution with five-year age groups, I find the coefficients to be almost identical. Thus, all analysis in the paper uses the crude fatality rates.

In the next set of regressions, I decompose total motor vehicle fatality rate into risk (i.e. fatalities per million VMT) and exposure (i.e. million VMT per 100,000 people). Equation 2 shows that with the outcome logged, motor vehicle fatality rate can be decomposed into the sum of logged risk and logged exposure. As shown in Cotti and Tefft's (2011), this decomposition allows me to conduct two separate regression analysis with each component set as the outcome. Again, the purpose of the decomposition is to assess the contribution of each component to the pro-cyclical relationship between unemployment and motor vehicle fatality rates.

$$\ln\left(\frac{\text{Motor Vehicle Fatality Rate}}{100,000 \text{ people}}\right) = \ln\left(\frac{\text{Fatalities}}{\text{VMT}}\right) + \ln\left(\frac{\text{VMT}}{100,000 \text{ People}}\right) \quad (\text{Eq. 2})$$

Finally, I run regression analysis with the outcome as motor vehicle fatality rate for each of the five types of crashes introduced earlier in the paper and their complements. By disaggregating motor vehicle fatality rates into types of crashes, I examine previously unexplored mechanisms that can provide insight into the pro-cyclical patterns of motor vehicle deaths.

Results

Descriptive Trends

I first show descriptive trends of the independent and dependent variables during this study period. Figure 2a illustrates the large variation in average state unemployment rate between 2003 and 2013. At the onset of the Great Recession in 2007, unemployment rate sits low at just under 4.5 percent on average across states but soon jumped to almost 9 percent at the end of the recession in 2010. In more recent years, unemployment rate on average has experienced a steady decline and is on pace to return to pre-recession levels.

Figure 2b shows the trend for total motor vehicle fatality rate during the 11-year study period. Average state motor vehicle fatality rate holds steady at above 16 per 100,000 from 2003 to 2006. In 2007, the average fatality rate drops below 16 per 100,000 and continues to fall until it reaches just below 12 per 100,000 in 2011. After an increase in 2012, average motor vehicle fatality rate falls to the lowest level in 2013. The decline in average motor vehicle fatality rates is 8.4 percent annually during the years of the Great Recession in 2007–2009, which is significantly larger than the declines from 2003–2006. Figure 2c and 2d compares the trend between the risk and exposure components of the decomposition in Equation 2. The trend in risk (2c) is represented by average state motor vehicle deaths per

million VMT while exposure (2d) is the average state million VMT per 100,000 people. Whereas the risk term appears to mimic the fatality rate trend in Figure 2c, the exposure component remains relatively flat from 2003 to 2013.

Detrended Relationships

Figures 3a to 3f illustrate bivariate relationships between unemployment rate and different types of motor vehicle fatality rates from 2003 to 2013. All rates have been detrended and normalized in order to understand associations as rates rise above and below the linear trend measured in standard deviations from the mean rate. Figure 3a clearly shows the pro-cyclical nature of all motor vehicle fatality rates – as the economy improves in the first half of the study period (using the proxy of unemployment declining below the trend), motor vehicle fatality rates increase above the trend. I find the pro-cyclical pattern to persist into the second half of the study period.

The rest of the Figure 3 examines complementary pairs of motor vehicle fatality rates with unemployment rate. Moving from Figures 3b to 3f, I compare large truck and non-large truck fatality rates (3b), speeding and non-speeding fatality rates (3c), drunk and non-drunk fatality rates (3d), single and multiple vehicle fatality rates (3e), and rural and urban fatality rates (3f). While pro-cyclical nature cannot be visually determined alone, several noticeable deviations around the timing of the Great Recession should be mentioned. The graph in Figure 3b shows that fatalities involving large trucks (triangle icon) decline to over two standard deviations below the mean in 2009 compared to less than one standard deviation below the mean for non-large truck fatality rates (square icon). Similarly, in Figure 3f, fatality rates in urban areas (triangle icon) drop to almost two standard deviations below the mean in 2009 compared to rural fatality rates (square icon) which deviate less than one standard deviation below the mean. The patterns for the other pairs, including drunk and non-drunk fatalities, are rather similar, and procyclicality for all the pairs cannot be discerned by the graphs alone. However, fatalities involving large trucks falls sharply toward the end of the Great Recession and could be a significant contributor to the pro-cyclical relationship between unemployment and motor vehicle fatalities.

Regression Analysis

Building on the descriptive graphs, I run multivariate regression analysis to assess the significance of the associations at the state-level. Table 1 displays the regression results for the association between state unemployment rate and total state motor vehicle fatality rate. The coefficient in the first model with just state fixed effects and national linear time trend is -0.0282 ($p < 0.05$). For each percentage point increase in unemployment rate, motor vehicle fatality decreases by 2.82 percent. With the inclusion of tax and policy controls, the coefficient changes slightly to -0.0288 ($p < 0.05$). Results from Table 1 suggests that the significant, pro-cyclical nature of motor vehicle fatality has persisted in the recent decade and through the Great Recession.

In order to better understand what is driving the pro-cyclical nature of motor vehicle fatalities, I decompose total motor vehicle fatality rate into aforementioned risk and exposure components. As stipulated by Equation 2, the regression coefficient from the risk

and exposure components would add up to the coefficient for total fatality rate (-0.0288). Table 2 presents this decomposition result with three different models that have the same independent variables but three different outcomes (i.e. total fatality rate, risk component, and exposure component). The interpretation for Table 2 is that for each percentage point increase in unemployment, the risk (i.e. fatalities per million VMT) decreases by 2.5 percent ($p<0.05$) compared to a 0.4 percent nonsignificant decrease in the exposure (i.e. a million VMT per 100,000 people). The decomposed coefficients also mean that the risk component accounts for 88 percent ($0.0252/0.0288$) of the motor vehicle pro-cyclical relationship. This finding is not surprising given the descriptive graph in Figure 2d depicts a flat line for the exposure component.

After establishing that the risk, and not exposure, accounts for almost all of the motor vehicle pro-cyclical relationship, I now examine the relationship between unemployment and various crash types in order to pinpoint specific types of crashes that elevate fatality risk. Table 3 presents the regression coefficients for unemployment rate for the five types of crashes and their complements. I only show the main unemployment coefficients in Table 3 because only three coefficients for the control variables have significant associations with the outcome. Detailed results with all coefficients are presented in Table A2. Although adding tax and policy control variables do not change the unemployment coefficients significantly, I direct my attention to the results in the second and fourth column with the full control variables included.

The first row of Table 3 compares the cyclical relationship between motor vehicle fatalities involving large trucks and those not involving large trucks. The regression coefficients for large truck fatalities is significant at -0.0837 ($p<0.001$). Each percentage increase in unemployment rate equates to an 8.4 percent decrease in fatalities involving large trucks. In contrast, fatality rates for crashes that do not involve large trucks are not significant (coefficient = -0.0207 , NS).

The second row examines fatality rates for crashes involving speeding and those not involving speeding. Results show speeding-related fatalities are significantly pro-cyclical (coefficient = -0.0503 , $p<0.05$) while fatalities not involving speeding are not significantly procyclical (coefficient = -0.0201 , NS). Each percentage increase in unemployment rate is met with a 5.3 percent decrease in speeding-related motor vehicle fatalities.

Moving onto the next row in Table 3, I find that both drunk driving and non-drunk driving fatalities are significantly pro-cyclical. When unemployment increases by one percentage point, drunk driving fatality rates are expected to fall 3.6 percent ($p<0.05$) compared to 2.5 percent for non-drunk driving fatality rates ($p<0.05$).

The fourth row compares single-vehicle fatalities and multi-vehicle fatalities. I find multi-vehicle fatality rates to be pro-cyclical whereas single-vehicle fatality rates are a-cyclical. Multi-vehicle fatality rates are expected to decline 4.1 percent ($p<0.05$) as unemployment rate climbs by one percentage point compared to only a 2 percent (NS) decrease for single-vehicle fatality rates.

Finally, the last row in Table 3 shows regression coefficients for rural and urban motor vehicle fatality rates. Fatality rates in urban areas respond more strongly to changes in unemployment. For each percentage point increase in unemployment rate is expected to lower urban fatality rates by 4.6 percent ($p < 0.05$) and rural fatality rates by 1.7 percent (NS).

Collectively, the results in Table 3 reveal significant pro-cyclical motor vehicle fatality for crashes involving large trucks, crashes involving speeding, multi-vehicle crashes, crashes in urban areas, and both drunk and non-drunk driving crashes. Although past research singularly focuses on drunk driving crashes as an explanation for motor vehicle fluctuations, these results illuminate other types of crashes that sync with the macroeconomic cycle.

Additional Analysis

To rule out the alternative hypothesis that alcohol-related driving is the underlying cause of these other types of fatal crashes, I conduct the same regression analysis with only fatalities involving no alcohol ($BAC = 0$) to see if the results remain robust. If these other types of crashes are indeed related to drunk driving, then the significant results in Table 3 would not hold in the no-alcohol involved sample. Table 4 shows the results of this additional analysis for the four types of crashes – those involving large trucks, speeding vehicles, multiple vehicles, and in urban areas. All the regression coefficients remained robust in Table 4 except for urban crashes which are no longer significant due to larger standard errors (coefficient = -0.0408 , NS). For speeding crashes and multi-vehicle crashes, each percentage point increase in unemployment is associated with a 5.4 and 3.9 percent decrease (both $p < 0.05$) in fatality rates, respectively. The same increase in unemployment is expected to decrease no-alcohol related large truck fatality rates by over 10 percent ($p < 0.001$).

Discussion and Conclusion

Following up on the objectives of the paper, my results confirm that total motor vehicle fatality has remained strongly pro-cyclical in the recent decade including the years through the Great Recession. For all fatal motor vehicle crashes, each percentage point increase in unemployment rate predicts a significant 2.9 percent decrease in fatality rate. Both the magnitude and the direction of this association is consistent with or even larger than those in past findings (Cotti and Tefft, 2011; French and Gumus, 2014; Ruhm, 2015). I also show that the risk of fatalities per million VMT contributes 88 percent to the magnitude of the pro-cyclical relationship. The significance of the risk component also aligns with previous findings (Cotti and Tefft, 2011). This result suggests that reductions in motor vehicle fatalities during economic downturns cannot be explained by fewer miles driven on average but by reduction in the risk of death per miles driven.

More importantly, the results offer new explanations for why motor vehicle fatality rates fluctuate with changes in unemployment. Previous studies have almost solely focused on drunk driving as the explanation for pro-cyclical motor vehicle fatality (Wagenaar and Streff, 1989; Ruhm, 1995, Cotti and Tefft, 2011). Contradicting Cotti and Tefft's (2011) previous assertion that only drunk driving fatalities are pro-cyclical, I find both drunk-driving and non-drunk driving related crashes to exhibit pro-cyclical patterns. Combined with the

significant findings by crash type, I dismantle the existing explanation that changes in drunk driving alone are sufficient to explain the pro-cyclical of motor vehicle fatalities.

The most compelling finding is that fatalities involving large truck are predicted to drop over 8 percent for each percentage point increase in unemployment rate. Among crashes without alcohol, large truck fatalities are expected to decrease by an astonishing 10 percent for each percentage point rise in unemployment rate. These numbers stand in stark contrast to only a nonsignificant 2 percent decrease in fatalities not involving large trucks given the same change in unemployment rate. Large trucks over 10,000 lbs, as defined in this paper, are most likely tied to commercial uses. French and Gumus (2014) previously raise the (untested) hypothesis that motor vehicle fatalities increase during economic booms because of the changing composition of vehicles on the road. Specifically, more trucks on the road could lead to more dangerous driving conditions and more severe crashes for smaller passenger cars and motorcycles. Figure 4 shows the trend for proportion of truck registrations as a proxy for truck composition. Indeed, while proportion of truck registration climbs steadily in the beginning of the study period, it stalled during the Great Recession from 2007 to 2009 before rising again. This trend supports the hypothesis that fatalities involving large trucks increase when the economy improves because of changes in vehicle mix.

The results also reveal significant pro-cyclical relationships between unemployment and crashes involving multiple-vehicles and those in urban areas. A temporary increase in these types of crashes, along with commercial trucks, when the economy improves suggests mechanisms related to congested urban traffic. While the decomposition analysis does not find *number* of miles travelled to vary with the economic cycle, it is possible that the distance travelled remain relatively stable but are *distributed* differently across economic cycles. For instance, cars might be more likely to be travelling at the same time along the same flow of traffic, syncing with a typical commuting schedule. In that case, driving during economic booms can increase drivers' exposure to other cars on the road by driving at the same time, thus elevating their risk of colliding in a multi-vehicle crash. While multi-vehicle crashes remain robust to the analysis of only no-alcohol involved crashes, results for urban crashes are no longer tenable in the same analysis, suggesting that urban fatalities are more likely related to drunk driving. These new findings on the significant pro-cyclical of multi-vehicle crashes and, to a lesser extent, urban crashes expand our current understanding of mechanisms beyond the drunk driving paradigm.

I also test the hypothesis that speeding-related fatalities increase during temporary economic improvements. Proposed by Cotti and Tefft (2011), the theory is that people are more likely to drive in a hurry when the opportunity cost of time is high. Speeding-related fatalities are indeed significantly pro-cyclical even when I exclude alcohol-related crashes, suggesting that speeding is not only a by product of drunk driving behaviors (Liu, Chen, Subramanian, & Utter, 2005). Instead, the risk of speeding fatalities is a function of opportunity costs.

This study is not without limitations. First, FARS data is based on aggregated reports, including original police reports at the scene of the crash. The reliability of these reports may come into question with less concrete variables, such as speeding, which are based on

eyewitness reports. However, even without witnesses, excessive speeding may be inferred from the severity of the crash. A second limitation lies in operationalizing exposure to motor vehicle crash. Vehicle miles travelled (VMT) only measures exposure by distance and does not capture total time spent driving or exposure to numbers of cars on the road. Another potential problem with VMT is that the average number of passengers in vehicles can vary across time due to changes in carpooling, for example, and thus lead to variations in exposure not captured by VMT. However, data from the U.S. Census Bureau suggests that carpooling rates for commuting purposes have experienced a small and steady decline with no observable differences during the recent recession (McKenzie and Rapino, 2011; McKenzie, 2015). Nevertheless, I include VMT because it is a reliable, nationally reported measure that has been consistently used in previous studies. Future research can explore different exposure factors by taking advantage of transportation time-use data such as those from the National Household Travel Survey. Finally, there is an issue with endogeneity and causality. To alleviate concerns of endogenous variables, I include state fixed effects and national time trends in the regression. Even with fixed effects and a host of state-level controls, I am not able to account for other unobserved, time-varying variables that might correlate with the independent and dependent variables. Moreover, the regression results can only suggest strong associations between macroeconomic change and fatality rates rather than causal relationships. While I cannot rule out reverse causation, it is certainly more plausible for state-level unemployment to cause changes in state-level motor vehicle fatality rates than the reverse direction.

The findings carry important implications for informing policy and future research on reducing motor vehicle fatalities. Implementing policies targeting fatalities involving commercial trucks would be valuable toward the goal of reducing total motor vehicle deaths. Future research should examine whether the fault lies with truck drivers or the other drivers. If drivers of commercial trucks are inadequately trained or overworked, then the point of intervention should start in the trucking industry. On the other hand, perhaps passenger car drivers do not know how to navigate around large trucks. In that case, urban planner and road safety organizations should determine how to improve driving conditions when large and small vehicles share the road. Another direction for future research is to understand how time and space constraints can explain the pro-cyclical patterns of these crashes. Commercial activity on the road may be occurring at the same time each day, creating congested roads that make navigating traffic difficult and unsafe. If these types of fatal crashes take place at certain times, such as during rush hour, policy implications might be to incentivize workers to take public transportation, implement telework programs, or create different routes for commuters and commercial traffic.

The subject of how population-level mortality fluctuates with the economic cycle is of interest to many social scientists. Research on previous recessionary periods suggests that economic downturns may lead to temporary improvements in population health and mortality. But Ruhm's (2015) recent paper asserts that pro-cyclical of total mortality have waned in the recent cycle because some causes of death, such as cancer and poisoning, have emerged as counter-cyclical. Despite weakening relationships for the overall trend, motor vehicle crash is one of the few causes of death that remains pro-cyclical through recent years (Ruhm 2015). The findings in this paper bolster evidence on the persistent strength of motor

vehicle fluctuations across the economic cycle. My findings reveal the important role large truck, multi-vehicle, and speeding crashes play in influencing the pro-cyclical relationship. Collectively, these are risk factors that broadly suggests motor vehicle fatality rates rise during economic booms because of a direct increase in commercial activity and brings to light the potential traffic hazards of work itself. The policy implications should help practitioners and policymakers alike pinpoint specific areas where they could intervene to reduce preventable motor vehicle fatalities in the future.

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Appendix

Table A1

Definitions and Sources for Control Variables

Variable	Definition	Sources
Beer Tax	State excise beer tax, per gallon, in 2013 dollars	Tax Foundation
Gas Prices	State gas prices include excise tax, per gallon, in 2013 dollars	U.S. Energy Information Administration
Texting Ban	All-driver ban on texting while driving	McCartt, Kidd, and Teoh (2014); Insurance Institute for Highway Safety (IIHS)
Handheld Ban	All-driver ban on handheld cellphone conversations	McCartt, Kidd, and Teoh (2014); Insurance Institute for Highway Safety (IIHS)
BAC Limit	Blood alcohol content (BAC) limit decreases from 0.10 to 0.08	Alcohol Policy Information System
Seat belt law	Primary enforcement of mandatory seat belt laws	IIHS
GDL	Presence of a graduated driver licensing (GDL) program rated as "good" by the IIHS. A good state GDL program is defined as having a mandatory learner's period of at least 6 months and either a night driving restriction from 10PM or allowing no more than one teen passenger until the age of 17. I select the good rating because many states implemented or upgraded their programs to this top rating during the study period.	IIHS; Dee et al. (2005)

Table A2

Regression Coefficients (SE) for the Relationship between State Unemployment Rate and MV Fatality Rates by Crash Type with Controls, 2003–2013

	Large Trucks	No Large Trucks	Speeding	Non-Speeding	Drunk Driving	NonDrunk Driving	Single-Vehicle	Multi-Vehicle	Rural	Urban
Unemployment Rate	-0.0837*** (0.021)	-0.0207 (0.011)	-0.0503* (0.020)	-0.0201 (0.013)	-0.0362*** (0.014)	-0.0254* (0.011)	-0.0202 (0.011)	-0.0406* (0.016)	-0.0174 (0.013)	-0.0457* (0.019)
Beer Tax (in 2013 \$)	0.1023 (0.125)	-0.0262 (0.048)	-0.0644 (0.134)	0.0182 (0.056)	-0.0460 (0.058)	0.0250 (0.064)	-0.0273 (0.048)	0.0420 (0.085)	-0.0060 (0.067)	0.0730 (0.095)
Gas Prices (in 2013 \$)	0.3876* (0.170)	0.0879 (0.069)	-0.0388 (0.208)	0.2127* (0.088)	0.0683 (0.134)	0.1280 (0.075)	-0.0071 (0.076)	0.2744* (0.123)	0.1450 (0.143)	-0.1070 (0.162)
Texting Ban	0.0199 (0.047)	0.0150 (0.021)	0.0449 (0.065)	-0.0015 (0.029)	0.0310 (0.034)	0.0269 (0.024)	0.0290 (0.025)	0.0069 (0.028)	-0.0007 (0.042)	0.1095 (0.077)
Handheld Ban	-0.0182 (0.066)	-0.0363 (0.039)	0.1147 (0.156)	-0.0747 (0.041)	-0.0191 (0.053)	-0.0626 (0.038)	-0.0256 (0.041)	-0.0681 (0.052)	-0.0958 (0.056)	-0.0533 (0.065)
BAC Limit	-0.0221 (0.096)	-0.0217 (0.057)	0.0362 (0.100)	-0.0566 (0.045)	-0.0161 (0.060)	-0.0212 (0.053)	-0.0154 (0.061)	-0.0091 (0.044)	0.0476 (0.068)	-0.0944 (0.083)
Seatbelt Law	0.0268 (0.052)	-0.0118 (0.026)	-0.0433 (0.051)	-0.0017 (0.032)	-0.0412 (0.037)	-0.0024 (0.027)	-0.0203 (0.032)	0.0004 (0.027)	-0.0229 (0.049)	-0.1096 (0.062)
GDL	0.0313 (0.040)	0.0167 (0.022)	0.0447 (0.065)	0.0112 (0.028)	0.0273 (0.034)	0.0049 (0.022)	0.0222 (0.025)	0.0068 (0.026)	0.0111 (0.042)	0.0524 (0.041)

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- Motor vehicle (MV) fatalities exhibit strong pro-cyclical patterns in the recent decade.
- Crashes involving large commercial trucks offer a new explanation for the pro-cyclical pattern.
- Unemployment may affect MV fatalities by directly impacting commercial activities on the road

Figure 1.
Examples of Trucks over 10,000 lbs
Source: Michigan Automobile Insurance Placement Facility, 2015

Figure 2.
Descriptive Trends for Main Independent and Dependent Variables, 2003–2013

Figure 3.
Detrended and Normalized Rates for Unemployment and MV Fatalities, 2003–2013

Figure 4.
Truck Registrations As Percent of All Motor Vehicle Registrations, 2003–2013

Table 1

Regression Coefficients (SE) for the Relationship between State Unemployment Rate and Total MV Fatality Rate, 2003–2013

	Total MV Fatality Rate	Total MV Fatality Rate
Unemployment Rate	−0.0282 *	−0.0288 *
	(0.012)	(0.012)
Beer Tax (in 2013 \$)		0.0006
		(0.057)
Gas Prices (in 2013 \$)		0.1156
		(0.075)
Texting Ban		0.0201
		(0.021)
Handheld Ban		−0.0409
		(0.040)
BAC Limit		−0.0144
		(0.050)
Seat Belt Law		−0.0114
		(0.027)
GDL		0.0158
		(0.022)

Includes state fixed effects and national linear time trend.

*
p<0.05,

**
p<0.01,

p<0.001

Source: FARS, NHTSA, 2003–2013

Table 2

Decomposing Regression Coefficients (SE) into Risk and Exposure of MV Fatality Rate, 2003–2013

	MV Fatality Rate (Fatalities per 100,000)	Risk Component (Fatalities per Million VMT)	Exposure Component (Million VMT per 100,000)
Unemployment Rate	−0.0288 *	−0.0252 *	−0.0036
	(0.012)	(0.010)	(0.004)
Beer Tax (in 2013 \$)	0.0006	−0.0109	0.0115
	(0.057)	(0.044)	(0.026)
Gas Prices (in 2013 \$)	0.1156	0.0396	0.0760 *
	(0.075)	(0.082)	(0.035)
Texting Ban	0.0201	0.0155	0.0046
	(0.021)	(0.019)	(0.010)
Handheld Ban	−0.0409	−0.0366	−0.0044
	(0.040)	(0.034)	(0.016)
BAC Limit	−0.0144	−0.0182	0.0038
	(0.050)	(0.047)	(0.013)
Seat Belt Law	−0.0114	−0.0046	−0.0068
	(0.027)	(0.024)	(0.011)
GDL	0.0158	0.0060	0.0099
	(0.022)	(0.021)	(0.010)

Includes state fixed effects and national linear time trend.

*
p<0.05,**
p<0.01,***
p<0.001

Source: FARS, NHTSA, 2003–2013

Table 3

Regression Coefficients (SE) for the Relationship between State Unemployment Rate and MV Fatality Rates by Crash Type, 2003–201

No controls	Full controls	No controls	Full controls
<u>Large Trucks</u>	<u>Large Trucks</u>	<u>Non-Large Trucks</u>	<u>Non-Large Trucks</u>
–0.0761 ***	–0.0837 ***	–0.0207	–0.0207
(0.021)	(0.021)	(0.011)	(0.011)
<u>Speeding</u>	<u>Speeding</u>	<u>Non-Speeding</u>	<u>Non-Speeding</u>
–0.0449 *	–0.0503 *	–0.0199	–0.0201
(0.022)	(0.020)	(0.013)	(0.013)
<u>Drunk Driving</u>	<u>Drunk Driving</u>	<u>Non-Drunk Driving</u>	<u>Non-Drunk Driving</u>
–0.0357 **	–0.0362 *	–0.0255 *	–0.0254 *
(0.013)	(0.014)	(0.011)	(0.011)
<u>Single-Vehicle</u>	<u>Single-Vehicle</u>	<u>Multi-Vehicle</u>	<u>Multi-Vehicle</u>
–0.0206	–0.0202	–0.0389 *	–0.0406 *
(0.011)	(0.011)	(0.016)	(0.016)
<u>Rural</u>	<u>Rural</u>	<u>Urban</u>	<u>Urban</u>
–0.0191	–0.0174	–0.0455 *	–0.0457 *
(0.014)	(0.013)	(0.018)	(0.019)

Includes state fixed effects and national linear time trend.

*
p<0.05,

**
p<0.01,

p<0.001

Source: FARS, NHTSA, 2003–2013

Table 4

Regression Coefficients (SE) for the Relationship between State Unemployment Rate and No-Alcohol Involved MV Fatality Rates, 2003–2013

	Large Trucks	Speeding	Multi-Vehicle	Urban
Unemployment Rate	−0.1038 ***	−0.0541 *	−0.0394 *	−0.0408
	(0.023)	(0.024)	(0.017)	(0.022)
Beer Tax (in 2013 \$)	0.1439	0.1198	0.1302	0.1151
	(0.140)	(0.186)	(0.087)	(0.130)
Gas Prices (in 2013 \$)	0.4671	0.0054	0.3018 *	−0.1844
	(0.252)	(0.201)	(0.125)	(0.242)
Texting Ban	0.0328	0.0867	0.0412	0.0589
	(0.062)	(0.080)	(0.043)	(0.060)
Handheld Ban	−0.0407	0.0446	−0.2055 **	−0.1065
	(0.070)	(0.151)	(0.063)	(0.056)
BAC Limit	−0.2195	−0.0671	−0.177	−0.3008 *
	(0.161)	(0.120)	(0.101)	(0.147)
Seat Belt Law	−0.0296	−0.1109	−0.0096	−0.0584
	(0.072)	(0.074)	(0.043)	(0.063)
GDL	0.0049	0.0046	−0.0319	0.0255
	(0.096)	(0.080)	(0.048)	(0.053)

Includes state fixed effect and national linear time trend

*
p<0.05,

**
p<0.01,

p<0.001

Source: FARS, NHTSA, 2003–2013