2019

THE RELATIONSHIP BETWEEN COMMUTING HABITS AND MORTALITY RATES IN THE UNITED STATES

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By

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Bachelor of Arts in Economics, University of Montana, Missoula, MT, 2017

Thesis

presented in partial fulfillment of the requirements
for the degree of

Master of Arts
in Economics

The University of Montana
Missoula, MT

August 2019

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Abstract

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In recent years, policy makers have invested in public transportation and infrastructure to promote walking and cycling to work. There is also a large body of economic research that has found mortality rates increase during economic expansions. While there has been a number of epidemiological studies that investigate the impact of commuting mode choice on individual health outcomes, there is a lack of research on the aggregate health effects of alternative transportation methods, such as biking, walking, or using public transportation. This paper uses a fixed-effect model to investigate the impact of an increase in total employment on mortality rates, and whether the impact of increased employment on mortality varies between counties with differing commuting habits.

Findings suggest an increase in total employment is associated with a decrease in all-cause, respiratory, and suicide mortality rates, and that this effect is stronger in counties with a lower than median proportion of commuters who drive to work, and in counties with a higher than median proportion of commuters who walk, bike, or take public transportation to work. The principal conclusions of this paper are two-fold: first, procyclical fluctuations in mortality rates found in previous studies do not come from higher total employment; and second, findings provide evidence that an increase in total employment decreases mortality rates more in communities which have a relatively high proportion of pedestrians, cyclists, and public transportation users, and a relatively low proportion of commuters dependent on personal automobiles.

1 Introduction

The debate about transportation infrastructure has reached a fevered pitch in recent years. Cities from Missoula, Montana to New York City have implemented policies designed to limit congestion on major roadways, and invested significant time, energy, and money into installing bike lanes and pedestrian facilities (Sadik-Khan, 2017). This has lead to backlash from auto commuters concerned about increased congestion induced by fewer lanes devoted to automobile traffic, a reduction in parking spaces, and potential collisions with cyclists and pedestrians. The potential health impacts of varied commuting modes often go overlooked for the more immediate concerns of convenience and conflict between commuters who choose different means of transportation to work.

Cities' varied policy responses to the debate about infrastructure for different transportation modes has created large variations in commuting characteristics between counties. For example, in the sprawling metropolitan area of Atlanta the average person travels 34.1 miles per day in an automobile. Denser urban areas like Philadelphia and Chicago are much less car-dependent, with the average person travelling 16.9 miles per day by car in Philadelphia, and 19.9 miles per day in Chicago (Frumkin, 2016).

Despite the push for less auto-dependent communities in many cities in the United States, there have been few econometric studies on the impact of investment in pedestrian friendly infrastructure or public transit use on mortality rates. This question is difficult to answer from an econometric perspective, given the likelihood of endogeneity issues associated with commuting decisions and mortality rates. In particular, it is likely that differences in commuting habits in a community are related to other community characteristics, like active lifestyles and eating habits, that influence mortality rates. This issue is less concerning when using longitudinal data and a fixed effects model, but the potential for endogeneity issues still exists. In order to mitigate these issues I employ a novel identification strategy, using the business cycle as a source of exogenous variation in the amount of commuting to estimate the impact of commuting characteristics on mortality outcomes.

I use increases in total employment as a source of exogenous variation in the amount of commuting at the county level. I show that an increase in employment is associated with an increase in aggregate travel time to work, and that an increase in total employment does not significantly effect the proportion of commuters that use a given mode of transportation. I categorize each county by whether it has a higher or lower than median proportion of commuters who drive to work, walk or bike to work, and take public transportation to work, then use business cycle fluctuations as a source of exogenous variation in the amount of commuting to estimate the impact of a change the level of employment on mortality rates in counties with different commuting characteristics.

Previous economic studies have found that mortality follows a procyclical pattern, implying that expanding business cycles and a lower unemployment rate lead to increases in mortality rates (e.g. Ruhm, 2000, 2007; Miller, Page, Stevens, & Filipski, 2009). The present study is also a continuation of the research investigating the relationship between employment and mortality by estimating whether mortality rates change differently in counties with different commuting characteristics, given an increase in total employment.

This paper presents two primary findings. First, results suggest that an increase in total employment decreases all-cause, respiratory, and suicide mortality rates. These findings do not directly contradict earlier studies which find that mortality fluctuates procyclically because total employment and the unemployment rate can (and often do) move in the same direction. In fact, the results of previous studies implying procyclical fluctuation in mortality rates is corroborated with the data in this study when the unemployment rate is used instead of total employment. That said, this research suggests an increase in employment and an increase in the unemployment rate could reduce mortality rates if both occured simultaneously due to an increase in the the labor force. Second, this paper provides evidence that an increase in employment is associated with a greater decrease in mortality rates in counties that have a high proportion of active commuters and public transportation users, or a low proportion of commuters who drive to work. Results indicate that a 1% increase in total employment is associated with 881 fewer deaths in counties with a relatively low proportion of auto-dependent commuters, but a statistically insignificant increase of 14 deaths in counties with a relatively high proportion of auto commuters. This suggests that further investment in infrastructure and policies that promote alternative forms of transportation may attenuate the negative impacts, or amplify the beneficial effects of an expanding business cycle on mortality rates.

2 Literature Review

Recently, policy makers increased their focus on commuting as a predictor of life satisfaction, and potential public health issue as a source of stress and pollution (Legrain, Eluru, & El-Geneidy, 2015a; Evans & Wener, 2006). This has coincided with a significant amount of economic research that finds mortality varies procyclically, implying that improving economic conditions are associated with higher mortality rates (e.g. Ruhm, 2000, 2015; Granados, Roux, & Portes, 2009). If a community is dependent on cars to get to a place of employment, the increase in commuters associated with a strong economy will lead to more stress, obesity, pollution, which negatively effect health outcomes. On the other hand, if a community has invested heavily in infrastructure for bikers, pedestrians, and public transit use, an increase in employment will lead to more people doing moderate amounts of exercise to get to work, and the increase in pollution will not be as severe, possibly leading to better health outcomes. This section will first review literature regarding the impacts of commuting habits and transportation mode on health outcomes, followed by a closer examination of the health impacts of active commuting, before concluding with a brief summary of the literature regarding procyclical fluctuations in mortality rates.

2.1 Health Impacts of Commuting

Long car commutes, particularly on crowded highways, have been shown to be associated with high blood pressure, increased cholestrol, and an increased risk of obesity and heart attack (Samimi & Mohammadian, 2009). In a study of middle-aged men and women, Kan et al. (2008) find long term exposure to traffic increased participants' risk of developing coronary heart disease, and Hoek, Brunekreef, Goldbohm, Fischer, and van den Brandt (2002) find that living near a major road was associated with an increase in deaths due to cardiopulmonary diseases and lung cancer among a cohort aged 55-69. Other studies have found the increases in pollution and noise associated with traffic cause increased risk of heart disease, lung cancer, and a host of other health issues (Foraster et al., 2011; K. Zhang & Batterman, 2013).

Epidemiological studies investigating the impact of commute time and transportation mode on health outcomes have consistently found long commutes to be associated with a host of health issues. Hansson, Mattisson, Björk, Östergren, and Jakobsson (2011) find a longer commute is associated with more reported sleep disturbances, stress, and exhaustion, lower self-reported health, and more absences from work due to illness. Generally, epidemiological literature on the impact of commuting finds that long car commutes are associated with negative health effects (Legrain, Eluru, & El-Geneidy, 2015b; Oliveira, Moura, Viana, Tigre, & Sampaio, 2015), although these studies use cross-sectional data sets and could be biased by unobserved characteristics that impact both commuting characteristics and health outcomes.

Künn-Nelen (2016) uses a fixed effects model and finds long distance commuters report worse subjective health outcomes, and more visits to a general practitioner, with the effect being particularly strong among car commuters. Knittel, Miller, and Sanders (2016) employ an instrument variable (IV) approach to determine the impact of air pollution on infant health, exploiting seasonal variation in pollution levels in California, and find that higher levels of traffic increase infant mortality. A study by Currie and Walker (2011) also uses an IV approach to exploit variations in traffic congestion due to electronic toll systems, and finds a decrease in congestion significantly decreased occurrences of premature birth and low birth weight among women within 2 kilometers of toll systems, providing further evidence that increases in traffic can have significant impacts on populations around busy roadways. These findings indicate that commuting characteristics could have significant impacts on non-commuters in traffic dense areas, and raise the possibility that an increase in vehicle commuters could impact non-traffic mortality.

A study by Sandow, Westerlund, and Lindgren (2014) use a propensity score matching strategy on a panel of 55 year old Swedes from 1985-2008, and find that a long commute was associated with a significantly higher mortality rate among women, but not among men. This model relies on the assumption that the decision of one individual to become a long distance commuter does not impact the mortality of other commuters. Given the amount of pollution and congestion that long distance commuters cause, this assumption is unlikely to hold. This means that propensity score matching techniques are likely to underestimate the impact of long distance commuting on mortality rates, because they only capture the impact of an individual becoming a long term commuter on their own mortality. Using an aggregate measure of commuting decisions in a fixed effects model only requires the assumption that commuting decisions in one geographic area do not impact mortality rates in other areas.

2.2 Active Commuting Methods

The association between health and walking or biking to work is relatively straight forward, with reductions in obesity and related complications being the main causal mechanism driving the relationship. Frank, Andresen, and Schmid (2004) finds a one hour increase in daily car commuting is associated with a 6% increase in the likelihood of obesity, while each additional kilometer walked per day is associated with a 4.8% reduction in the likelihood of obesity. In a study of nearly 100,000 US individuals, Furie and Desai (2012) find active transportation is associated with lower BMI and waist circumference, a lower risk of hypertension and diabetes. In a study of more than 200,000 individuals in the United Kingdom Celis-Morales et al. (2017) find walking decreases the risk of cardiovascular disease, and bicycle commuting is associated with a lower risk of cardiovascular disease, cancer, and all cause mortality. Conversely, automobile use contributes significantly to local air pollution, pedestrian injuries and death, and a lack of physical activity (Maibach, Steg, & Anable, 2009), and X. Zhang et al. (2014) find higher automobile dependency is associated with increased obesity in urban areas, and longer commute times are associated with increased obesity in in large metropolitan, micropolitan, and non-core areas.

Beyond promoting individual health, there is also a collective benefit from increases in active transportation. Jacobsen (2003) finds the probability a person walking or biking being struck by a vehicle varies inversely with the amount of walking/biking in the area, estimating that a doubling of the population walking or biking is associated with a 32% increase in traffic related injuries. This effect is the result of drivers becoming more aware of bicyclists and walkers, and implies that increased health benefits from less obesity and pollution are likely to outweigh the impact of more pedestrian-involved traffic accidents. For example, Lindsay, Macmillan, and Woodward (2011) estimate a 5% shift in vehicle miles travelled to bike trips in New Zealand would lead to 116 prevented deaths due to increased physical activity, 6 deaths prevented from reductions in air pollution, and with only 5 additional deaths due to fatal biking accidents.

2.3 The Business Cycle and Mortality Rates

With few exceptions, studies have found an inverse relationship between the unemployment rate and mortality. Ruhm (2000) employed a panel model to find that, while mortality steadily dropped over the period of observation, mortality rates dropped more slowly in counties with decreasing unemployment rates. Ruhm concludes that a 1 percentage point increase in the unemployment rate decreases all-cause mortality by 0.5%. More recently, Ruhm (2015) finds that the relationship between mortality and unemployment has diminished in recent years, although mortality from cardiovascular diseases and traffic mortality remain procyclical. Strumpf, Charters, Harper, and Nandi (2017) decompose mortality by age group and find a 1 percentage point increase in unemployment is associated with a 9% decrease in mortality due to cardiovascular disease for the elderly, and a smaller, but still significant decrease of roughly 0.5% in traffic mortality among those who were younger than 65. Toffolutti and Suhrcke (2014) examine the relationship between mortality and unemployment in the European Union during the great recession and find a one percentage point increase in unemployment rate is associated with a 3.4% decrease in all-cause mortality, and a 11.5% decrease in motor-vehicle accident related mortality.

Recent studies that look at the relationship between economic activity and traffic mortality rates have used a technique developed by Cotti and Tefft (2011), which decomposes changes in traffic mortality into a "risk" component (represented by fatal accidents per VMT), and an "exposure" component (represented by vehicle miles travelled per capita). He (2016) notes that after years of stability, fatalities due to motor vehicle accidents dropped 18% during the 2007–2009 economic crisis. The author uses state-level panel data from 2003-2013 to analyze the impact of changes in VMT on motor vehicle fatality, and estimates the impact of unemployment on motor vehicle mortality rate and finds a 1% increase in unemployment is associated with a 2.8% decrease in the motor vehicle fatality rate. He then uses Cotti and Tefft's decomposition technique, and finds that an increase in the fatality rate per vehicle mile travelled (i.e. the risk of driving per mile) is the primary driver of the effect, corroborating Cotti and Tefft's earlier findings.

3 Data & Empirical Strategy

I use county level data from the 2005-2009 American Community Survey (ACS) on the total number of commuters and means of transportation to work (ACS Table B08006), including number of commuters who drive, use public transportation, walk, and bike for all counties with populations greater than 65,000. This data is used to calculate the proportion of commuters who drive, are active commuters (i.e. commuters who walk or bike), and use public transportation. Employment data is from the Bureau of Labor Statistics Local Areas Employment Statistics tables. Annual data on age and racial demographics is gathered from the Surveillance, Epidemiology, and End Results (SEER) population database, and data on educational attainment and population density comes from one-year ACS estimates from 2005-2017.

Data regarding means of transportation to work is combined with county level mortality rates for different causes of death from the CDC Wonder Underlying Cause of Death database, including transport accidents, diseases of the circulatory system, diseases of the respiratory system, and intentional self harm.[1] All-cause mortality is the total number of deaths per 100,000 people. Transportation mortality includes deaths resulting from any type of transportation related accident, including car crashes, accidents involving pedestrians and bicyclists, industrial accidents involving vehicles, bus collisions, and more. Diseases of the circulatory system include hypertensive diseases, pulmonary and ischaemic heat disease, and diseases involving veins, arteries, and capillaries. Respiratory diseases include respiratory

[1] International Statistical Classification of Diseases and Related Health Problems (ICD-10) Codes for transportation deaths: V01-V99, diseases of the circulatory system: I00-I99, diseases of the respiratory system: J00-J98, and intentional self harm: X60-X84

infections, influenza and pneumonia, lung disease, and chronic respiratory conditions. Infectious and parasitic diseases include intestinal infections, tuberculosis, viral infections, and sexually transmitted infections. Demographic data from the SEER population database on age, racial makeup, and population density, and educational attainment data from the American Community Survey (table B06009) for each county in the United States will be used to control for variations in age population demographics during the study period.

Table 1: Summary Statistics

	mean	median	sd	observations
Total Population	325,603.05	155,677.00	570,214.07	10,421.00
Employment	152,812.62	72,134.42	265,537.18	10,434.00
All-Cause Mortality Rate	860.22	849.45	219.45	10,396.00
Transporation Mortality Rate	15.41	13.60	8.15	6,047.00
Circulatory Mortality Rate	268.58	261.50	81.54	10,396.00
Respiratory Mortality Rate	87.03	83.50	29.21	10,386.00
Suicide Mortality Rate	14.50	13.70	5.45	5,748.00

Summary Statistics show that the average county in the study has a population of 325,603 people, with 152,812 employed. The mean all-cause mortality rate is 860 deaths per 100,000 population. Circulatory mortality is the most common cause of death with 269 deaths per 100,000, and respiratory mortality (87 deaths/100,000). Deaths due to transportation related injuries (15 deaths/100,000), and suicide (15 deaths/100,000) are far less common. Mortality data is censored in any county with less than ten deaths in a given mortality category.

3.1 Empirical Strategy

Car commuting is the predominant method for Americans to get to work. In the average US county in this study, nearly 90% of commuters travel to work in a car, truck or van, while roughly 3% walk or bike to work, and 2.24% use public transportation. Table 2 shows the median drive proportion is 91.3%, and figure 1 shows the distribution of the percent of commuters who drive to work in the counties included in the analysis is roughly normal. The median proportion of active commuters is 2.35%, and figure 2 shows the distribution of the percent of active commuters is roughly normal with a long right tail. The median proportion of public transit use is 0.81%, and figure 3 shows the proportion of public transit users is skewed left, with more than 60% of observations having almost no public transportation use.

I treat commuting characteristics as time invariant, and create categorical variables for communities with low and high levels of auto-dependence, active commuting, and public transportation use in order to simplify the interpretation of the model. To justify the treatment of commuting characteristics as time invariant, I compare ACS estimates of the percent of drivers, active commuters, and public transportation users from the 2005-2009 ACS, and the 2013-2017 ACS. A summary of this analysis is presented in Table 3. While there has been some changes in commuting habits throughout the study period, most counties saw

Table 2: Summary Statistics for Transportation Characteristics

	mean	median	sd	observations
Drive (%)	89.69	91.34	7.25	10,443.00
Active (%)	3.02	2.35	2.27	10,443.00
Transit (%)	2.24	0.81	5.47	10,443.00

very little change in the proportion of drivers, active commuters, and public transportation users. The proportion of drivers saw the largest average change, with a mean decrease of 0.46%, and a standard deviation of 1.34%. The distribution of the change in the proportion of drivers is shown in Figure 4. The distribution of the change in active commuting is shown in Figure 5, and Table 3 shows active commuting decreased by 0.09% in the average county (sd 0.70). Figure 6 shows the distribution of the change in public transportation use over the course of the study, and Table 3 shows public transportation use saw an average increase of 0.06% (sd 0.50).

Results in Table 4 show that increased employment is associated with an increase in aggregate commute time to work, as proxied by total travel time to work, and that increased employment is not associated with a practically significant change in commuting characteristics. Column 1, which shows the relationship between an increase in employment and travel time to work, shows that a 1% increase in employment is associated with a 0.77% increase in total travel time. While results in column 2 indicate an increase in employment is associated with a slight decrease in the proportion of commuters who drive to work, this result is not practically significant, with a 1% increase in employment being associated with a decrease in the percent of commuters who drive to work of 0.032 percentage points. The relationship between an increase in employment and the proportion of active commuters and

Table 3: Summary of Changes in Commuting Characteristics from 2005-2017

	mean	sd	min	max
Δ Drive (%)	-0.458	1.34	-5.34	6.35
Δ Active (%)	-0.091	0.702	-2.96	5.99
Δ Transit (%)	0.057	0.499	-2.16	3.72

public transportation users, shown in columns 3 and 4, are statistically insignificant.

To construct categorical variables for commuting characteristics, I use the median proportion of commuters using each mode of transportation as a cutoff point. A community is in the low category of auto-dependence (i.e. a $LowDrive$ county) if the proportion of its residents who drive to work is below the median proportion of commuters who drive to work in the 2005-2009 American Community Survey, and is categorized as a $HighDrive$ county if the proportion of commuters who drive to work is above the median level for all counties. For Example, any county with greater than 91.34% of commuters driving is categorized as $HighDrive$. The same procedure is followed to categorize each community as a low, or high active commuting community using the average percent of commuters who walk or bike to work between 2005 and 2009, and for public transit use. Counties with greater than 2.35% of commuters walking or biking to work is categorized as $HighActive$, and any county with greater than 0.81% of commuters using public transportation is categorized as $HighTransit$.

Table 4: Relationship between Employment and Transportation Characteristics

	(1)	(2)	(3)	(4)
	log(Travel Time)	Drive (%)	Active (%)	Transit (%)
log(employment)	0.774***	-3.216***	0.785	1.150
	(0.0208)	(0.827)	(0.421)	(0.589)
Observations	10319	5409	5409	5409

Robust All models include county fixed-effects. Robust standard errors in parentheses..
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

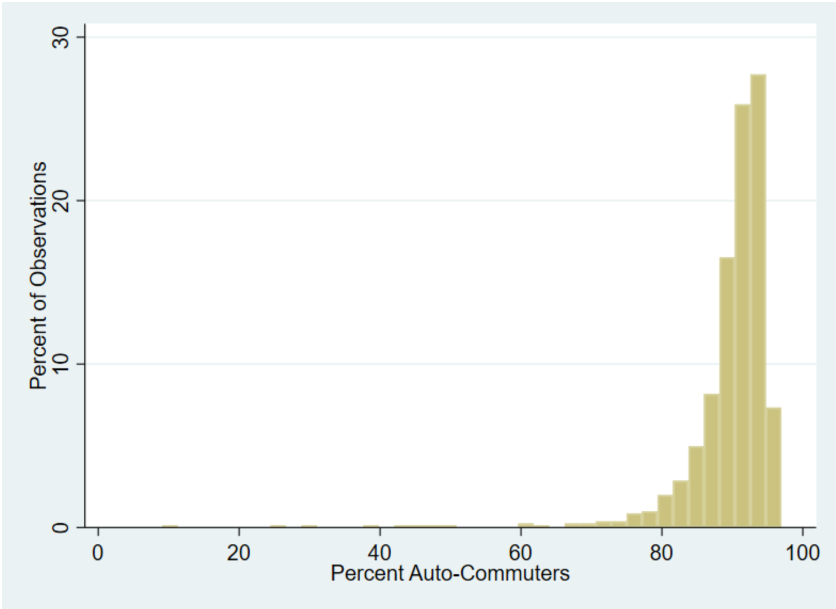

Figure 1: Distribution of the Percent of Auto-Commuters

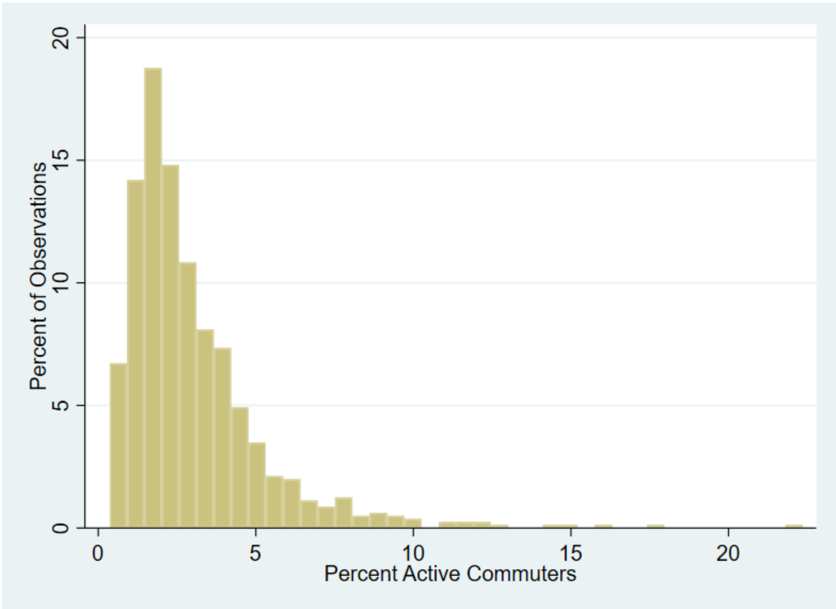

Figure 2: Distribution of the Percent of Active Commuters

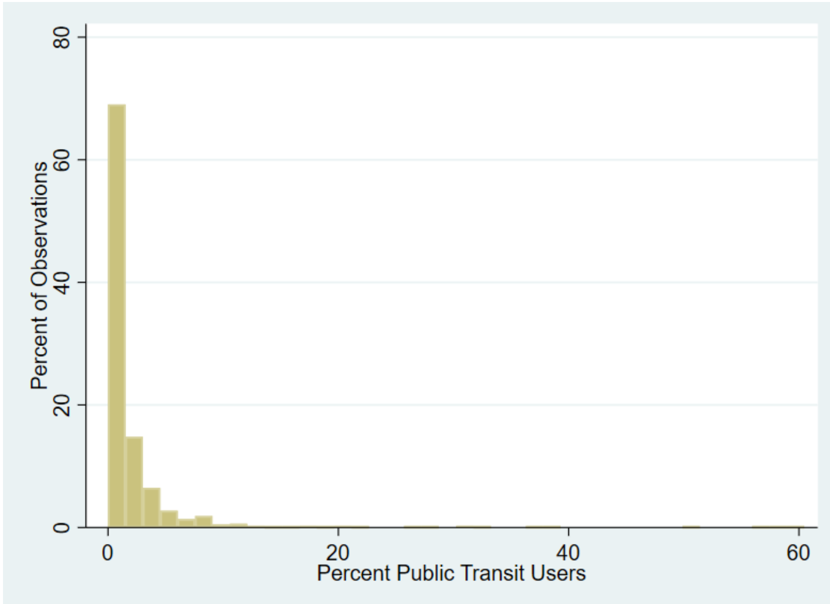

Figure 3: Distribution of the Percent of Public Transit Users

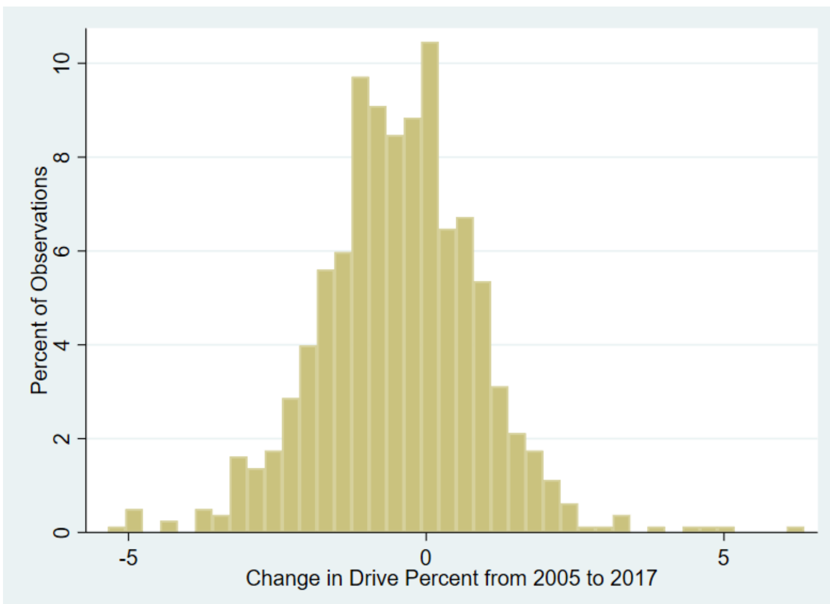

Figure 4: Change in Auto-Commuting Percent from 2005 to 2017

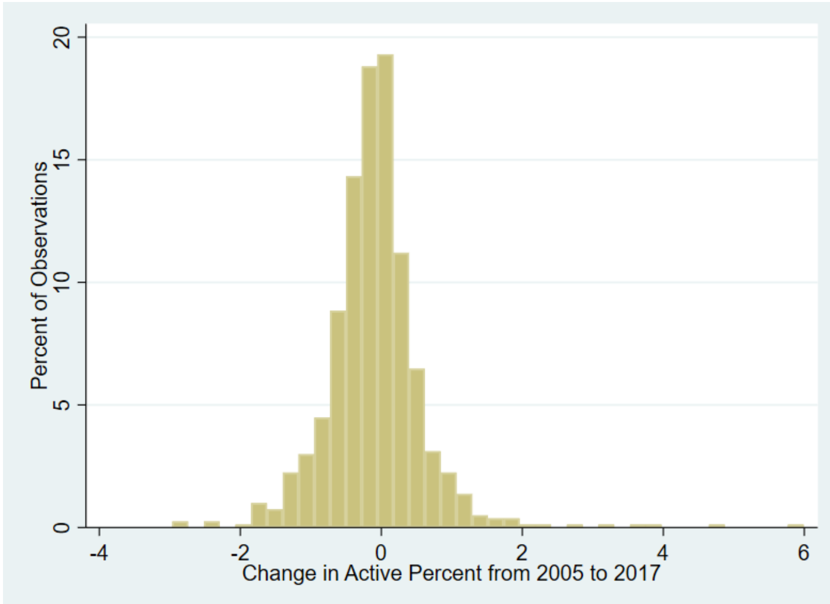

Figure 5: Change in Active Commuting Percent from 2005 to 2017

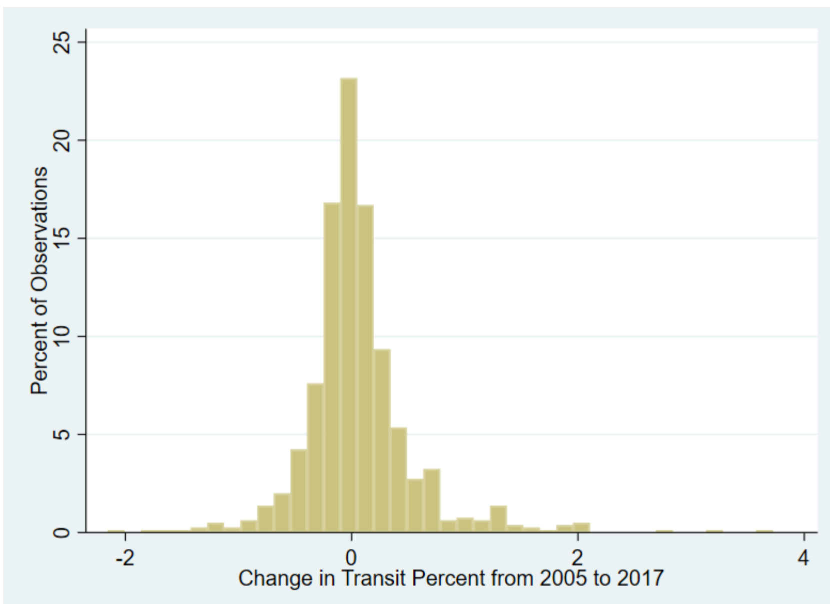

Figure 6: Change in Transit Commuting Percent from 2005 to 2017

Following (Ruhm, 2000), the general econometric treatment to study the relationship between the business cycle and mortality is:

$$mortality_{it} = \alpha_i + \theta_t + \beta_1 * employment_{it} + \gamma * X_{it} + \varepsilon_{it} \tag{1}$$

where $mortality_{it}$ is mortality in county i at time t, $employment_{it}$ represents a business cycle indicator. The variables α_i and θ_t represent county and year fixed effects, respectively, and $\gamma * X_{it}$ is a vector of demographic controls for area i at time t.

I use an interaction between employment and commuting category to model various types of mortality to determine if an increase in employment changes mortality differently depending on the commuting characteristics in a given county.

$$\begin{aligned} mortality_{it} = \alpha_i + \theta_t + \beta_1 * commute_{it} + \beta_2 * employment_{it} + \\ \beta_3 * commute_{it} * employment_{it} + \gamma * X_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

Equation 2 is identical to equation 1, except for the inclusion of $commute_{it}$, which represents the categorical variable constructed for commuting characteristics, and its interaction with the the natural log of the number of employed people ($commute_{it} * employment_{it}$). A fixed-effects model is used to account for any time invariant confounding variables, and a robust set of demographic controls, including the proportion of the population under 20 years old, the proportion of the population between 20 and 49 years old, the proportion of the population between 50 and 59 years old, the proportion of the population between 50 and 59 years old, the proportion of the population between 60 and 79 years old, the proportion of the population who are college graduates, college dropouts, have less than a high school education, the proportion of the population in 3 racial demographics (black, white, and other), the natural log of median income, and the population density of each county are included to control for potentially biasing time-variant community characteristics. This specification allows for estimation of the impact of a change in the unemployment rate on mortality for different proportions of commuters who use the transportation mode of interest (e.g. drive, walk to work).

The categorical variable for commuting characteristics is interacted with the natural log of employment to give estimates of the impact of increased employment on mortality in counties with different commuting characteristics. Because the category does not change within individual counties, the categorical variable $commute_i$ is omitted from the equation due to perfect colinearity in the fixed effects model. To account for potential time variance in commuting habits, I also estimate a model which only includes counties without significant variation in commuting characteristics between 2005 and 2017, and another which only includes counties in the lower and upper quartile of each commuting characteristic to check the robustness of the results.

I also estimate the total change in the deaths associated with a 1% increase in employment using the formula:

$$\Delta Deaths = \frac{\%\Delta MortalityRate_c}{100} * \frac{Mort\overline{ality}Rate_c * Population_c}{100,000} \tag{3}$$

where $\frac{\%\Delta MortalityRate_c}{100}$ is the estimated percent change in the mortality rate in counties in the given commuting category divided by 100 (i.e. $\frac{\beta}{100}$), $Mort\overline{ality}Rate_c$ is the population weighted mean of the mortality rate of all counties in commuting category c, and $Population_c$ is the total population living in in commuting category c.

3.2 Hypotheses

There are two primary hypotheses for this study.

> **H.1** As discussed in Section 2.3, previous studies regarding the relationship between the business cycle and mortality rates suggest that better economic conditions lead to higher mortality rates for all types of mortality, except for suicide mortality. Given these previous findings, I would expect to find an increase in total employment to be associated with a decrease in suicide mortality rates, and an increase in all-cause mortality rates, transportation mortality rates, circulatory mortality rates, and respiratory mortality rates.
>
> **H.2** As discussed in Sections 2.1 and 2.2, epidemiological and economic research the impact of transportation on health outcomes have generally found active modes of transportation to be associated with better health outcomes, and driving to be associated with worse health outcomes. Therefore, I expect low levels of auto-dependence, high levels of active transportation, and high levels of public transportation use to attenuate negative effects or amplify positive effects of increased employment on health outcomes.

4 Results

Results indicate an improving economy (as proxied by the number of employed people in a county) is associated with either a decrease or no significant changes in mortality rates. Table 5 shows the full model specification used for all mortality types, not including interaction terms for commuting characteristics. These results show that a 1% increase in employment is associated with a 0.11% decrease in respiratory mortality, and a 0.17% decrease in suicide mortality, a 0.03% decrease in all-cause mortality, a 0.12% decrease in transportation mortality, and a 0.002% increase in circulatory mortality, although the findings for circulatory mortality are not statistically significant. Using equation 3, the results shown in Table 5 indicate 1% increase in employment is associated with 642 fewer total deaths, with 204 fewer deaths due to respiratory diseases, 67 fewer deaths due to suicide, and 35 fewer deaths due to transportation accidents.

These results contradict previous finding that mortality rates fluctuate procyclically, although regressions run using the unemployment rate in place of total employment do indicate that mortality fluctuates procyclically. These seemingly contradictory findings could be explained by the fact that, while total employment and the unemployment rate are related, they do not always move together. Unemployment rates can increase while total employment increases if more people enter the labor force as employment increases. Conversely, unemployment rates can decrease while total employment decreases if unemployed people drop out of the workforce, although this happens less often (see Figure 7). National employment statistics show that there were a total of thirty months between 2005 and 2017 where the unemployment rate and total employment both increased, and four months during the

Table 5: Full Specification Without Commuting Characteristics

	(1) All-Cause	(2) Traffic	(3) Circulatory	(4) Respiratory	(5) Suicide
log(employment)	-0.0348*	-0.124*	0.00277	-0.102**	-0.193***
	(0.0198)	(0.0659)	(0.0280)	(0.0417)	(0.0712)
Age Under 20	-0.0769***	0.0190	-0.115***	-0.0880***	-0.0118
	(0.00857)	(0.0183)	(0.00945)	(0.0145)	(0.0174)
Age 20-49	-0.0849***	0.0366**	-0.117***	-0.114***	-0.0179
	(0.00879)	(0.0186)	(0.00958)	(0.0144)	(0.0174)
Age 50-59	-0.0708***	0.0445**	-0.109***	-0.0847***	-0.00847
	(0.00974)	(0.0198)	(0.0109)	(0.0159)	(0.0197)
Age 60-79	-0.0586***	0.0341*	-0.0997***	-0.0891***	-0.0103
	(0.00916)	(0.0202)	(0.0100)	(0.0155)	(0.0193)
Black	0.00599***	-0.00338	0.00722***	0.00202	0.00330
	(0.00145)	(0.00485)	(0.00187)	(0.00317)	(0.00502)
Other	-0.00568***	-0.0106	-0.00356	-0.0259***	-0.00304
	(0.00207)	(0.00717)	(0.00280)	(0.00606)	(0.00723)
Less than HS	-0.000469	-0.00520**	0.000318	-0.00336***	0.00118
	(0.000428)	(0.00240)	(0.000712)	(0.00115)	(0.00250)
Some College	-0.000149	-0.00631***	-0.000116	0.000420	-0.000751
	(0.000363)	(0.00220)	(0.000569)	(0.000893)	(0.00207)
College Graduate	-0.000965***	-0.00670***	-0.00132**	-0.000179	-0.00108
	(0.000369)	(0.00198)	(0.000574)	(0.000921)	(0.00195)
Population Density	-5.063***	-4.397**	-6.429***	-4.390	-3.230*
	(0.785)	(2.043)	(1.089)	(2.692)	(1.900)
log(Median Income)	0.0421***	0.201***	0.0253	-0.0284	0.202***
	(0.0124)	(0.0647)	(0.0188)	(0.0287)	(0.0609)
Constant	14.17***	-0.387	16.29***	15.68***	4.077**
	(0.861)	(1.885)	(0.979)	(1.437)	(1.826)
Observations	10256	6023	10256	10256	5747

All models include county fixed-effects. Robust standard errors in parentheses..

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

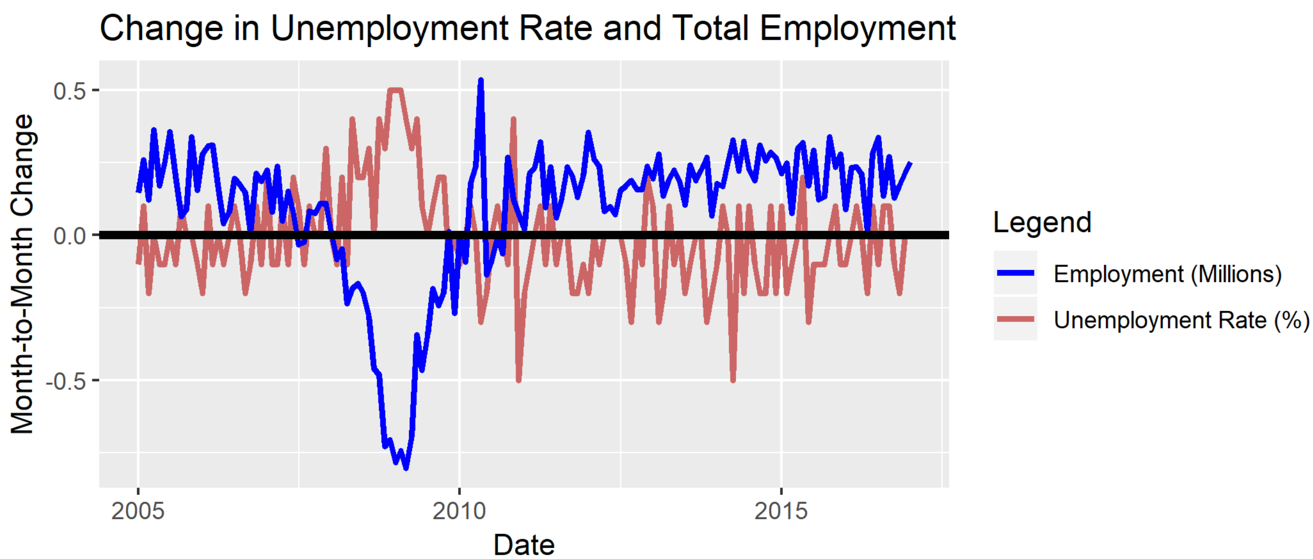

Figure 7: Month-to-month change in total employment and the unemployment rate. Note that there are a number of months where the unemployment rate and total employment move in the same direction.

same time period where the unemployment rate and total employment both decreased in the United States (U.S. Bureau of Labor Statistics, 2019b, 2019a). In roughly one third of the months in the study period total employment and the unemployment rate move in the same direction. For example, in May 2015 employment increased by 319,000 jobs, and the labor force increased by 599,000 workers. These numbers indicate an expanding economy, but the unemployment rate increased by 0.2 due to the large increase in labor force, relative to the increase in employment.

4.1 Analysis with Commuting Characteristics

Results in section 4.1 are organized by cause of death. In all tables in section 4.1, column 1 includes all counties with an average population greater than 65,000 during the study period. Column 2 only includes counties that are in the upper and lower quartile in the relevant commuting category, in other words the middle 50% of observations for the relevant commuting characteristic are excluded. To do this, I construct three separate variables that indicates which quartile of each commuting characteristic a given county is in, and restrict the regression to only include counties in quartiles one and four. Column 3 excludes any counties that had a change in proportion of commuters greater than one standard deviation or changed categories between 2005 and 2012. For example, counties below the median Drive Percent in 2005 and above the median Drive Percent in 2017, counties above the median Drive Percent in 2005 and below the median drive percent in 2017, and counties in which Drive Percent changes more than one standard deviation are excluded from the regressions with Drive Category as the commuting variable of interest.[2] Finally, the fourth column includes only counties that did have significant changes in commuting characteristics over the course of the study period (i.e. the set of observations in Column 4 is the complement of the set of observations in Column 3). This column is included to test if differences in statistical significance between columns 1 and 3 are due to the decreased sample size, or if they are due to differences in the effect on an increase in employment on mortality rates in counties that had substantial changes in commuting characteristics during the study period. All tables present the marginal effects of a 1% increase in employment, and the p-value presented above the number of observations is from a test to determine if the difference in

[2]Standard deviation of the percent change between the 2005-2009 ACS and the 2013-2017 ACS is found in Table 3. In regressions where auto-dependence is the commuting category of interest, any county that had a change in auto-dependent commuters greater than 1.34 percentage points is excluded; in regressions regarding active commuting, any county with a change in active commuters greater than 0.70 percentage points is excluded; in regressions regarding public transportation use, any county with a change in transit users greater than 0.49 percentage points is excluded.

the marginal coefficients for counties with different commuting characteristics are statistically different from zero.

4.1.1 All-Cause Mortality

Table 6 shows the impact of a 1% increase in employment on all-cause mortality. Results in column 1 indicate an increase in employment significantly decreases all-cause mortality rates in *LowDrive*, *HighActive*, and *HighTransit* counties, while the same increase in employment is not associated with a statistically significant change in the mortality rate in *HighDrive*, *LowActive*, and *LowTransit* counties. More specifically, results in column 1 indicate a 1% increase in employment is associated with a 0.06% decrease in total mortality in *LowDrive* counties, a 0.08% decrease in total mortality in *HighActive* counties, and a 0.06% decrease in total mortality in *HighTransit* counties.

Using equation 3 and the coefficients in Table 6 column 1, these findings indicate that a 1% increase in employment is associated with 881 fewer deaths in *LowDrive* counties, 889 fewer deaths in *HighActive* counties, and 899 fewer deaths in *HighTransit* counties when all counties are included in the analysis. That said, when the sample is restricted to counties in the top and bottom quartile of each commuting characteristic (column 2) results are only significant at the 10% level. When the sample is restricted to counties that had little change in each commuting characteristic (column 3) there are some dramatic changes in the coefficients, and the coefficients for *LowDrive*, ad *HighTransit* become statistically insignificant. This raises questions about the robustness of these findings, and indicates counties in the middle quartiles of auto-dependence and public transportation use may be substantially different from those in the upper and lower quartiles of those commuting characteristics.

In column 2 the magnitude of the coefficients associated with a 1% increase in employment in $HighDrive$ and $LowTransit$ counties increase significantly and become much closer to the coefficients for $LowDrive$ and $HighTransit$ counties, which increase slightly, but are only significant at the 10% level. That said, the difference in the coefficients for $Drive$ and $Transit$ categories remains significant at the 5% level. These changes could be due to counties in the lower and upper quartile of each commuting characteristic differing in other important ways which effect changes in mortality. In column 3, only the coefficient for $HighActive$ counties is negative and signficant at the 10% level, and the coefficients associated with $HighDrive$ and $LowDrive$ become positive, and the magnitude of the coefficient for $LowTransit$ counties becomes greater than the magnitude of the coefficient for $HighTransit$ counties. These changes indicate that counties with relatively large changes in commuting characteristics may be driving the results found in column 1.

Table 7 shows the same analysis, with the sample restricted to counties that did not have restricted mortality data for transportation mortality, circulatory mortality, respiratory mortality, and suicide mortality to allow a straight-forward comparison of results decomposed by different mortality rates in following sections. Results when using the restricted sample are similar to those obtained from the unrestricted sample, although some of the coefficients change magnitude and sign in column 3. A comparison of results in columns 3 and 4 suggest that there are important and significant differences in the impact of an increase in employment in counties that saw a significant change in commuting characteristics throughout the study period, and those which had no significant changes. The difference between $HighDrive$ and $LowDrive$ counties remains significant in column 4 despite a dramatically reduced sample size, while it becomes insignificant in column 3, with similar results for the difference between $HighTransit$ and $LowTransit$ counties.

These results, where they are significant, show that an increase in employment is associated with a lower mortality rate in most cases, contradicting my first hypothesis that mortality will fluctuate procyclically. The results presented in column 1 of Tables 6 and 7 support my second hypothesis, that low levels of auto-dependence and high levels of active commuting and public transportation use amplify the positive effects of increases in employment on health outcomes. That said, it is important to note that the difference in the coefficients for $HighTransit$ and $LowTransit$ counties in Tables 6 and 7 are not statistically different from zero, with the exception of results presented in column 4, which only includes counties that had significant changes in commuting characteristics during the study period and explicitly violates the assumption of time invariant commuting characteristics made in the identification strategy.

Table 6: Marginal Effects of Increased Employment on All Cause Mortality by Commuting Category

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
log(employment)				
High Drive	0.00125	-0.0531*	0.0240	0.0355
	(0.0204)	(0.0307)	(0.0220)	(0.0387)
Low Drive	-0.0609**	-0.0766*	0.0161	-0.145***
	(0.0253)	(0.0430)	(0.0371)	(0.0397)
p(High Drive = Low Drive)	0.0252	0.608	0.842	0.000229
Observations	10256	5118	6719	3537

	(1)	(2)	(3)	(4)
log(employment)				
Low Active	-0.0112	0.0136	0.00302	-0.0658
	(0.0227)	(0.0281)	(0.0260)	(0.0501)
High Active	-0.0752***	-0.0766*	-0.0447*	-0.103**
	(0.0251)	(0.0405)	(0.0261)	(0.0455)
p(High Active = Low Active)	0.0223	0.0325	0.113	0.512
Observations	10256	5093	7628	2628

	(1)	(2)	(3)	(4)
log(employment)				
Low Transit	-0.0131	-0.0499	-0.0239	0.0933*
	(0.0231)	(0.0400)	(0.0251)	(0.0517)
High Transit	-0.0576**	-0.0679*	-0.00520	-0.0725*
	(0.0266)	(0.0373)	(0.0296)	(0.0423)
p(High Transit = Low Transit)	0.144	0.703	0.559	0.00502
Observations	10256	5080	7795	2461

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Marginal Effects of Increased Employment on All Cause Mortality by Commute Category, Restricted Sample

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
log(employment)				
High Drive	0.0148	-0.0321	-0.00540	0.0361
	(0.0307)	(0.0558)	(0.0322)	(0.0618)
Low Drive	-0.0747**	-0.0930	-0.0236	-0.161***
	(0.0316)	(0.0572)	(0.0427)	(0.0542)
p(High Drive = Low Drive)	0.0123	0.413	0.674	0.00430
Observations	4783	2241	3067	1716

	(1)	(2)	(3)	(4)
log(employment)				
Low Active	-0.0227	0.0238	-0.00390	-0.117
	(0.0317)	(0.0431)	(0.0354)	(0.0776)
High Active	-0.0965***	-0.112*	-0.0511	-0.155**
	(0.0351)	(0.0619)	(0.0359)	(0.0695)
p(High Active = Low Active)	0.0459	0.0278	0.212	0.606
Observations	4783	2039	3802	981

	(1)	(2)	(3)	(4)
log(employment)				
Low Transit	-0.00640	-0.0822	-0.0396	0.167***
	(0.0400)	(0.0690)	(0.0440)	(0.0448)
High Transit	-0.0749**	-0.0782*	-0.0307	-0.0961*
	(0.0328)	(0.0420)	(0.0377)	(0.0539)
p(High Transit = Low Transit)	0.114	0.956	0.832	0.00000328
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.1.2 Transportation Mortality

Table 8 shows the marginal effects of a 1% increase in employment on transportation mortality. Results in column 1 show a 1% increase in employment is associated with a statistically significant decrease of 0.23% in $HighDrive$ counties, which corresponds to 16 fewer deaths due to transportation accidents in the counties sampled. Results also indicate a 1% increase in employment is associated with a decrease of 0.149% in transportation mortality in $LowActive$ counties, which corresponds to 18 fewer deaths. Results in column 1 are insignificant for $LowDrive$ and $HighActive$ counties, and both transit categories. Results in column 2 show a 1% increase in employment is associated with a 0.34% decrease in transportation mortality in $LowTransit$ counties. All other marginal coefficients in column 2 are insignificant, and similar to the results found in column 1, although the coefficients for $LowDrive$ and $HighTransit$ switch signs and become positive. Results in column 3 are similar to those in column 2, with the only significant marginal coefficient being for $LowTransit$ counties. It is also notable that $High$ and Low categories are not statistically different from each other for all regressions with the exception of the difference between $HighTransit$ and $LowTransit$ in column 2.

Results in Table 8 contradict both of my main hypotheses. All significant coefficients are negative, indicating transportation mortality fluctuations counter-cyclically. Results also indicate that low levels of auto-dependence, high levels of public transportation use, and (if statistical significance is disregarded) high levels of active transportation all decrease the positive effects of increased employment on transportation mortality rates. This can potentially be explained by previous studies which have found that the dominant mechanism

Table 8: Marginal Effects of Increased Employment on Transportation Mortality by Commuting Category

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
log(employment)				
High Drive	-0.225**	-0.226	-0.235*	-0.284*
	(0.105)	(0.231)	(0.135)	(0.149)
Low Drive	-0.0472	0.116	0.0324	-0.220
	(0.0958)	(0.201)	(0.134)	(0.139)
p(High Drive = Low Drive)	0.161	0.270	0.114	0.706
Observations	4783	2241	3067	1716
	(1)	(2)	(3)	(4)
log(employment)				
Low Active	-0.149*	-0.147	-0.111	-0.496**
	(0.0873)	(0.127)	(0.0957)	(0.227)
High Active	-0.00767	-0.0208	0.0647	-0.204
	(0.121)	(0.197)	(0.136)	(0.233)
p(High Active = Low Active)	0.286	0.562	0.221	0.326
Observations	4783	2039	3802	981
	(1)	(2)	(3)	(4)
log(employment)				
Low Transit	-0.178	-0.340*	-0.276**	0.287
	(0.117)	(0.184)	(0.133)	(0.198)
High Transit	-0.0502	0.0363	-0.0917	0.0163
	(0.0905)	(0.138)	(0.144)	(0.178)
p(High Transit = Low Transit)	0.343	0.0600	0.248	0.254
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

behind procyclical traffic mortality is an increase in the risk of death per mile travelled, not an increase in the amount of exposure to traffic (e.g. Cotti & Tefft, 2011). If pedestrians and cyclists face a greater risk of being involved in an accident during economic expansions, this would likely increase the transportation mortality rate more in counties with a relatively high number of commuters who do not drive to work, given that pedestrians and cyclists are more vulnerable and have a higher risk of serious injury or death if they are struck by a vehicle.

4.1.3 Circulatory Mortality

Table 9 shows the marginal effects of a 1% increase in employment on circulatory mortality. The only coefficient statistically different from zero is the marginal coefficient associated with $LowTransit$ counties in column 2, which indicates a 1% increase in employment is associated with a 0.14% decrease in the circulatory mortality rate in $LowTransit$ counties. Generally, these results, along with the results presented in Table 5 show that there is no significant relationship between employment, means of transportation, and mortality rates. This is somewhat surprising, given that previous studies regarding the relationship between the business cycle and mortality rates have found circulatory mortality contributes significantly to the procyclical pattern in mortality found in previous research.

Table 9: Marginal Effects of Increased Employment on Circulatory Mortality by Commuting Category

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
log(employment)				
High Drive	-0.00331	-0.0636	-0.0128	0.00189
	(0.0517)	(0.0741)	(0.0571)	(0.108)
Low Drive	0.0107	-0.0628	0.0636	-0.0544
	(0.0476)	(0.0775)	(0.0630)	(0.0762)
p(High Drive = Low Drive)	0.814	0.994	0.283	0.624
Observations	4783	2241	3067	1716
	(1)	(2)	(3)	(4)
log(employment)				
Low Active	0.0342	0.0696	0.0452	-0.0590
	(0.0445)	(0.0555)	(0.0486)	(0.101)
High Active	-0.0448	-0.0557	-0.00636	-0.0924
	(0.0532)	(0.0848)	(0.0554)	(0.106)
p(High Active = Low Active)	0.162	0.138	0.376	0.783
Observations	4783	2039	3802	981
	(1)	(2)	(3)	(4)
log(employment)				
Low Transit	0.0127	-0.143*	-0.0407	0.147
	(0.0579)	(0.0829)	(0.0615)	(0.121)
High Transit	0.00271	0.0470	0.0117	-0.0703
	(0.0462)	(0.0674)	(0.0572)	(0.0762)
p(High Transit = Low Transit)	0.876	0.0465	0.433	0.0902
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.1.4 Respiratory Mortality

Table 10 shows the impact of a 1% increase in total employment on respiratory mortality rates. Column 1 shows an increase in employment is associated with a decrease in the respiratory mortality rate in *LowDrive* counties, *HighActive* and *HighTransit* categories, while the marginal coefficient for *HighDrive*, *LowActive*, and *LowTransit* counties are statistically insignificant. Results show a 1% increase in employment is associated with a 0.20% decrease in respiratory mortality in *LowDrive* counties, a 0.23% decrease in respiratory mortality in *HighActive* counties, and a 0.15% decrease in respiratory mortality in *HighTransit* categories. Using equation 3, these results indicate a 1% increase in employment is associated with 263 fewer deaths due to respiratory diseases in *LowDrive* counties, 258 fewer deaths due to respiratory diseases in *HighActive* counties, and 215 fewer deaths due to respiratory diseases in *HighTransit* counties. In column 2, the coefficients do not change significantly in magnitude, but the coefficient associated with *HighActive* counties loses statistical significant. In column 3, all coefficients lose statistical significance, and the coefficient for *HighTransit* changes sign.

Results in column 1 generally contradict the hypothesis that increased employment will be associated with increased mortality rates, but support my second hypothesis that having a low level of auto-dependence, a high level of active commuting, or a high level of public transportation use will increase positive health impacts of increased employment. That said, it is important to note that the difference in *HighTransit* and *LowTransit* coefficients is not statistically different than zero, and the difference between the *HighActive* and *LowActive* coefficients are only signficantly different from zero at the 10% level in column 1, while the

Table 10: Marginal Effects of Increased Employment on Respiratory Mortality by Commuting Category

	(1)	(2)	(3)	(4)
	Full Sample	Outer Quartiles	No Change	Significant Change
log(employment)				
High Drive	0.0507	0.0619	0.0296	0.0721
	(0.0872)	(0.0902)	(0.111)	(0.0916)
Low Drive	-0.198***	-0.203*	-0.0600	-0.471***
	(0.0654)	(0.119)	(0.0772)	(0.0975)
p(High Drive = Low Drive)	0.00941	0.0486	0.452	0.00000405
Observations	4783	2241	3067	1716
	(1)	(2)	(3)	(4)
log(employment)				
Low Active	-0.0669	0.0620	-0.0144	-0.222
	(0.0692)	(0.108)	(0.0783)	(0.164)
High Active	-0.233***	-0.168	-0.174*	-0.257**
	(0.0841)	(0.143)	(0.104)	(0.103)
p(High Active = Low Active)	0.0623	0.128	0.125	0.828
Observations	4783	2039	3802	981
	(1)	(2)	(3)	(4)
log(employment)				
Low Transit	-0.0858	0.00775	-0.0574	-0.120
	(0.0674)	(0.144)	(0.0773)	(0.126)
High Transit	-0.150*	-0.199**	0.0153	-0.264**
	(0.0820)	(0.101)	(0.101)	(0.124)
p(High Transit = Low Transit)	0.476	0.180	0.443	0.346
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

difference between the $HighDrive$ and $LowDrive$ coefficients are significantly different from zero in columns 1, 2, and 4.

4.1.5 Suicide Mortality

Table 11 shows the marginal effect of a 1% increase in total employment on suicide mortality. Results in column 1 indicate that an increase in total employment decreases suicide mortality in $LowDrive$, and $HighTransit$ counties, with not significant effect in $HighDrive$ and $LowTransit$ communities. Results also show an increase in employment is associated with decreases in suicide in both $LowActive$ and $HighActive$ counties, although the magnitude of the coefficient is higher in $HighActive$ counties. More specifically, a 1% increase in employment is associated with a 0.34% decrease in suicide mortality in $LowDrive$ counties, a 0.29% decrease in suicide mortality in $HighActive$ counties, and a 0.36% decrease in suicide mortality in $HighTransit$ counties. Using equation 3, this implies a 1% increase in employment is associated with 79 fewer suicides in $LowDrive$ drive counties, 54 fewer suicides in $HighActive$ counties, and 90 fewer suicides in $HighTransitCounties$. Results in column 2 are generally consistent with column 1, although the marginal coefficient for $HighActive$ counties is only significant at the 10% level, and the marginal coefficient associated with $LowActive$ counties loses its significance. It is important to note the differences between the $HighActive$ and $LowActive$ coefficients are not statistically different in any of the results for suicide mortality, while the difference between the $HighDrive$ and $LowDrive$ coefficients are statistically signficant at the 5% level in columns 1, 3 and 4, and the difference between the $HighTransit$ and $LowTransit$ coefficients are statistically significant at the 5% level in columns 1, 2 and 3.

Table 11: Marginal Effects of Increased Employment on Suicide Mortality by Commuting Category

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
log(employment)				
High Drive	0.0456	-0.117	-0.0759	0.229
	(0.122)	(0.165)	(0.116)	(0.266)
Low Drive	-0.336***	-0.293**	-0.332***	-0.338***
	(0.0744)	(0.123)	(0.0900)	(0.125)
p(High Drive = Low Drive)	0.00159	0.337	0.0383	0.0267
Observations	4783	2241	3067	1716
	(1)	(2)	(3)	(4)
log(employment)				
Low Active	-0.189**	-0.107	-0.218**	0.0988
	(0.0857)	(0.151)	(0.0944)	(0.227)
High Active	-0.290***	-0.435**	-0.351***	-0.172
	(0.109)	(0.193)	(0.125)	(0.177)
p(High Active = Low Active)	0.382	0.120	0.300	0.279
Observations	4783	2039	3802	981
	(1)	(2)	(3)	(4)
log(employment)				
Low Transit	-0.00140	-0.0477	0.0749	-0.264
	(0.114)	(0.164)	(0.131)	(0.167)
High Transit	-0.364***	-0.485***	-0.223**	-0.493***
	(0.0787)	(0.110)	(0.111)	(0.143)
p(High Transit = Low Transit)	0.00208	0.0107	0.0199	0.233
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This is perhaps the least surprising result presented, as previous studies regarding the relationship between suicide mortality and the business cycle have consistently shown suicide mortality fluctuates counter cyclically. This is likely due to the increased financial and emotional stress associated with being jobless. Results also support my second hypothesis that high levels of auto-dependence, low levels of active commuting, and low levels of public transportation use will attenuate any positive impacts of employment growth.

4.2 Results using the Unemployment Rate

Although I use the natural log of total employment as a proxy for the business cycle, and as a source of exogenous variation in the amount of commuting in a given county, previous studies regarding the impact of the business cycle on mortality rates generally use the unemployment rate as a measurement of the business cycle. Results using the unemployment rate in place of the natural log of total mortality are presented in the Appendix (Section 6.2). As opposed to results using total employment as a business cycle indicator which generally show counter-cyclical variation in mortality rates, results using the unemployment rate as a business cycle indicator show all types of mortality examined except suicide fluctuate procyclically. These results are similar to those of previous studies that have found mortality rates fluctuate procyclically.

Coefficients in Table 16 indicate a 1 percentage point increase in the unemployment rate is associated with a 0.3% decrease in the all-cause mortality rate. Decomposition of this result by cause of death indicates a 1 percentage point increase in the unemployment rate is associated with a 2.4% decrease in the transportation mortality rate, a 0.3% decrease in circulatory and respiratory mortality rates, and a 1.1% increase in the suicide mortality rate. The apparent contradiction between results using the unemployment rate and total employment as a proxy for the business cycle can potentially be explained by variations in the labor force, as the total employment and the unemployment rate can increase simultaneously if there is a large enough increase in the labor force.

Given that this study uses business cycle fluctuations as a source of variation in the total amount of commuting in a county, using total employment as a proxy for the business cycle has a number of advantages. First and foremost, changes in total employment are a more direct representation of a change in the total number of commuters, and is not dependent on total labor force fluctuations. Secondly, in the medium to long term, total employment has cyclical fluctuations and secular trends as populations grow and migrate. This makes information about the relationship between total employment and mortality rates more useful to policy makers, who can use information about a county's demographic composition to infer the impact of promoting alternative commuting methods on future mortality rates. Knowledge about the relationship between the unemployment rate and mortality rates are less useful in this context, as the linear nature of the results imply that any changes in mortality rates during an economic expansion would be reversed during the next economic contraction.

5 Conclusion

Generally, this study reveals important differences between counties with different commuting characteristics regarding the relationship between employment and mortality rates.

All-cause mortality is shown to decrease with an increase in total employment, which raises some questions about the assumptions made by previous studies that find mortality fluctuates procyclically. Total employment and the unemployment rate can move in the same direction at times, but these results suggest that increases in total employment are not the primary mechanism driving the relationship between the unemployment rate and the business cycle. Findings also show that an increase in employment is associated with a greater decrease in all-cause mortality in counties with a below median proportion of auto-dependent commuters, and an above median proportion of active commuters and public transportation users. These findings indicate that investment in infrastructure and campaigns to decrease the use of personal auto-mobiles, and increase active commuting and public transportation use can amplify the benefits and attenuate adverse impacts of increased employment on public health.

Decomposition of this effect by mortality type shows this effect is not driven by transportation or circulatory mortality rates, where results indicate either no significant relationship between changes in employment, commuting characteristics, and mortality rates, or show results that contradict findings for the all-cause mortality. Results for respiratory mortality, and suicide mortality are similar to those for all-cause mortality, but not large enough to fully explain the difference between commuting categories found for all-cause mortality. It is notable that findings are generally not robust to the exclusion of counties with significant changes in commuting characteristics during the study period, and the use of counties in the upper and lower quartile of each commuting category. This indicates that counties with significant changes in commuting characteristics during the study period may be primary drivers of the benefits of low auto-dependence, high active transportation rates, and high public transit use found by this study. It also indicates there may be important differences between counties with very high and very low proportions of each type of transportation and those closer to the median that impacts the relationship between employment, transportation characteristics, and mortality rates.

Results presented in this study are plausibly causal, and indicate that a 1% increase in employment is associated with 881 fewer deaths in counties with a below-median proportion of commuters that drive to work, while the same increase in employment is associated with (a statistically insignificant) increase of 14 deaths in counties with a high proportion of auto-dependent commuters. That said, there are reasons to be skeptical about interpreting these results as a causal estimation of the impact of commuting characteristics on mortality rates. First, the identification strategy depends on the assumption that there are no omitted time variant endogenous variables that affect the relationship between employment and mortality rates. Any omitted variables would be particularly troublesome if they impacted the relationship between employment and mortality rates differently in counties with different commuting characteristics. While I did control for the more obvious potentially confounding variables, like demographics, population density, and median income, I cannot guarantee that other unobserved community characteristics did not impact the results of this study. Somewhat worrying in this context is the finding in Table 5 that in increase in median income is associated with an increase in all-cause mortality rates. Given the unlikelihood that in an increase in income is associated with increased mortality rates when controlling for factors like age and educational demographics, this could indicate an unobserved endogenous variable is impacting the results of the model. Another key assumption in the model is that commuting characteristics are time invariant. This assumption is called into question by summary statistics, and the differing results between regressions that include counties with potentially problematic time variance in commuting characteristics, and those which exclude those counties from the regression.

In order to confirm the results of this study, future research could focus on the impact of the installation of pedestrian and cyclist friendly infrastructure, or the implementation of policies like free bus fare on mortality rates and other health outcomes. The results of this study suggest the health benefits of active commuting are generally larger and more consistent than those associated with public transportation use. If this finding is confirmed by future research, it would indicate that policy makers can create public health benefits by passing zoning laws which allow and encourage denser, more pedestrian and cyclist friendly neighborhoods without the expense of public transportation services.

6 Appendix

6.1 Detailed Summary Statistics

Table 12: Summary Statistics for Control Variables

	mean	sd	count
Under 10	12.8	1.9	10421
Age 10-19	13.76	1.6	10421
Age 20-29	13.9	3.6	10421
Age 30-39	12.7	1.6	10421
Age 40-49	13.7	1.8	10421
Age 50-59	13.6	1.5	10421
Age 60-69	10.1	2.3	10421
Age 70-79	5.9	1.8	10421
White	83.1	14.2	10421
Black	11.9	12.7	10421
Other	5.1	7.6	10421
No High School	4.8	3.2	10332
High School Dropout	8.1	3.1	10332
Some College	21.6	3.9	10332
College Graduate	35.6	10.1	10332
Population Density	834.3	3375.6	10421

Table 13: Summary Statistics for Mortality Rates in 2005 & 2017

	2005	2017
Total Mortality Rate	847.0	924.2
	(214.1)	(235.6)
Circulatory Mortality Rate	291.7	275.8
	(87.16)	(81.93)
Respiratory Mortality Rate	85.50	95.33
	(26.67)	(33.06)
Cancer Mortality Rate	199.4	200.7
	(50.55)	(50.68)
Suicide Mortality Rate	12.40	16.80
	(4.745)	(6.177)
Traffic Mortality Rate	18.48	15.19
	(8.570)	(8.076)
Infections Mortality Rate	24.69	24.60
	(10.44)	(8.987)

Note: Means reported, standard deviation in parentheses

Table 14: Summary Statistics for Mortality Rates by Commuting Category

	Low Drive	High Drive	Low Active	High Active	Low Transit	High Transit
Total Mortality Rate	778.8	906.9	833.9	824.6	893.2	799.0
	(201.5)	(206.3)	(228.0)	(196.6)	(236.8)	(193.2)
Circulatory Mortality Rate	242.6	280.3	257.4	257.5	274.2	249.6
	(73.53)	(77.06)	(83.44)	(70.48)	(86.57)	(70.95)
Respiratory Mortality Rate	73.30	92.07	82.77	78.64	92.52	75.09
	(23.91)	(25.74)	(28.11)	(24.22)	(29.65)	(22.49)
Cancer Mortality Rate	183.2	206.6	193.7	191.1	205.7	186.1
	(48.70)	(47.88)	(54.15)	(44.90)	(58.19)	(43.77)
Suicide Mortality Rate	12.71	15.12	14.09	13.23	16.53	12.30
	(4.966)	(4.606)	(4.646)	(5.233)	(5.187)	(4.232)
Traffic Mortality Rate	11.20	15.68	14.30	11.65	17.04	11.04
	(5.067)	(5.749)	(5.863)	(5.374)	(6.350)	(4.298)
Infections Mortality Rate	22.02	24.54	22.58	23.44	23.11	22.97
	(9.401)	(7.954)	(7.711)	(9.991)	(7.775)	(9.447)

Note: Means reported, standard deviation in parentheses

Table 15: Comparison of Control Variable Means by Commuting Category

	(1)	(2)	(3)
Age Under 20	-0.613***	1.292***	0.275***
	(0.000)	(0.000)	(0.000)
Age 20-49	1.431***	-1.236***	-2.234***
	(0.000)	(0.000)	(0.000)
Age 50-59	-0.287***	0.210***	0.238***
	(0.000)	(0.000)	(0.000)
Age 60-79	-0.620***	0.191*	1.654***
	(0.000)	(0.013)	(0.000)
Age Over 80	0.0892***	-0.457***	0.0665**
	(0.000)	(0.000)	(0.004)
White	-1.286***	-1.329***	6.593***
	(0.000)	(0.000)	(0.000)
Black	-2.903***	3.463***	-3.847***
	(0.000)	(0.000)	(0.000)
Other	4.190***	-2.134***	-2.746***
	(0.000)	(0.000)	(0.000)
Less than HS	-2.053***	1.376***	1.740***
	(0.000)	(0.000)	(0.000)
Some College	-0.852***	1.138***	1.295***
	(0.000)	(0.000)	(0.000)
College Graduate	8.606***	-3.598***	-8.241***
	(0.000)	(0.000)	(0.000)
Population Density	994.0***	-746.8***	-1188.0***
	(0.000)	(0.000)	(0.000)
Median Income	2627.3***	1351.1***	-3425.7***
	(0.000)	(0.000)	(0.000)
Observations	10434	10434	10434

Mean difference reported ($LowCommute - HighCommute$)
p value in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

6.2 Regressions using Unemployment Rate

Table 16: Full Specification Without Commuting Characteristics

	(1) All-Cause	(2) Traffic	(3) Circulatory	(4) Respiratory	(5) Suicide
Unemployment Rate	-0.00320***	-0.0242***	-0.00307***	-0.00266*	0.0109***
	(0.000530)	(0.00368)	(0.000929)	(0.00138)	(0.00276)
Age Under 20	-0.0785***	0.00471	-0.117***	-0.0889***	-0.00402
	(0.00876)	(0.0184)	(0.00955)	(0.0149)	(0.0176)
Age 20-49	-0.0863***	0.0259	-0.118***	-0.115***	-0.0110
	(0.00900)	(0.0188)	(0.00967)	(0.0148)	(0.0176)
Age 50-59	-0.0729***	0.0282	-0.111***	-0.0861***	0.00194
	(0.00996)	(0.0203)	(0.0110)	(0.0164)	(0.0202)
Age 60-79	-0.0600***	0.0189	-0.102***	-0.0885***	0.00362
	(0.00945)	(0.0206)	(0.0102)	(0.0161)	(0.0197)
Black	0.00606***	-0.00302	0.00743***	0.00178	0.00203
	(0.00143)	(0.00479)	(0.00188)	(0.00317)	(0.00508)
Other	-0.00588***	-0.00984	-0.00318	-0.0273***	-0.00631
	(0.00204)	(0.00664)	(0.00280)	(0.00616)	(0.00732)
Less than HS	-0.000512	-0.00511**	0.000346	-0.00353***	0.000512
	(0.000421)	(0.00237)	(0.000707)	(0.00114)	(0.00252)
Some College	-0.0000517	-0.00545**	-0.0000558	0.000569	-0.000723
	(0.000363)	(0.00215)	(0.000572)	(0.000897)	(0.00209)
College Graduate	-0.00101***	-0.00671***	-0.00129**	-0.000365	-0.00142
	(0.000369)	(0.00192)	(0.000573)	(0.000923)	(0.00196)
Population Density	-5.241***	-5.119***	-6.452***	-4.837*	-3.744*
	(0.844)	(1.821)	(1.077)	(2.623)	(2.131)
log(Median Income)	0.0281**	0.0834	0.0161	-0.0487*	0.212***
	(0.0123)	(0.0633)	(0.0188)	(0.0288)	(0.0602)
Constant	14.07***	0.682	16.59***	14.78***	0.787
	(0.880)	(1.820)	(0.969)	(1.452)	(1.764)
Observations	10256	6023	10256	10256	5747

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Marginal Effects of Unemployment Rate on All Cause Mortality

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
Unemployment Rate				
High Drive	-0.00158**	-0.00600***	-0.00281***	0.000748
	(0.000750)	(0.000666)	(0.000876)	(0.00130)
Low Drive	-0.00212***	-0.00689***	-0.00338***	0.0000763
	(0.000717)	(0.000572)	(0.000802)	(0.00136)
p(High Drive = Low Drive)	0.209	0.210	0.250	0.407
Observations	4783	2241	3067	1716
	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Active	-0.00195***	-0.00130	-0.00254***	0.0000727
	(0.000706)	(0.00110)	(0.000726)	(0.00190)
High Active	-0.00198**	-0.00198	-0.00253***	-0.0000789
	(0.000774)	(0.00132)	(0.000800)	(0.00185)
p(High Active = Low Active)	0.950	0.340	0.989	0.908
Observations	4783	2039	3802	981
	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Transit	-0.00131*	-0.00194*	-0.00137*	-0.00412**
	(0.000746)	(0.00117)	(0.000795)	(0.00163)
High Transit	-0.00231***	-0.00257***	-0.00294***	-0.00274**
	(0.000731)	(0.000951)	(0.000786)	(0.00132)
p(High Transit = Low Transit)	0.0450	0.481	0.00270	0.291
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Marginal Effects of Unemployment Rate on Transportation Mortality

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
Unemployment Rate				
High Drive	-0.0192***	-0.0194***	-0.0202***	-0.0172***
	(0.00490)	(0.00601)	(0.00658)	(0.00646)
Low Drive	-0.0285***	-0.0342***	-0.0309***	-0.0237***
	(0.00433)	(0.00286)	(0.00570)	(0.00661)
p(High Drive = Low Drive)	0.0100	0.0245	0.0241	0.191
Observations	4783	2241	3067	1716
	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Active	-0.0251***	-0.0220***	-0.0305***	0.000980
	(0.00468)	(0.00747)	(0.00442)	(0.0137)
High Active	-0.0267***	-0.0290***	-0.0309***	-0.00851
	(0.00435)	(0.00727)	(0.00468)	(0.00953)
p(High Active = Low Active)	0.647	0.235	0.895	0.301
Observations	4783	2039	3802	981
	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Transit	-0.0193***	-0.0210***	-0.0166***	-0.0352***
	(0.00495)	(0.00634)	(0.00577)	(0.00904)
High Transit	-0.0291***	-0.0303***	-0.0271***	-0.0353***
	(0.00436)	(0.00735)	(0.00550)	(0.00730)
p(High Transit = Low Transit)	0.0108	0.0503	0.0151	0.997
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 19: Marginal Effects of Unemployment Rate on Circulatory Mortality

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
Unemployment Rate				
High Drive	-0.00212	-0.00864***	-0.00298*	-0.000786
	(0.00134)	(0.00128)	(0.00167)	(0.00228)
Low Drive	-0.00299**	-0.0110***	-0.00471***	-0.000249
	(0.00126)	(0.00102)	(0.00157)	(0.00196)
p(High Drive = Low Drive)	0.347	0.108	0.113	0.765
Observations	4783	2241	3067	1716

	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Active	-0.00306**	-0.00318*	-0.00389***	0.000923
	(0.00124)	(0.00188)	(0.00132)	(0.00334)
High Active	-0.00212	-0.00186	-0.00264*	0.0000415
	(0.00130)	(0.00203)	(0.00138)	(0.00330)
p(High Active = Low Active)	0.269	0.337	0.165	0.737
Observations	4783	2039	3802	981

	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Transit	-0.00240*	-0.00335	-0.00301*	-0.000163
	(0.00141)	(0.00250)	(0.00159)	(0.00357)
High Transit	-0.00291**	-0.00439**	-0.00439***	0.0000740
	(0.00126)	(0.00186)	(0.00145)	(0.00221)
p(High Transit = Low Transit)	0.642	0.622	0.232	0.944
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 20: Marginal Effects of Unemployment Rate on Respiratory Mortality

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
Unemployment Rate				
High Drive	-0.00112	-0.00655***	-0.00362	0.00360
	(0.00194)	(0.00182)	(0.00222)	(0.00377)
Low Drive	-0.000243	-0.00606***	-0.00353	0.00587
	(0.00192)	(0.00148)	(0.00220)	(0.00368)
p(High Drive = Low Drive)	0.530	0.818	0.952	0.443
Observations	4783	2241	3067	1716
	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Active	-0.000457	0.000931	-0.00136	0.00470
	(0.00185)	(0.00295)	(0.00191)	(0.00534)
High Active	-0.000593	0.00127	-0.000397	-0.00174
	(0.00207)	(0.00382)	(0.00226)	(0.00421)
p(High Active = Low Active)	0.920	0.889	0.523	0.0950
Observations	4783	2039	3802	981
	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Transit	-0.000559	-0.00140	-0.00150	-0.00198
	(0.00187)	(0.00313)	(0.00204)	(0.00460)
High Transit	-0.000476	0.000662	-0.00301	0.00273
	(0.00198)	(0.00288)	(0.00213)	(0.00414)
p(High Transit = Low Transit)	0.953	0.418	0.317	0.272
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 21: Marginal Effects of Unemployment Rate on Suicide Mortality

	(1) Full Sample	(2) Outer Quartiles	(3) No Change	(4) Significant Change
Unemployment Rate				
High Drive	0.00856***	0.00265	0.00954**	0.00757
	(0.00323)	(0.00325)	(0.00398)	(0.00527)
Low Drive	0.0137***	0.00900***	0.0141***	0.0131**
	(0.00320)	(0.00222)	(0.00368)	(0.00590)
p(High Drive = Low Drive)	0.0248	0.0650	0.109	0.174
Observations	4783	2241	3067	1716

	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Active	0.0116***	0.0124**	0.0116***	0.0124*
	(0.00307)	(0.00514)	(0.00347)	(0.00634)
High Active	0.0132***	0.0178***	0.0129***	0.0151**
	(0.00339)	(0.00612)	(0.00389)	(0.00608)
p(High Active = Low Active)	0.471	0.112	0.593	0.525
Observations	4783	2039	3802	981

	(1)	(2)	(3)	(4)
Unemployment Rate				
Low Transit	0.0101***	0.00668	0.00842**	0.0105
	(0.00320)	(0.00487)	(0.00359)	(0.00702)
High Transit	0.0133***	0.0118**	0.0105***	0.0158***
	(0.00323)	(0.00471)	(0.00367)	(0.00607)
p(High Transit = Low Transit)	0.158	0.130	0.431	0.375
Observations	4783	2482	3404	1379

All models include county fixed-effects. Robust standard errors in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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